

Chapter 8

Classification: Basic Concepts

8.1 Bibliographic Notes

Classification is fundamental topic in machine learning, statistics, and pattern recognition. Many textbooks from these fields highlight classification methods, such as Mitchell [Mit97], Bishop [Bis06], Duda, Hart, and Stork [DHS01], Theodoridis and Koutroumbas [TK08], Hastie, Tibshirani, and Friedman [HTF09], Alpaydin [Alp11], and Marsland [Mar09].

For decision tree induction, the C4.5 algorithm is described in a book by Quinlan [Qui93]. The CART system is detailed in *Classification and Regression Trees* by Breiman, Friedman, Olshen, and Stone [BFOS84]. Both books give an excellent presentation of many of the issues regarding decision tree induction. C4.5 has a commercial successor, known as C5.0, which can be found at www.rulequest.com. ID3, a predecessor of C4.5, is detailed in Quinlan [Qui86]. It expands on pioneering work on concept learning systems, described by Hunt, Marin, and Stone [HMS66]. Other algorithms for decision tree induction include FACT (Loh and Vanichsetakul [LV88]), QUEST (Loh and Shih [LS97]), PUBLIC (Rastogi and Shim [RS98]), and CHAID (Kass [Kas80] and Magidson [Mag94]). INFERULE (Uthurusamy, Fayyad, and Spangler [UFS91]) learns decision trees from inconclusive data, where probabilistic rather than categorical classification rules are obtained. KATE (Manago and Kodratoff [MK91]) learns decision trees from complex structured data. Incremental versions of ID3 include ID4 (Schlimmer and Fisher [SF86]) and ID5 (Utgoff [Utg88]), the latter of which is extended in Utgoff, Berkman, and Clouse [UBC97]. An incremental version of CART is described in Crawford [Cra89]. BOAT (Gehrke, Ganti, Ramakrishnan, and Loh [GGR99]), a decision tree algorithm that addresses the scalability issue in data mining, is also incremental. Other decision tree algorithms that address scalability include SLIQ (Mehta, Agrawal, and Rissanan [MAR96]), SPRINT (Shafer, Agrawal, and Mehta [SAM96]), RainForest

(Gehrke, Ramakrishnan, and Ganti [GRG98]), and earlier approaches, such as Catlet [Cat91] and Chan and Stolfo [CS93a, CS93b]. For a comprehensive survey of many salient issues relating to decision tree induction, such as attribute selection and pruning, see Murthy [Mur98]. Perception Based Classification (PBC), a visual and interactive approach to decision tree construction, is presented in Ankerst, Elsen, Ester, and Kriegel [AEEK99].

For a detailed discussion on attribute selection measures, see Kononenko and Hong [KH97]. Information gain was proposed by Quinlan [Qui86] and is based on pioneering work on information theory by Shannon and Weaver [SW49]. The gain ratio, proposed as an extension to information gain, is described as part of C4.5 [Qui93]. The Gini index was proposed for CART [BFOS84]. The G-statistic, based on information theory, is given in Sokal and Rohlf [SR81]. Comparisons of attribute selection measures include Buntine and Niblett [BN92], Fayyad and Irani [FI92], Kononenko [Kon95], Loh and Shih [LS97], and Shih [Shi99]. Fayyad and Irani [FI92] show limitations of impurity-based measures such as information gain and Gini index. They propose a class of attribute selection measures called C-SEP (Class SEParation), which outperform impurity-based measures in certain cases. Kononenko [Kon95] notes that attribute selection measures based on the minimum description length principle have the least bias toward multi-valued attributes. Martin and Hirschberg [MH95] proved that the time complexity of decision tree induction increases exponentially with respect to tree height in the worst case, and under fairly general conditions in the average case. Fayyad and Irani [FI90] found that shallow decision trees tend to have many leaves and higher error rates for a large variety of domains. Attribute (or feature) construction is described in Liu and Motoda [LM98, Le98].

