

Chapter 1

DATA MINING FOR INTRUSION DETECTION

A Critical Review

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Abstract Data mining techniques have been successfully applied in many different fields including marketing, manufacturing, process control, fraud detection, and network management. Over the past five years, a growing number of research projects have applied data mining to various problems in intrusion detection. This chapter surveys a representative cross section of these research efforts. Moreover, four characteristics of contemporary research are identified and discussed in a critical manner. Conclusions are drawn and directions for future research are suggested.

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1. Introduction

Intrusion detection is the process of monitoring and analyzing the events occurring in a computer system in order to detect signs of security problems (Bace, 2000). Over the past ten years, intrusion detection and other security technologies such as cryptography, authentication, and firewalls have increasingly gained in importance (Allen et al., 2000). However, intrusion detection is not yet a perfect technology (Lippmann et al., 2000; Allen et al., 2000). This has given data mining the opportunity to make several important contributions to the field of intrusion detection (cf. Section 3).

This chapter gives a critical account of the past five years of data mining research in intrusion detection. To this end, we begin by introducing

data mining basics in Section 2. Section 3 surveys a representative selection of research projects that used data mining to address problems in intrusion detection. In Section 4, we identify and discuss four characteristics of contemporary and past research efforts. This discussion leads to Section 5, where we suggest new directions for future research. Section 6 summarizes the chapter.

We have attempted to make this chapter as self-contained as possible. However, given the interdisciplinary nature of the topic, it was not possible to write complete introductions to both, intrusion detection and data mining. We assumed that the reader has an intrusion detection background, and consequently put more emphasis on data mining basics. Complementary to this chapter, there is an abundance of excellent introductory material to both intrusion detection (Bace, 2000; Allen et al., 2000; Debar et al., 2000) as well as data mining (Han and Kamber, 2000; Mannila et al., 2001; Berry and Linoff, 1997) that can be consulted if needed.

2. Data Mining Basics

Historically, the notion of finding useful patterns in data has been given a variety of names including data mining, knowledge discovery in databases, information harvesting, data archaeology, and data pattern analysis (Fayyad et al., 1996a; Han and Kamber, 2000). Moreover, there has been some confusion about how data mining relates to the fields machine learning and statistics (Mannila, 1996). In Subsection 2.1, we clarify the terminology and the link to related fields. Section 2.2 describes four well-known data mining techniques that have been extensively used in intrusion detection. Section 2.3 concludes the discussion by summarizing several open research challenges in the field of data mining.

2.1 Data Mining, KDD, and Related Fields

The term *data mining* is frequently used to designate the process of extracting useful information from large databases. In this chapter, we adopt a slightly different view, which is identical to the one expressed by Fayyad et al. (1996b, Chapter 1)¹. In this view, the term *knowledge discovery in databases (KDD)* is used to denote the process of extracting useful knowledge from large data sets. *Data mining*, by contrast, refers to one particular step in this process. Specifically, the data mining step applies so-called *data mining techniques* to extract patterns from the data. Additionally, it is preceded and followed by other KDD steps, which ensure that the extracted patterns actually correspond to

useful knowledge. Indeed, without these additional KDD steps, there is a high risk of finding meaningless or uninteresting patterns (Fayyad, 1998; Klemettinen et al., 1997; Stedman, 1997).

In other words, the KDD process uses data mining techniques along with any required pre- and post-processing to extract high-level knowledge from low-level data. In practice, the KDD process is interactive and iterative, involving numerous steps with many decisions being made by the user (Fayyad et al., 1996b, Chapter 2). Here, we broadly outline some of the most basic KDD steps:

- 1. Understanding the application domain:** First is developing an understanding of the application domain, the relevant background knowledge, and the specific goals of the KDD endeavor.
- 2. Data integration and selection:** Second is the integration of multiple (potentially heterogeneous) data sources and the selection of the subset of data that is relevant to the analysis task.
- 3. Data mining:** Third is the application of specific algorithms for extracting patterns from data.
- 4. Pattern evaluation:** Fourth is the interpretation and validation of the discovered patterns. The goal of this step is to guarantee that actual knowledge is being discovered.
- 5. Knowledge representation:** This step involves documenting and using the discovered knowledge.

