Combining Data Mining and Machine Learning for Effective Fraud Detection*

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Abstract

This paper describes the automatic design of methods for detecting fraudulent behavior. Much of the design is accomplished using a series of machine learning methods. In particular, we combine data mining and constructive induction with more standard machine learning techniques to design methods for detecting fraudulent usage of cellular telephones based on profiling customer behavior. Specifically, we use a rule-learning program to uncover indicators of fraudulent behavior from a large database of cellular calls. These indicators are used to create profilers, which then serve as features to a system that combines evidence from multiple profilers to generate high-confidence alarms. Experiments indicate that this automatic approach performs nearly as well as the best hand-tuned methods for detecting fraud.

Introduction

In the United States, cellular fraud costs the telecommunications industry hundreds of millions of dollars per year (Walters & Wilkinson 1994). A specific kind of cellular fraud called *cloning* is particularly expensive and epidemic in major cities throughout the United States. Existing methods for detecting cloning fraud are *ad hoc* and their evaluation is virtually nonexistent. We have embarked on a program of systematic analysis of cellular call data for the purpose of designing and evaluating methods for detecting fraudulent behavior.

This paper presents a framework for automatically generating fraud detectors. The framework has several components, and uses data at two levels of aggregation. Massive numbers of cellular calls are first analyzed to determine general patterns of fraudulent usage. These patterns are then used to profile each individual customer's usage on an account-day basis. The profiles determine when a customer's behavior has become uncharacteristic in a way that suggests fraud.

Our framework includes a data mining component for discovering indicators of fraud. A constructive induction component generates profiling detectors that use the discovered indicators. A final evidence-combining component determines how to combine signals from the profiling detectors to generate alarms. The rest of this paper describes the domain, the framework and the implemented system, the data, and results.

Cellular Cloning Fraud and its Detection

Every cellular phone periodically transmits two unique identification numbers: its *Mobile Identification Number* (MIN) and its *Electronic Serial Number* (ESN). These two numbers are broadcast unencrypted over the airwaves, and can be received, decoded and stored using special equipment that is relatively inexpensive. *Cloning* occurs when a customer's MIN and ESN are programmed into a cellular telephone not belonging to the customer. When this telephone is used, the network sees the customer's MIN and ESN and subsequently bills the usage to the customer. With the stolen MIN and ESN, a cloned phone user (whom we shall call a *bandit*) can make virtually unlimited calls, whose charges are billed to the customer.[1] If the fraudulent usage goes undetected, the customer's next bill will include the corresponding charges. Typically, the customer then calls the cellular service provider (the *carrier*) and denies the usage. The carrier and customer then determine which calls were made by the "bandit" and which were legitimate calls. The fraudulent charges are credited to the customer's account, and measures are taken to prohibit further fraudulent charges, usually by assigning the customer a (new) Personal Identification Number.

Fraud causes considerable inconvenience both to the carrier and to the customer. Fraudulent usage also incurs significant financial losses due to costs of land-line

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[1]According to the Cellular Telecommunications Industry Association, MIN-ESN pairs are sold on the streets of major US cities for between $5 and $50 apiece.

usage (most cellular calls are to non-cellular destinations), costs of congestion in the cellular system, loss of revenue by the crediting process, and costs paid to other cellular companies when a customer's MIN and ESN are used outside the carrier's home territory.

Cellular carriers therefore have a strong interest in detecting cloning fraud as soon as possible. Standard methods of fraud detection include analyzing call data for overlapping calls (*collisions*), or calls in temporal proximity that could not have been placed by the same user due to geographic dispersion (*velocity checks*) (Davis & Goyal 1993). More sophisticated methods involve profiling user behavior and looking for significant deviations from normal patterns. This paper addresses the automatic design of such methods.

One approach to detecting fraud automatically is to learn a classifier for individual calls. We have not had success using standard machine learning techniques to construct such a classifier. Context is very important: a call that would be unusual for one customer would be typical for another. Furthermore, legitimate subscribers occasionally make isolated calls that look suspicious, so in general decisions of fraud should not be made on the basis of individual calls.

To detect fraud reliably it is necessary to determine the normal behavior of each account with respect to certain indicators, and to determine when that behavior has deviated significantly. Three issues arise:

1. *Which call features are important?* Which features or combinations of features are useful for distinguishing legitimate behavior from fraudulent behavior?
2. *How should profiles be created?* Given an important feature identified in Step 1, how should we characterize the behavior of a subscriber with respect to the feature?
3. *When should alarms be issued?* Given a set of profiling criteria identified in Step 2, how should we combine them to determine when fraud has occurred?