There are numerous algorithms for decision tree pruning, including cost complexity pruning (Breiman, Friedman, Olshen, and Stone [BFOS84]), reduced error pruning (Quinlan [Qui87]), and pessimistic pruning (Quinlan [Qui86]). PUBLIC (Rastogi and Shim [RS98]) integrates decision tree construction with tree pruning. MDL-based pruning methods can be found in Quinlan and Rivest [QR89], Mehta, Agrawal, and Rissanen [MRA95], and Rastogi and Shim [RS98]. Other methods include Niblett and Bratko [NB86], and Hosking, Pednault, and Sudan [HPS97]. For an empirical comparison of pruning methods, see Mingers [Min89] and Malerba, Floriana, and Semeraro [MFS95]. For a survey on simplifying decision trees, see Breslow and Aha [BA97].

Thorough presentations of Bayesian classification can be found in Duda, Hart, and Stork [DHS01], Weiss and Kulikowski [WK91], and Mitchell [Mit97]. For an analysis of the predictive power of naïve Bayesian classifiers when the class conditional independence assumption is violated, see Domingos and Pazzani [DP96]. Experiments with kernel density estimation for continuous-valued attributes, rather than Gaussian estimation, have been reported for naïve Bayesian classifiers in John [Joh97].

There are several examples of rule-based classifiers. These include AQ15 (Hong, Mozetic, and Michalski [HMM86]), CN2 (Clark and Niblett [CN89]), ITRULE (Smyth and Goodman [SG92]), RISE (Domingos [Dom94]), IREP (Furnkranz and Widmer [FW94]), RIPPER (Cohen [Coh95]), FOIL (Quin-

lan and Cameron-Jones [Qui90, QCJ93]), and Swap-1 (Weiss and Indurkhy [WI98]). Rule-based classifiers that are based on frequent-pattern mining are described in Chapter 9. For the extraction of rules from decision trees, see Quinlan [Qui87, Qui93]. Rule refinement strategies that identify the most interesting rules among a given rule set can be found in Major and Mangano [MM95].

Issues involved in estimating classifier accuracy are described in Weiss and Kulikowski [WK91] and Witten and Frank [WF05]. Sensitivity, specificity, and precision are discussed in most information retrieval text books. For the F and F_β measures, see van Rijsbergen [vR90]. The use of stratified 10-fold cross-validation for estimating classifier accuracy is recommended over the holdout, cross-validation, leave-one-out (Stone [Sto74]) and bootstrapping (Efron and Tibshirani [ET93]) methods, based on a theoretical and empirical study by Kohavi [Koh95]. See Freedman, Pisani, and Purves [FPP07] for the confidence limits and statistical tests of significance. For ROC analysis, see Egan [Ega75], Swets [Swe88], and Vuk and Cuk [VC06]. Bagging is proposed in Breiman [Bre96]. Freund and Schapire [FS97] proposed AdaBoost. The boosting technique of has been applied to several different classifiers, including decision tree induction (Quinlan [Qui96]) and naïve Bayesian classification (Elkan [Elk97]). Friedman [Fri01] proposed the gradient boosting machine for regression. The ensemble technique of random forests is described by Breiman [Bre01]. Seni and Elder [SE10] proposed the Importance Sampling Learning Ensembles (ISLE) framework, which views bagging, Adaboost, random forests, and gradient boosting as special cases of a generic ensemble generation procedure. Friedman and Popescu [FB08, FP05] present Rule Ensembles, an ISLE-based model where the classifiers combined are composed of simple readable rules. Such ensembles were observed to have comparable or greater accuracy and greater interpretability. There are many online software packages for ensemble routines, including bagging, Adaboost, gradient boosting, and random forests. Studies on the class imbalance problem and/or cost-sensitive learning include Weiss [Wei04], Zhou and Liu [ZL06], Zapkowicz and Stephen [ZS02], Elkan [Elk01], and Domingos [Dom99].

The University of California at Irvine (UCI) maintains a Machine Learning Repository of data sets for the development and testing of classification algorithms. It also maintains a Knowledge Discovery in Databases (KDD) Archive, an online repository of large data sets that encompasses a wide variety of data types, analysis tasks, and application areas. For information on these two repositories, see www.ics.uci.edu/~mlearn/MLRepository.html and <http://kdd.ics.uci.edu>.

No classification method is superior over all others for all data types and domains. Empirical comparisons of classification methods include [Qui88, SMT91, BCP93, CM94, MST94, BU95], and [LLS00].