We next turn to the link between data mining and the related disciplines of machine learning and statistics. To begin with, data mining extensively uses known techniques from machine learning, statistics, and other fields. Nevertheless, several differences between data mining and related fields have been identified in the literature (Mannila, 1996; Glymour et al., 1997; Fayyad et al., 1996a). Specifically, one of the most frequently cited characteristics of data mining is its focus on finding relatively simple, but interpretable models in an efficient and scalable manner.

In other words, data mining emphasizes the efficient discovery of simple, but understandable models that can be interpreted as interesting or useful knowledge. Thus, for example, neural networks — although a powerful modeling tool — are relatively difficult to understand compared to rules (Cohen, 1995), trees (Quinlan, 1986), sequential patterns (Rigoutsos and Floratos, 1998), or associations (Agrawal et al., 1993). As a consequence, neural networks are of less practical importance in

data mining. This should not come as a surprise. In fact, data mining is just a step in the KDD process. As such, it has to contribute to the overall goal of knowledge discovery. Clearly, only understandable patterns can qualify as “knowledge”. Hence the importance of understandability in data mining.

2.2 Some Data Mining Techniques

Data mining techniques essentially are pattern discovery algorithms. Some techniques such as association rules (Agrawal et al., 1993) are unique to data mining, but most are drawn from related fields such as machine learning or pattern recognition. In this section, we introduce four well-known data mining techniques that have been widely used in intrusion detection. A broader and more detailed treatment of data mining techniques can be found elsewhere (Han and Kamber, 2000; Mannila et al., 2001; Berry and Linoff, 1997).

A potential source of confusion is that different data mining techniques assume different input data representations. For example, association rules have historically been discussed under the assumption that the input data is represented as a set of transactions (Agrawal et al., 1993; Agrawal and Srikant, 1994). Later, association rule mining over relational databases has been investigated (Srikant and Agrawal, 1996; Miller and Yang, 1997). Depending on the input data representations (sets of transactions versus relational databases), the association rule concept is presented differently. A related problem is that there are many different ways to represent the same data set in a relational database (Elmasri and Navathe, 1994). So one might wonder whether all these representations are equally adequate for the purpose of data mining. To avoid issues of data representation, we next define a unified input data format, for which all subsequent data mining techniques will be described. In practice, the available input data does not necessarily follow this format. Then, it is the responsibility of the second KDD step (“Data integration and selection”, as defined on page 3) to transform the available data into the format required by the data mining techniques.

2.2.1 Association Rules. [...]

2.2.2 Frequent Episode Rules. [...]

2.2.3 Classification. [...]

2.2.4 Clustering. [...]

2.3 Research Challenges in Data Mining

In a recent paper, Smyth (2001) has identified research challenges in data mining. Three years earlier, a similar list had been compiled by different authors (Grossman et al., 1998). In this section, we summarize the subset of the research challenges that are of direct relevance to intrusion detection:

[...]

3. Data Mining Meets Intrusion Detection

The goal of intrusion detection is to detect security violations in information systems. Intrusion detection is a passive approach to security as it monitors information systems and raises alarms when security violations are detected. Examples of security violations include the abuse of privileges or the use of attacks to exploit software or protocol vulnerabilities.

Traditionally, intrusion detection techniques are classified into two broad categories: *misuse detection* and *anomaly detection* (Mounji, 1997, Chapter 2). Misuse detection works by searching for the traces or patterns of well-known attacks. Clearly, only known attacks that leave characteristic traces can be detected that way. Anomaly detection, on the other hand, uses a model of normal user or system behavior and flags significant deviations from this model as potentially malicious. This model of normal user or system behavior is commonly known as the *user or system profile*. A strength of anomaly detection is its ability to detect previously unknown attacks.