Our goal is to automate the design of user-profiling systems. Each of these issues corresponds to a component of our framework.

The Framework and the DC-1 System

Our system framework is illustrated in Figure 1. The framework uses data mining to discover indicators of fraudulent behavior, and then builds modules to profile each user's behavior with respect to these indicators. The *profilers* capture the typical behavior of an account and, in use, describe how far an account is from this typical behavior. The profilers are combined into a single *detector*, which learns how to detect fraud effectively based on the profiler outputs. When the detector has enough evidence of fraudulent activity on an account, based on the indications of the profilers, it generates an alarm.

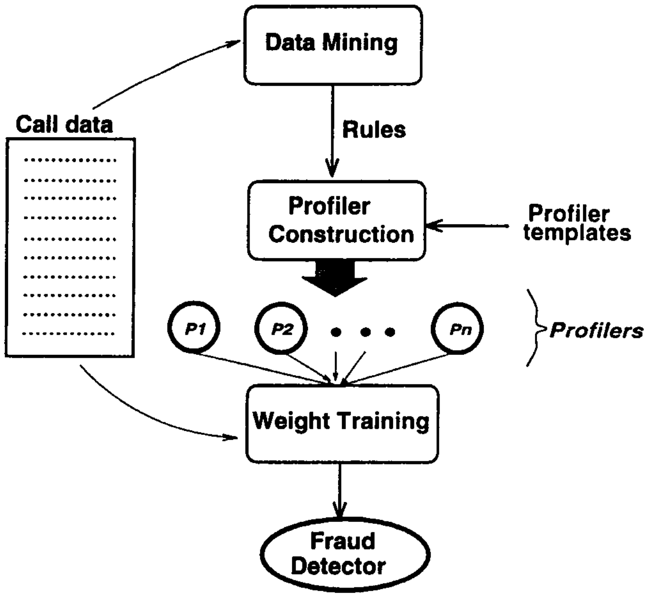


Figure 1: A framework for automatically constructing fraud detectors.

Figure 1 depicts the automatic generation of a fraud detector from a set of data on fraudulent and legitimate calls. The system takes as input a set of *call data*, which are chronological records of the calls made by each subscriber, organized by account. The call data describe individual calls using features such as TIME-OF-DAY, DURATION and CELL-SITE. The constructor also takes as input a set of *profiler templates*, which are the basis for the construction of the individual profilers.

Mining the Call Data

The first stage of detector construction, *data mining*, involves combing through the call data searching for indicators of fraud. In the DC-1 system, the indicators are conjunctive rules discovered by a standard rule-learning program. We use the RL program (Clearwater & Provost 1990), which is similar to other Meta-DENDRAL-style rule learners (Buchanan & Mitchell 1978; Segal & Etzioni 1994). RL searches for rules with certainty factors above a user-defined threshold. The certainty factor we used for these runs was a simple frequency-based probability estimate, corrected for small samples (Quinlan 1987).

The call data are organized by account, and each call record is labeled as fraudulent or legitimate. When RL is applied to an account's calls it produces a set of rules that serve to distinguish, within that account, the fraudulent calls from the legitimate calls. As an example, the following rule would be a relatively good indicator of fraud:

```
(TIME-OF-DAY = NIGHT) AND (LOCATION = BRONX)
                  ==> FRAUD
          Certainty factor = 0.89
```

This rule denotes that a call placed at night from The Bronx (a Borough of New York City) is likely to be fraudulent. The `Certainty factor = 0.89` means that, for this account, a call matching this rule has an 89% probability of being fraudulent.

Each account generates a set of such rules. Each rule is recorded along with the account from which it was generated. After all accounts have been processed, a rule selection step is performed, the purpose of which is to derive a general covering set of rules that will serve as fraud indicators.

The set of accounts is traversed again. For each account, the list of rules generated by that account is sorted by the frequency of occurrence in the entire account set. The highest frequency unchosen rule is selected. If an account has been covered already by four chosen rules, it is skipped. The resulting set of rules is used in profiler construction.