Bibliography

- [AEEK99] M. Ankerst, C. Elsen, M. Ester, and H.-P. Kriegel. Visual classification: An interactive approach to decision tree construction. In *Proc. 1999 Int. Conf. Knowledge Discovery and Data Mining (KDD'99)*, pages 392–396, San Diego, CA, Aug. 1999.
- [Alp11] E. Alpaydin. *Introduction to Machine Learning (2nd ed.)*. MIT Press, 2011.
- [BA97] L. A. Breslow and D. W. Aha. Simplifying decision trees: A survey. *Knowledge Engineering Review*, 12:1–40, 1997.
- [BCP93] D. E. Brown, V. Corruble, and C. L. Pittard. A comparison of decision tree classifiers with backpropagation neural networks for multimodal classification problems. *Pattern Recognition*, 26:953–961, 1993.
- [BFOS84] L. Breiman, J. Friedman, R. Olshen, and C. Stone. *Classification and Regression Trees*. Wadsworth International Group, 1984.
- [Bis06] C. M. Bishop. *Pattern Recognition and Machine Learning*. Springer, 2006.
- [BN92] W. L. Buntine and T. Niblett. A further comparison of splitting rules for decision-tree induction. *Machine Learning*, 8:75–85, 1992.
- [Bre96] L. Breiman. Bagging predictors. *Machine Learning*, 24:123–140, 1996.
- [Bre01] L. Breiman. Random forests. *Machine Learning*, 45:5–32, 2001.
- [BU95] C. E. Brodley and P. E. Utgoff. Multivariate decision trees. *Machine Learning*, 19:45–77, 1995.
- [Cat91] J. Catlett. *Megainduction: Machine Learning on Very large Databases*. Ph.D. Thesis, University of Sydney, 1991.
- [CM94] S. P. Curram and J. Mingers. Neural networks, decision tree induction and discriminant analysis: An empirical comparison. *J. Operational Research Society*, 45:440–450, 1994.

- [CN89] P. Clark and T. Niblett. The CN2 induction algorithm. *Machine Learning*, 3:261–283, 1989.
- [Coh95] W. Cohen. Fast effective rule induction. In *Proc. 1995 Int. Conf. Machine Learning (ICML'95)*, pages 115–123, Tahoe City, CA, July 1995.
- [Cra89] S. L. Crawford. Extensions to the CART algorithm. *Int. J. Man-Machine Studies*, 31:197–217, Aug. 1989.
- [CS93a] P. K. Chan and S. J. Stolfo. Experiments on multistrategy learning by metalearning. In *Proc. 2nd. Int. Conf. Information and Knowledge Management (CIKM'93)*, pages 314–323, Washington, DC, Nov. 1993.
- [CS93b] P. K. Chan and S. J. Stolfo. Toward multi-strategy parallel & distributed learning in sequence analysis. In *Proc. 1st Int. Conf. Intelligent Systems for Molecular Biology (ISMB'93)*, pages 65–73, Bethesda, MD, July 1993.
- [DHS01] R. O. Duda, P. E. Hart, and D. G. Stork. *Pattern Classification* (2nd ed.). John Wiley & Sons, 2001.
- [Dom94] P. Domingos. The RISE system: Conquering without separating. In *Proc. 1994 IEEE Int. Conf. Tools with Artificial Intelligence (TAI'94)*, pages 704–707, New Orleans, LA, 1994.
- [Dom99] P. Domingos. The role of Occam’s razor in knowledge discovery. *Data Mining and Knowledge Discovery*, 3:409–425, 1999.
- [DP96] P. Domingos and M. Pazzani. Beyond independence: Conditions for the optimality of the simple Bayesian classifier. In *Proc. 1996 Int. Conf. Machine Learning (ML'96)*, pages 105–112, Bari, Italy, July 1996.
- [Ega75] J. P. Egan. *Signal Detection Theory and ROC Analysis*. Academic Press, 1975.
- [Elk97] C. Elkan. Boosting and naive Bayesian learning. In *Technical Report CS97-557*, Department of Computer Science and Engineering, Univ. Calif. at San Diego, Sept. 1997.
- [Elk01] C. Elkan. The foundations of cost-sensitive learning. In *Proc. 17th Intl. Joint Conf. Artificial Intelligence (IJCAI'01)*, pages 973–978, 2001.
- [ET93] B. Efron and R. Tibshirani. *An Introduction to the Bootstrap*. Chapman & Hall, 1993.
- [FB08] J. Friedman and E. P. Bogdan. Predictive learning via rule ensembles. *Ann. Applied Statistics*, 2:916–954, 2008.