Additionally, intrusion detection systems (IDSs) are categorized according to the kind of input information they analyze. This leads to the distinction between *host-based* and *network-based* IDSs. Host-based IDSs analyze host-bound audit sources such as operating system audit trails, system logs, or application logs. Network-based IDSs analyze network packets that are captured on a network. More information on intrusion detection in general can be found, for example, in a recent book by Bace (2000).

In the past five years, a growing number of research projects have applied data mining to intrusion detection. Here, we survey a representative cross section of these projects. The intention of this survey is to give the reader a broad overview of the work that has been done at the intersection between intrusion detection and data mining. As a consequence, this section includes the most prominent projects in the field as well as some interesting niche projects that pursue less known

avenues. Specifically, our rationale for including the various projects into this survey is as follows:

- MADAM ID (cf. Section 3.1) is one of the first and, with almost a dozen conference and journal papers, certainly one of the best-known data mining projects in intrusion detection.
- In our eyes, ADAM (cf. Section 3.2) is the second most widely known and well-published project in the field.
- The clustering project of Section 3.3 is still very young and probably less known, but represents a novel and interesting research thrust.
- All of the above projects perform data mining on raw network data. In Section 3.4, we present three projects that apply data mining to intrusion detection alarms. This will broaden and balance our overview of the field.
- Section 3.5 rounds off this review and briefly mentions some of the other projects that we could not discuss in more detail.

3.1 MADAM ID

[...]

3.2 ADAM

[...]

3.3 Clustering of Unlabeled ID Data

[...]

3.4 Mining the Alarm Stream

[...]

3.5 Further Reading

In this section, we briefly survey other relevant work that has not yet been mentioned². *Wisdom & Sense* (Vaccaro and Liepins, 1989) is probably the earliest system that can be considered as being based on data mining. *Wisdom & Sense* is an anomaly detection system that mines association rules from historical audit data to represent normal behavior. Similarly, Teng et al. (1990) use a form of automatically learned frequent episode rules to represent normal user behavior. The idea of Lankewicz

and Benard (1991) is to cluster audit log records and to represent each cluster by a single “typical” audit record. These typical audit records form the model of normal behavior against which future audit records are compared. A similar idea has been pursued by Lane and Brodley (1999), who cluster attack-free shell command sequences and define the “cluster centers” to represent normal behavior. Subsequently, anomalous command sequences can be detected based on their distance to the cluster centers. Mukkamala et al. (1999) use data mining techniques to reduce the amount of audit data that needs to be maintained and analyzed for intrusion detection. Similar work in audit data reduction has been reported by Lam et al. (1996). Finally, there is a long list of research projects that have tried to model system call sequences by a variety of different models, including neural networks, hidden Markov models, as well as fixed and variable length patterns. The work by Warrander et al. (1999) and Debar et al. (1998) is representative of this thrust of research.

4. Observations on the State of the Art

This section makes the following four observations about contemporary data mining efforts in intrusion detection:

- Most research concentrates on the construction of operational IDSs, rather than on the discovery of new and fundamental insights into the nature of attacks and false positives.
- It is very common to focus on the data mining step, while the other KDD steps are largely ignored.
- Much research is based on strong assumptions that complicate practical application.
- Up to now, data mining in intrusion detection focuses on a small subset of the spectrum of possible applications.

In the following sections, these observations will be discussed in a critical manner.

4.1 Data Mining, but no Knowledge Discovery

[...]

4.2 Disregard of Other KDD Steps

[...]

4.3 Too Strong Assumptions

[...]

4.4 Narrow Scope of Research Activities

[...]

5. Future Research Directions

[...]