Constructing Profilers

The second stage of detector construction, *profiler construction*, generates a set of profilers from the discovered fraud rules. The profiler constructor has a set of templates which are instantiated by rule conditions. The profiler constructor is given a set of rules and a set of templates, and generates a profiler from each rule-template pair. Every profiler has a *Training* step, in which it is trained on typical (non-fraud) account activity; and a *Use* step, in which it describes how far from the typical behavior a current account-day is. For example, a simple profiler template would be:

- **Given:** *Rule conditions* from a fraud rule.
- **Training:** On a daily basis, count the number of calls that satisfy *rule conditions.* Keep track of the maximum as *daily-threshold.*
- **Use:** Given an account-day, output 1 if the number of calls in a day exceeds *daily-threshold,* else output 0.

Assume the Bronx-at-night rule mentioned earlier was used with this template. The resulting instantiated profiler would determine, for a given account, the maximum number of calls made from The Bronx at night in any 24-hour period. In use, this profiler would emit a 1 whenever an account-day exceeded this threshold.

Different kinds of profilers are possible. A *thresholding* profiler yields a binary feature corresponding to whether the user's behavior was above threshold for the given day. A *counting* profiler yields a feature corresponding to its count (*e.g.*, the number of calls from BRONX at NIGHT). A *percentage* profiler yields a feature whose value is between zero and one hundred, representing the percentage of calls in the account-day that satisfy the conditions. Each type of profiler is produced by a different type of profiling template.

Combining Evidence from the Profilers

The third stage of detector construction learns how to combine evidence from the set of profilers generated by the previous stage. For this stage, the outputs of the profilers are used as features to a standard machine learning program. Training is done on account data, and profilers evaluate a complete account-day at a time. In training, the profilers' outputs are presented along with the desired output (the account-day's classification). The evidence combination learns which combinations of profiler outputs indicate fraud with high confidence.

Many training methods for evidence combining are possible. After experimenting with several methods, we chose a simple Linear Threshold Unit (LTU) for our experiments. An LTU is simple and fast, and enables a good first-order judgment of the features' worth.

A feature selection process is used to reduce the number of profilers in the final detector. Some of the rules do not perform well when used in profilers, and some profilers overlap in their fraud detection coverage. We therefore employ a sequential forward selection process (Kittler 1986) which chooses a small set of useful profilers. Empirically, this simplifies the final detector and increases its accuracy.

The Detector

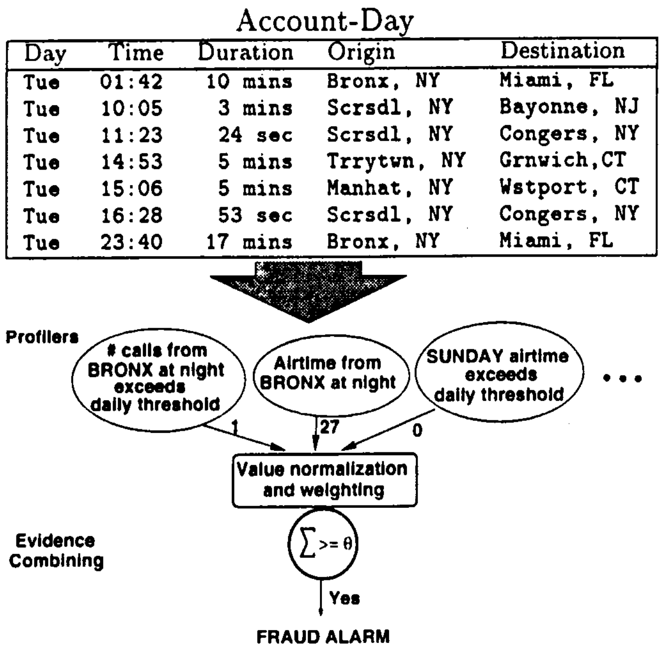
The final output of the constructor is a detector that profiles each user's behavior based on several indicators, and produces an alarm if there is sufficient evidence of fraudulent activity. Figure 2 shows an example of a simple detector evaluating an account-day.

Before being used on an account, the profilers undergo a *profiling period* (usually 30 days) during which they measure unfrauded usage. In our study, these initial 30 account-days were guaranteed free of fraud, but were not otherwise guaranteed to be typical. From this initial profiling period, each profiler measures a characteristic level of activity.

The Data

The call data used for this study are records of cellular calls placed over four months by users in the New York City area—an area with very high levels of fraud. The calls are labeled as legitimate or fraudulent by cross referencing a database of all calls that were credited as being fraudulent for the same time period. Each call is described by 31 attributes, such as the phone number of the caller, the duration of the call, the geographical origin and destination of the call, and any long-distance carrier used.