- [FI90] U. M. Fayyad and K. B. Irani. What should be minimized in a decision tree? In *Proc. 1990 Nat. Conf. Artificial Intelligence (AAAI'90)*, pages 749–754, AAAI/MIT Press, 1990.
- [FI92] U. M. Fayyad and K. B. Irani. The attribute selection problem in decision tree generation. In *Proc. 1992 Nat. Conf. Artificial Intelligence (AAAI'92)*, pages 104–110, AAAI/MIT Press, 1992.
- [FP05] J. Friedman and B. E. Popescu. Predictive learning via rule ensembles. In *Technical Report*, Department of Statistics, Standford University, 2005.
- [FPP07] D. Freedman, R. Pisani, and R. Purves. *Statistics (4th ed.)*. W. W. Norton & Co., 2007.
- [Fri01] J. H. Friedman. Greedy function approximation: A gradient boosting machine. *Ann. Statistics*, 29:1189–1232, 2001.
- [FS97] Y. Freund and R. E. Schapire. A decision-theoretic generalization of on-line learning and an application to boosting. *J. Computer and System Sciences*, 55:119–139, 1997.
- [FW94] J. Furnkranz and G. Widmer. Incremental reduced error pruning. In *Proc. 1994 Int. Conf. Machine Learning (ICML'94)*, pages 70–77, New Brunswick, NJ, 1994.
- [GGRL99] J. Gehrke, V. Ganti, R. Ramakrishnan, and W.-Y. Loh. BOAT—optimistic decision tree construction. In *Proc. 1999 ACM-SIGMOD Int. Conf. Management of Data (SIGMOD'99)*, pages 169–180, Philadelphia, PA, June 1999.
- [GRG98] J. Gehrke, R. Ramakrishnan, and V. Ganti. RainForest: A framework for fast decision tree construction of large datasets. In *Proc. 1998 Int. Conf. Very Large Data Bases (VLDB'98)*, pages 416–427, New York, NY, Aug. 1998.
- [HMM86] J. Hong, I. Mozetic, and R. S. Michalski. AQ15: Incremental learning of attribute-based descriptions from examples, the method and user’s guide. In *Report ISG 85-5, UIUCDCS-F-86-949*,, Department of Comp. Science, University of Illinois at Urbana-Champaign, 1986.
- [HMS66] E. B. Hunt, J. Marin, and P. T. Stone. *Experiments in Induction*. Academic Press, 1966.
- [HPS97] J. Hosking, E. Pednault, and M. Sudan. A statistical perspective on data mining. *Future Generation Computer Systems*, 13:117–134, 1997.
- [HTF09] T. Hastie, R. Tibshirani, and J. Friedman. *The Elements of Statistical Learning: Data Mining, Inference, and Prediction* (2nd ed.). Springer Verlag, 2009.

- [Joh97] G. H. John. *Enhancements to the Data Mining Process*. Ph.D. Thesis, Computer Science Department, Stanford University, 1997.
- [Kas80] G. V. Kass. An exploratory technique for investigating large quantities of categorical data. *Applied Statistics*, 29:119–127, 1980.
- [KH97] I. Kononenko and S. J. Hong. Attribute selection for modeling. *Future Generation Computer Systems*, 13:181–195, 1997.
- [Koh95] R. Kohavi. A study of cross-validation and bootstrap for accuracy estimation and model selection. In *Proc. 14th Joint Int. Conf. Artificial Intelligence (IJCAI'95)*, volume 2, pages 1137–1143, Montreal, Canada, Aug. 1995.
- [Kon95] I. Kononenko. On biases in estimating multi-valued attributes. In *Proc. 14th Joint Int. Conf. Artificial Intelligence (IJCAI'95)*, volume 2, pages 1034–1040, Montreal, Canada, Aug. 1995.
- [Le98] H. Liu and H. Motoda (eds.). *Feature Extraction, Construction, and Selection: A Data Mining Perspective*. Kluwer Academic, 1998.
- [LLS00] T.-S. Lim, W.-Y. Loh, and Y.-S. Shih. A comparison of prediction accuracy, complexity, and training time of thirty-three old and new classification algorithms. *Machine Learning*, 40:203–228, 2000.
- [LM98] H. Liu and H. Motoda. *Feature Selection for Knowledge Discovery and Data Mining*. Kluwer Academic, 1998.
- [LS97] W. Y. Loh and Y. S. Shih. Split selection methods for classification trees. *Statistica Sinica*, 7:815–840, 1997.
- [LV88] W. Y. Loh and N. Vanichsetakul. Tree-structured classification via generalized discriminant analysis. *J. American Statistical Association*, 83:715–728, 1988.
- [Mag94] J. Magidson. The CHAID approach to segmentation modeling: CHI-squared automatic interaction detection. In R. P. Bagozzi, editor, *Advanced Methods of Marketing Research*, pages 118–159. Blackwell Business, 1994.
- [MAR96] M. Mehta, R. Agrawal, and J. Rissanen. SLIQ: A fast scalable classifier for data mining. In *Proc. 1996 Int. Conf. Extending Database Technology (EDBT'96)*, pages 18–32, Avignon, France, Mar. 1996.
- [Mar09] S. Marsland. *Machine Learning: An Algorithmic Perspective*. Chapman and Hall/CRC, 2009.
- [MFS95] D. Malerba, E. Floriana, and G. Semeraro. A further comparison of simplification methods for decision tree induction. In D. Fisher and H. Lenz, editors, *Learning from Data: AI and Statistics*. Springer Verlag, 1995.