6. Summary

This chapter has reviewed the past five years of data mining in intrusion detection. Based on this review, we have made four observations about contemporary and past research efforts. Very briefly, we observed a focus on building operational IDSs, a disregard for the overall KDD process, the reliance on labeled high-quality training data, and the focus on a few, admittedly important problems. We have discussed these observations in a critical manner, which has lead us to the following recommendations for future research:

- Future projects should pay closer attention to the KDD process.
- Either more work should address the (semi-)automatic generation of high-quality labeled training data, or the existence of such data should no longer be assumed.
- Future projects should explore novel applications of data mining that do not fall into the categories feature selection and anomaly detection.
- To deal with some of the general challenges in data mining, it might be best to develop special-purpose solutions that are tailored to intrusion detection.

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Notes

1. Other authors also support this view (Mannila, 1996; Han and Kamber, 2000).
2. To avoid redundancy, we deliberately refrain from discussing the other papers in this volume.

References

- Agrawal, R., Imielinski, T., and Swami, A. (1993). Mining Associations between Sets of Items in Massive Databases. In *Proceedings of the ACM-SIGMOD 1993 International Conference on Management of Data*, pages 207–216.
- Agrawal, R. and Srikant, R. (1994). Fast Algorithms for Mining Association Rules. In *Proceedings of the 20th International Conference on Very Large Databases*, pages 487–499.
- Allen, J., Christie, A., Fithen, W., McHugh, J., Pickel, J., and Stoner, E. (2000). State of the Practice of Intrusion Detection Technologies. Technical report, Carnegie Mellon University. <http://www.cert.org/archive/pdf/99tr028.pdf>.
- Almgren, M., Debar, H., and Dacier, M. (2000). A Lightweight Tool for Detecting Web Server Attacks. In *Proceedings of the Network and Distributed System Security Symposium (NDSS'00)*, pages 157–170.
- Bace, R. (2000). *Intrusion Detection*. Macmillan Technical Publishing.
- Barbará, D., Couto, J., Jajodia, S., Popyack, L., and Wu, N. (2001a). ADAM: Detecting Intrusions by Data Mining. In *Proceedings of the IEEE Workshop on Information Assurance and Security*.
- Barbará, D., Wu, N., and Jajodia, S. (2001b). Detecting Novel Network Intrusions Using Bayes Estimators. In *Proceedings of the first SIAM International Conference on Data Mining (SDM'01)*.
- Berry, M. J. A. and Linoff, G. (1997). *Data Mining Techniques*. John Wiley and Sons, Inc.
- Brachman, R. J., Khabaza, T., Kloesgen, W., Piatetsky-Shapiro, G., and Simoudis, E. (1996). Mining Business Databases. *Communications of the ACM*, 39(11):42–48.
- Brejová, B., DiMarco, C., Vinar, T., and Hidalgo, S. (2000). Finding Patterns in Biological Sequences. Technical report, University of Waterloo.
- Brin, S., Motwani, R., Ullman, J., and Tsur, S. (1997). Dynamic Itemset Counting and Implication Rules for Market Basket Data. In *Proceedings of the ACM SIGMOD International Conference on Management of Data*, pages 255–264.