The call data were separated carefully into several partitions for data mining, profiler training and test-



Account-Day

Day	Time	Duration	Origin	Destination
Tue	01:42	10 mins	Bronx, NY	Miami, FL
Tue	10:05	3 mins	Scrsdl, NY	Bayonne, NJ
Tue	11:23	24 sec	Scrsdl, NY	Congers, NY
Tue	14:53	5 mins	Trrytwn, NY	Grnwich,CT
Tue	15:06	5 mins	Manhat, NY	Wstport, CT
Tue	16:28	53 sec	Scrsdl, NY	Congers, NY
Tue	23:40	17 mins	Bronx, NY	Miami, FL

Profilers
# calls from BRONX at night exceeds daily threshold
Airtime from BRONX at night
SUNDAY airtime exceeds daily threshold
...
1
27
0
Value normalization and weighting
Evidence Combining
$\sum >= \theta$
Yes
FRAUD ALARM

Figure 2: A DC-1 fraud detector processing a single account-day of data.

ing. Data mining used 610 accounts comprising approximately 350,000 calls.

Once the profilers are generated, the system transforms the raw call data into a series of account-days using the outputs of the profilers as features. Data for the profilers were drawn from a remaining pool of about 2500 accounts. We used randomly selected sets of 5000 account-days for training, and another set of 5000 account-days (drawn from separate accounts) for testing. Each account-day set was chosen to comprise 20% fraud and 80% non-fraud days. An account-day was classified as fraud if five or more minutes of fraudulent usage occurred; days including only one to four minutes of fraudulent usage were discarded.

Results

Data mining generated 3630 rules, each of which applied to two or more accounts. The rule selection process, in which rules are chosen in order of maximum account coverage, yielded a smaller set of 99 rules sufficient to cover the accounts. Each of the 99 rules was used to instantiate two profiler templates, yielding 198 profilers. The final feature selection step reduced this to nine profilers, with which the experiments were performed.

Each detector was run ten times on randomly selected training and testing accounts. Accuracy averages and standard deviations are shown in the leftmost column of Table 1. For comparison, we evaluated DC-1 along with other detection strategies:

- "Alarm on All" represents the policy of alarming on every account every day.
- "Alarm on None" represents the policy of allowing fraud to go completely unchecked. This corresponds to the maximum likelihood classification.
- "Collisions and Velocities" is a detector using two common methods for detecting cloning fraud, mentioned earlier. DC-1 was used to learn a threshold on the number of collision and velocity alarms necessary to generate a fraud alarm.
- The "High Usage" detector generates an alarm on any day in which airtime usage exceeded a threshold. The threshold was found empirically from training data.
- The best individual DC-1 profiler was used as an isolated detector. This experiment was done to determine the additional benefit of combining profilers. The best individual profiler was generated from the rule:
  ```
  (TIME-OF-DAY = EVENING) ==> FRAUD
  ```
  Data mining had discovered (in 119 accounts) that the sudden appearance of evening calls, in accounts that did not normally make them, was coincident with cloning fraud. The relatively high accuracy of this one profiler reveals that this is a valuable fraud indicator.
- The DC-1 detector incorporates all the profilers chosen by feature selection. We used the weight learning method described earlier to determine the weights for evidence combining.
- The SOTA ("State Of The Art") detector incorporates seven hand-crafted profiling methods that were the best individual detectors identified in a previous study. Each method profiles an account in a different way and produces a separate alarm. Weights for combining SOTA's alarms were determined by our weight-tuning algorithm.

In this domain, different types of errors have different costs, and a realistic evaluation must take these costs into account. A false positive error (a false alarm) corresponds to wrongly deciding that a customer has been cloned. Based on the cost of a fraud analyst's time, we estimate the cost of a false positive error to be about $5. A false negative error corresponds to letting a frauded account-day go undetected. Rather than using a uniform cost for all false negatives, we estimated a false negative to cost $.40 per minute of fraudulent airtime used on that account-day. This figure is based on the proportion of usage in local and non-local ("roaming") markets, and their corresponding costs.[2]

[2]We have still glossed over some complexity. For a given account, the only false negative fraud days that incur cost

Detector	Accuracy (%)	Cost ($US)	Accuracy at cost (%)
Alarm on All	20	20000	20
Alarm on None	80	18111 ± 961	80
Collisions + Velocities	81 ± .2	16988 ± 685	81 ± .3
High Usage	87 ± .4	6069 ± 280	85 ± 1.1
Best individual DC-1 profiler	88 ± .6	7652 ± 383	85 ± 1
DC-1 detector	91 ± .5	5442 ± 318	89 ± 1.3
State of the Art (SOTA)	94 ± .3	3303 ± 278	94 ± .3

Table 1: A comparison of accuracies and costs of various detectors.