- [MH95] J. K. Martin and D. S. Hirschberg. The time complexity of decision tree induction. In *Technical Report ICS-TR 95-27*, Department of Information and Computer Science, Univ. California, Irvine, CA, Aug. 1995.
- [Min89] J. Mingers. An empirical comparison of pruning methods for decision-tree induction. *Machine Learning*, 4:227–243, 1989.
- [Mit97] T. M. Mitchell. *Machine Learning*. McGraw-Hill, 1997.
- [MK91] M. Manago and Y. Kodratoff. Induction of decision trees from complex structured data. In G. Piatetsky-Shapiro and W. J. Frawley, editors, *Knowledge Discovery in Databases*, pages 289–306. AAAI/MIT Press, 1991.
- [MM95] J. Major and J. Mangano. Selecting among rules induced from a hurricane database. *J. Intelligent Information Systems*, 4:39–52, 1995.
- [MRA95] M. Metha, J. Rissanen, and R. Agrawal. MDL-based decision tree pruning. In *Proc. 1995 Int. Conf. Knowledge Discovery and Data Mining (KDD'95)*, pages 216–221, Montreal, Canada, Aug. 1995.
- [MST94] D. Michie, D. J. Spiegelhalter, and C. C. Taylor. *Machine Learning, Neural and Statistical Classification*. Ellis Horwood, Chichester, UK, 1994.
- [Mur98] S. K. Murthy. Automatic construction of decision trees from data: A multi-disciplinary survey. *Data Mining and Knowledge Discovery*, 2:345–389, 1998.
- [NB86] T. Niblett and I. Bratko. Learning decision rules in noisy domains. In M. A. Brammer, editor, *Expert Systems '86: Research and Development in Expert Systems III*, pages 25–34. British Computer Society Specialist Group on Expert Systems, Dec. 1986.
- [QCJ93] J. R. Quinlan and R. M. Cameron-Jones. FOIL: A midterm report. In *Proc. 1993 European Conf. Machine Learning (ECML'93)*, pages 3–20, Vienna, Austria, 1993.
- [QR89] J. R. Quinlan and R. L. Rivest. Inferring decision trees using the minimum description length principle. *Information and Computation*, 80:227–248, Mar. 1989.
- [Qui86] J. R. Quinlan. Induction of decision trees. *Machine Learning*, 1:81–106, 1986.
- [Qui87] J. R. Quinlan. Simplifying decision trees. *Int. J. Man-Machine Studies*, 27:221–234, 1987.