- Clifton, C. and Gengo, G. (2000). Developing Custom Intrusion Detection Filters Using Data Mining. In *Military Communications International Symposium (MILCOM2000)*.
- Cohen, W. W. (1995). Fast Effective Rule Induction. In *Proceedings 12th International Conference on Machine Learning*, pages 115–123.
- Dain, O. and Cunningham, R. K. (2001). Fusing Heterogeneous Alert Streams into Scenarios. In *Proceedings of the ACM CCS Workshop on Data Mining for Security Applications*.
- Debar, H., Dacier, M., Nassehi, M., and Wespi, A. (1998). Fixed vs. Variable-Length Patterns for Detecting Suspicious Process Behavior. In *Proceedings of the 5th European Symposium on Research in Computer Security*, pages 1–15.
- Debar, H., Dacier, M., and Wespi, A. (2000). A Revised Taxonomy for Intrusion Detection Systems. *Annales des Télécommunications*, 55(7–8):361–378.
- DEF CON (2000). DEF CON Capture The Flag Contest. <http://www.defcon.org>.
- Domingos, P. and Hulten, G. (2000). Mining High-Speed Data Streams. In *Proceedings of the 6th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 71–80.
- Elmasri, R. and Navathe, S. B. (1994). *Fundamentals of Database Systems*. Addison-Wesley.
- Eskin, E. (2000). Anomaly Detection over Noisy Data Using Learned Probability Distributions. In *Proceedings of the International Conference on Machine Learning (ICML)*.
- Ester, M., Kriegel, H.-P., Sander, J., Wimmer, M., and Xu, X. (1998). Incremental Clustering for Mining in a Data Warehousing Environment. In *Proceedings of the 24th International Conference on Very Large Databases (VLDB'98)*, pages 323–333.
- Fayyad, U. (1998). Mining Databases: Towards Algorithms for Knowledge Discovery. *Bulletin of the IEEE Computer Society Technical Committee on Data Engineering*, 22(1):39–48.
- Fayyad, U., Piatetsky-Shapiro, G., and Smyth, P. (1996a). From Data Mining to Knowledge Discovery in Databases. *AI Magazine*, 17(3):37–54.
- Fayyad, U. M., Piatetsky-Shapiro, G., Smyth, P., and Uthurusamy, R., editors (1996b). *Advances in Knowledge Discovery and Data Mining*. AAAI Press/MIT Press.
- Ganti, V., Gehrke, J., and Ramakrishnan, R. (1999). CACTUS – Clustering Categorical Data Using Summaries. In *5th ACM SIGKDD International Conference on Knowledge Discovery in Databases (SIGKDD)*, pages 73–83.

- Garofalakis, M. and Rastogi, R. (2001). Data Mining Meets Network Management: The Nemesis Project. In *Proceedings of the ACM SIGMOD International Workshop on Research Issues in Data Mining and Knowledge Discovery*.
- Glymour, C., Madigan, D., Pregibon, D., and Smyth, P. (1997). Statistical Themes and Lessons for Data Mining. *Data Mining and Knowledge Discovery*, 1(1):11–28.
- Gordon, A. (1999). *Classification*. Chapman and Hall.
- Grossman, R., Kasif, S., Moore, R., Rocke, D., and Ullman, J. (1998). Data Mining Research: Opportunities and Challenges. Technical report, Workshop on Managing and Mining Massive and Distributed Data (M3D2).
- Guha, S., Rastogi, R., and Shim, K. (2000). ROCK: A Robust Clustering Algorithm for Categorical Attributes. *Information Systems*, 25(5):345–366.
- Han, J., Cai, Y., and Cercone, N. (1992). Knowledge Discovery in Databases: An Attribute-Oriented Approach. In *Proceedings of the 18th International Conference on Very Large Databases*, pages 547–559.
- Han, J. and Fu, Y. (1995). Discovery of Multi-Level Association Rules from Large Databases. In *Proceedings of the 21th Very Large Databases Conference*, pages 420–431.
- Han, J. and Kamber, M. (2000). *Data Mining: Concepts and Techniques*. Morgan Kaufmann Publisher.
- Hätönen, K., Klemettinen, M., Mannila, H., Ronkainen, P., and Toivonen, H. (1996). Knowledge Discovery from Telecommunication Network Alarm Databases. In *Proceedings of the 12th International Conference on Data Engineering*, pages 115–122.
- Hellerstein, J. L. and Ma, S. (2000). Mining Event Data for Actionable Patterns. In *The Computer Measurement Group*. <http://www.research.ibm.com/PM/>.
- Jain, A. and Dubes, R. (1988). *Algorithms for Clustering Data*. Prentice-Hall.
- Jain, A., Murty, M., and Flynn, P. (1999). Data Clustering: A Review. *ACM Computing Surveys*, 31(3).
- Javitz, H. S. and Valdes, A. (1991). The SRI IDES Statistical Anomaly Detector. In *Proceedings of the IEEE Symposium on Security and Privacy, Oakland, CA*. SRI International.
- Julisch, K. (2001). Mining Alarm Clusters to Improve Alarm Handling Efficiency. In *Proceedings of the 17th Annual Computer Security Applications Conference (ACSAC)*.