Because LTU training methods try to minimize errors but not error costs, we employed a second step in training. After training, the LTU's threshold is adjusted to yield minimum error cost on the training set. This adjustment is done by moving the decision threshold from -1 to +1 in increments of .01 and computing the resulting error cost. After the minimum cost on training data is found, the threshold is clamped and the testing data are evaluated. The second column of Table 1 shows the mean and standard deviations of test set costs. The third column, "Accuracy at cost," is the corresponding classification accuracy of the detector when the threshold is set to yield lowest-cost classifications.

Discussion

The results in Table 1 demonstrate that DC-1 performs quite well. Though there is room for improvement, the DC-1 detector performs better than all but the hand-coded SOTA detector.

It is surprising that Collisions and Velocity Checks, commonly thought to be reliable indicators of cloning, performed poorly in our experiments. Preliminary analysis suggests that call collisions and velocity alarms may be more common among legitimate calls in our region than is generally believed.

In our experiments, lowest cost classification occurred at an accuracy somewhat lower than optimal. In other words, some classification accuracy could be sacrificed to decrease cost. More sophisticated methods could be used to produce cost sensitive classifiers, which would probably produce better results.

Related Work

Yuhas (1993) and Ezawa and Norton (1995) address the problem of uncollectible debt in telecommunications services. However, neither work deals with characterizing typical customer behavior, so mining the data to derive profiling features is not necessary. Ezawa and Norton's method of evidence combining is much more sophisticated than ours and faces some of the same problems (unequal error costs, skewed class distributions).

Methods that deal with time series are relevant to our work. However, time series analysis (Chatfield 1984; Farnum & Stanton 1989) strives to characterize an entire time series or to forecast future events in the series. Neither ability is directly useful to fraud detection. Hidden Markov Models (Rabiner & Juang 1986) are concerned with distinguishing recurring sequences of states and the transitions between them. However, fraud detection usually only deals with two states (the "frauded" and "un-frauded" states) with a single transition between them. It may be useful to recognize recurring un-frauded states of an account, but this ability is likely peripheral to the detection task.

Conclusions and Future Work

The detection of cellular cloning fraud is a relatively young field. Fraud behavior changes frequently as bandits adapt to detection techniques. A fraud detection system should be adaptive as well. However, in order to build usage profilers we must know which aspects of customers' behavior to profile. Historically, determining such aspects has involved a good deal of manual work, hypothesizing useful features, building profilers and testing them. Determining how to combine them involves much trial-and-error as well.

Our framework automates this process. Results show that the DC-1 detector performs better than the high-usage alarm and the collision/velocity alarm. Even with relatively simple components, DC-1 is able to exploit mined data to produce a detector whose performance approaches that of the state-of-the-art. The SOTA system took several person-months to build. The DC-1 detector took several CPU-hours. Furthermore, DC-1 can be retrained at any time as necessitated by the changing environment.

We believe our framework will be useful in other domains in which typical behavior is to be distinguished from unusual behavior. Prime candidates are similar domains involving fraud, such as credit-card fraud and toll fraud. In credit-card fraud, data mining may identify locations that arise as new hot-beds of fraud. The constructor would then incorporate profilers that no-

to the company are those prior to the *first* true positive alarm. After the fraud is detected, it is terminated. Thus, our analysis overestimates the costs slightly; a more thorough analysis would eliminate such days from the computation.

tice if a customer begins to charge more than usual from that location.

The DC-1 system is an initial prototype. Further work will develop two aspects of DC-1 in preparation for its deployment. First, we intend to expand the data mining step, particularly to exploit available background knowledge. We believe that there is a good deal of relevant background knowledge (for example, hierarchical geographical knowledge) that can augment the current calling data. Along with this, we hope to be able to characterize and describe the knowledge discovered in our system. Second, we hope to improve the method of combining profilers. We chose an LTU initially because it is simple and fast. A neural network could probably attain higher accuracy for DC-1, possibly matching that of SOTA.

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