- [Qui88] J. R. Quinlan. An empirical comparison of genetic and decision-tree classifiers. In *Proc. 1988 Int. Conf. Machine Learning (ICML'88)*, pages 135–141, Ann Arbor, MI, June 1988.
- [Qui90] J. R. Quinlan. Learning logic definitions from relations. *Machine Learning*, 5:139–166, 1990.
- [Qui93] J. R. Quinlan. *C4.5: Programs for Machine Learning*. Morgan Kaufmann, 1993.
- [Qui96] J. R. Quinlan. Bagging, boosting, and C4.5. In *Proc. 1996 Nat. Conf. Artificial Intelligence (AAAI'96)*, volume 1, pages 725–730, Portland, OR, Aug. 1996.
- [RS98] R. Rastogi and K. Shim. Public: A decision tree classifier that integrates building and pruning. In *Proc. 1998 Int. Conf. Very Large Data Bases (VLDB'98)*, pages 404–415, New York, NY, Aug. 1998.
- [SAM96] J. Shafer, R. Agrawal, and M. Mehta. SPRINT: A scalable parallel classifier for data mining. In *Proc. 1996 Int. Conf. Very Large Data Bases (VLDB'96)*, pages 544–555, Bombay, India, Sept. 1996.
- [SE10] G. Seni and J. F. Elder. *Ensemble Methods in Data Mining: Improving Accuracy Through Combining Predictions*. Morgan and Claypool, 2010.
- [SF86] J. C. Schlimmer and D. Fisher. A case study of incremental concept induction. In *Proc. 1986 Nat. Conf. Artificial Intelligence (AAAI'86)*, pages 496–501, Philadelphia, PA, 1986.
- [SG92] P. Smyth and R. M. Goodman. An information theoretic approach to rule induction. *IEEE Trans. Knowledge and Data Engineering*, 4:301–316, 1992.
- [Shi99] Y.-S. Shih. Families of splitting criteria for classification trees. *Statistics and Computing*, 9:309–315, 1999.
- [SMT91] J. W. Shavlik, R. J. Mooney, and G. G. Towell. Symbolic and neural learning algorithms: An experimental comparison. *Machine Learning*, 6:111–144, 1991.
- [SR81] R. Sokal and F. Rohlf. *Biometry*. Freeman, 1981.
- [Sto74] M. Stone. Cross-validatory choice and assessment of statistical predictions. *J. Royal Statistical Society*, 36:111–147, 1974.
- [SW49] C. E. Shannon and W. Weaver. *The mathematical theory of communication*. University of Illinois Press, 1949.
- [Swe88] J. Swets. Measuring the accuracy of diagnostic systems. *Science*, 240:1285–1293, 1988.

- [TK08] S. Theodoridis and K. Koutroumbas. *Pattern Recognition, 4th ed.* Academic Press, 2008.
- [UBC97] P. E. Utgoff, N. C. Berkman, and J. A. Clouse. Decision tree induction based on efficient tree restructuring. *Machine Learning*, 29:5–44, 1997.
- [UFS91] R. Uthurusamy, U. M. Fayyad, and S. Spangler. Learning useful rules from inconclusive data. In G. Piatetsky-Shapiro and W. J. Frawley, editors, *Knowledge Discovery in Databases*, pages 141–157. AAAI/MIT Press, 1991.
- [Utg88] P. E. Utgoff. An incremental ID3. In *Proc. Fifth Int. Conf. Machine Learning (ICML'88)*, pages 107–120, San Mateo, CA, 1988.
- [VC06] M. Vuk and T. Curk. ROC curve, lift chart and calibration plot. *Metodološki zvezki*, 3:89–108, 2006.
- [vR90] C. J. van Rijsbergen. *Information Retrieval*. Butterworth, 1990.
- [Wei04] G. M. Weiss. Mining with rarity: A unifying framework. *SIGKDD Explorations*, 6:7–19, 2004.
- [WF05] I. H. Witten and E. Frank. *Data Mining: Practical Machine Learning Tools and Techniques* (2nd ed.). Morgan Kaufmann, 2005.
- [WI98] S. M. Weiss and N. Indurkhya. *Predictive Data Mining*. Morgan Kaufmann, 1998.
- [WK91] S. M. Weiss and C. A. Kulikowski. *Computer Systems that Learn: Classification and Prediction Methods from Statistics, Neural Nets, Machine Learning, and Expert Systems*. Morgan Kaufman, 1991.
- [ZL06] Z.-H. Zhou and X.-Y. Liu. Training cost-sensitive neural networks with methods addressing the class imbalance problem. *IEEE Trans. on Knowledge and Data Engineering*, 18:63–77, 2006.
- [ZS02] N. Zapkowicz and S. Stephen. The class imbalance program: a systematic study. *Intelligence Data Analysis*, 6:429–450, 2002.