- Klemettinen, M. (1999). *A Knowledge Discovery Methodology for Telecommunication Network Alarm Data*. PhD thesis, University of Helsinki (Finland).
- Klemettinen, M., Mannila, H., Ronkainen, P., Toivonen, H., and Verkamo, A. (1994). Finding Interesting Rules from Large Sets of Discovered Association Rules. In *Proceedings of the 3rd International Conference on Information and Knowledge Management*, pages 401–407.
- Klemettinen, M., Mannila, H., and Toivonen, H. (1997). A Data Mining Methodology and Its Application to Semi-Automatic Knowledge Acquisition. In *Proceedings of the 8th International Workshop on Database and Expert System Applications (DEXA '97)*, pages 670–677.
- Lam, K.-Y., Hui, L., and Chung, S.-L. (1996). A Data Reduction Method for Intrusion Detection. *Journal of Systems and Software*, 33:101–108.
- Lane, T. and Brodley, C. E. (1999). Temporal Sequence Learning and Data Reduction for Anomaly Detection Lane. *ACM Transactions on Information and System Security*, 2(3):295–331.
- Lankewicz, L. and Benard, M. (1991). Real-Time Anomaly Detection Using a Non-Parametric Pattern Recognition Approach. In *Proceedings of the 7th Annual Computer Security Applications Conference*.
- Lee, W. and Stolfo, S. J. (2000). A Framework for Constructing Features and Models for Intrusion Detection Systems. *ACM Transactions on Information and System Security*, 3(4):227–261.
- Lee, W., Stolfo, S. J., and Mok, K. W. (1997). Data Mining Approaches for Intrusion Detection. In *Proceedings of the Seventh USENIX Security Symposium (SECURITY '98)*, pages 120–132.
- Lee, W., Stolfo, S. J., and Mok, K. W. (1998). Mining Audit Data to Build Intrusion Detection Models. In *Proceedings of the 4th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD'98)*, pages 66–72.
- Lee, W., Stolfo, S. J., and Mok, K. W. (1999a). A Data Mining Framework for Building Intrusion Detection Models. In *Proceedings of the 1999 IEEE Symposium on Security and Privacy*, pages 120–132.
- Lee, W., Stolfo, S. J., and Mok, K. W. (1999b). Mining in a Data-flow Environment: Experience in Network Intrusion Detection. In *Proceedings of the 5th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD'99)*, pages 114–124.
- Li, Y., Wu, N., Jajodia, S., and Wang, X. S. (2000). Enhancing Profiles for Anomaly Detection Using Time Granularities. In *Proceedings of the First ACM Workshop on Intrusion Detection Systems (WIDS)*.
- Lippmann, R. P., Fried, D. J., Graf, I., Haines, J. W., Kendall, K. R., McClung, D., Weber, D., Webster, S. E., Wyschogrod, D., Cunningham, R. K., and Zissman, M. A. (2000). Evaluating Intrusion Detection Sys-

- tems: The 1998 DARPA Off-Line Intrusion Detection Evaluation. In *Proceedings of the 2000 DARPA Information Survivability Conference and Exposition*, pages 12–26.
- Liu, B. and Hsu, W. (1996). Post-Analysis of Learned Rules. In *Proceedings of the 13th National Conference on Artificial Intelligence*, pages 828–834.
- Manganaris, S., Christensen, M., Zerkle, D., and Hermiz, K. (2000). A Data Mining Analysis of RTID Alarms. *Computer Networks*, 34(4).
- Mannila, H. (1996). Data Mining: Machine Learning, Statistics, and Databases. In *Proceedings of the 8th International Conference on Scientific and Statistical Database Management*, pages 1–8.
- Mannila, H., Smyth, P., and Hand, D. J. (2001). *Principles of Data Mining*. MIT Press.
- Mannila, H., Toivonen, H., and Verkamo, A. I. (1997). Discovery of Frequent Episodes in Event Sequences. *Data Mining and Knowledge Discovery*, 1:259–289.
- McHugh, J. (2000). The 1998 Lincoln Laboratory IDS Evaluation – A Critique. In *3th Workshop on Recent Advances in Intrusion Detection (RAID)*, pages 145–161.
- Miller, R. and Yang, T. (1997). Association Rules Over Interval Data. In *Proceedings of the 1997 ACM-SIGMOD Conference on Management of Data*, pages 452–461.
- Mitchell, T. M. (1997). *Machine Learning*. McGraw-Hill.
- Mounji, A. (1997). *Languages and Tools for Rule-Based Distributed Intrusion Detection*. PhD thesis, Facultés Universitaires Notre-Dame de la Paix Namur (Belgium).
- Mukkamala, R., Gagnon, J., and Jajodia, S. (1999). Integrating Data Mining Techniques with Intrusion Detection Methods. In *Proceedings of the 13th IFIP WG11.3 Working Conference on Database Security*, pages 33–46.
- Pevzner, P. A. and Sze, S.-H. (2000). Combinatorial Approaches to Finding Subtle Signals in DNA Sequences. In *Proceedings of the 8th International Conference on Intelligent Systems for Molecular Biology*, pages 269–278.
- Portnoy, L., Eskin, E., and Stolfo, S. J. (2001). Intrusion Detection with Unlabeled Data Using Clustering. In *Proceedings of the ACM CCS Workshop on Data Mining for Security Applications*.
- Quinlan, J. R. (1986). Induction of Decision Trees. *Machine Learning*, 1(1):81–106.
- Rigoutsos, I. and Floratos, A. (1998). Combinatorial Pattern Discovery in Biological Sequences: The TEIRESIAS Algorithm. *Bioinformatics*, 14(1):55–67.

- Silberschatz, A. and Tuzhilin, A. (1996). On Subjective Measures of Interestingness in Knowledge Discovery. In *Proceedings of the First International Conference on Knowledge Discovery and Data Mining*, pages 275–281.
- Smaha, S. E. (1988). Haystack: An Intrusion Detection System. In *Proceedings of the 4th IEEE Aerospace Computer Security Applications Conference, Orlando, FL*, pages 37–44.
- Smyth, P. (2001). Breaking out of the Black-Box: Research Challenges in Data Mining. In *Proceedings of the ACM SIGMOD International Workshop on Research Issues in Data Mining and Knowledge Discovery (DMKD'01)*.
- Srikant, R. and Agrawal, R. (1996). Mining Quantitative Association Rules in Large Relational Tables. In *Proceedings of the 1996 ACM-SIGMOD Conference on Management of Data*, pages 1–12.
- Stedman, C. (1997). Data Mining for Fool's Gold. *Computerworld*, 31(48).
- Teng, H. S., Chen, K., and Lu, S. C. (1990). Adaptive Real-Time Anomaly Detection Using Inductively Generated Sequential Patterns. In *Proceedings of the IEEE Symposium on Research in Security and Privacy, Oakland, CA*, pages 278–284.
- Vaccaro, H. S. and Liepins, G. E. (1989). Detection of Anomalous Computer Session Activity. In *Proceedings of the IEEE Symposium on Research in Security and Privacy, Oakland, CA*, pages 280–289.
- Warrender, C., Forrest, S., and Pearlmutter, B. (1999). Detecting Intrusions Using System Calls: Alternative Data Models. In *Proceedings of the IEEE Symposium on Research in Security and Privacy, Oakland, CA*, pages 133–145.