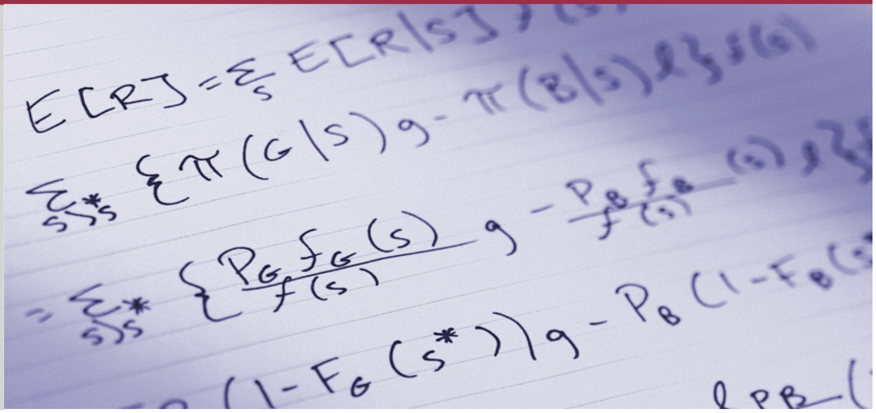
A FAIR ISAAC WHITE PAPER

Understanding Fraud Predictor Model Performance

Evaluating Fraud Predictor with Merchant Profiles model performance in comparison to Falcon™ Fraud Manager

May 2005



Summary:

Fair Isaac continuously strives to enable you to reduce fraud losses and achieve superior operational efficiencies. Fraud Predictor with Merchant Profiles provides the next leap in fraud detection capabilities by introducing a new, highly predictive data source—merchant data—into the fraud detection model. Extensive testing performed by Fair Isaac on a large consortium of payment account data has demonstrated the superiority of Fraud Predictor in detecting fraud more accurately, faster and with less impact on good customers. However, it is critical that while evaluating whether to upgrade from Falcon™ Fraud Manager to Fraud Predictor, you are able to correctly assess how the benefits of Fraud Predictor may apply to your business. Following the steps outlined in this paper will allow you to focus on the proper measurements and the correct approach in evaluating the performance of Fraud Predictor and Falcon Fraud Manager.

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Overview

Introduction

This document is intended to provide a guideline for quantifying the incremental fraud detection value of Fraud Predictor with Merchant Profiles, Fair Isaac's new fraud detection solution, as compared to Falcon Fraud Manager. It should be used by Falcon customers interested in understanding the potential benefits of upgrading to Fraud Predictor. In order to correctly assess the incremental detection benefits of Fraud Predictor, you must consider many factors, including the appropriate success measurements and appropriate measurement time periods.

Please note that all the comparisons outlined in this document relate to Fraud Predictor with Merchant Profiles US Credit model version 3.0 (Fraud Predictor) versus Falcon Fraud Manager US Credit model version 11.0 (Falcon).

Why Fraud Predictor detects more fraud than Falcon Fraud Manager

Fraud Predictor uses an enhanced profiling technology and a new data source, merchant data, to provide a significant performance lift over Falcon Fraud Manager, the industry leading payment card fraud detection solution.

Like Falcon Fraud Manger, Fraud Predictor runs a neural-network model that calculates a score ranging from 1 to 999 each time it is presented with an authorization transaction. The higher the score, the greater the likelihood that the account associated with the transaction has been used fraudulently. To calculate scores, the model evaluates the data generated by the current transaction along with, and in comparison to, characteristics established in profiles. Falcon Fraud Manager models make use of information only from a cardholder profile—a continuously updated history of the card account associated with a given transaction. Fraud Predictor makes use of information from a cardholder profile, but also uses a merchant profile.

Merchant profiles contain a regularly updated history of the merchant involved in the payment card transaction, as well as default profiles for each merchant category code (MCC) and one generic profile. Fair Isaac has developed a Merchant Profile Builder (MPB), which uses the data received from the merchant data supplier to update the merchant profiles.

Merchant Data Source

Fair Isaac receives the merchant data from MasterCard®. This data source is sufficiently representative of all credit and debit card traffic such that profiles prepared from it can be used for scoring Visa transactions as well. For those merchants with separate Visa and MasterCard merchant ID values, Fraud Predictor includes a copy of the MasterCard profiles for the equivalent Visa merchant IDs in most instances. The merchant profile update process follows a weekly schedule to capture the natural business cycle of most merchants. The MPB, located in the Arden Hills, Minnesota offices of Fair Isaac, uses data collected throughout the week, together with profile values from the previous week, to build new profiles, which are sent to all Fraud Predictor users either via a T-1 line or tape on a weekly basis.

Measuring Success

Choosing the most appropriate success measurements

A variety of statistical measures can be used to quantify the performance of a predictive model. In order to perform an adequate comparison of two models such as Falcon Fraud Manager and Fraud Predictor, it is important that you first establish which of those measurements will be the most appropriate indicators of success for your business.

A common pitfall that issuers can inadvertently make is to use measurements that do not reflect their true business objectives, and thus make an incorrect decision on which model to choose. For example, the sum of the available credit lines saved is sometimes used for the comparison. This is not an appropriate measurement to use since it is not a leading indicator of the objective of minimizing fraud losses while not impacting good customers. In addition, the use of such a measure may often augment errors inherent in imperfect sample selection (e.g., when VIP accounts are included in the sample for one model but not the other).

For illustration, the table below summarizes the performance of two models based on several measurements:

Model	Sum of Available Credit Saved	VDR (Value of fraudulent dollars detected)	AFPR (Account False Positive Rate)	Average Fraud Loss per account
Model A	$1,400,000	55%	10:1	$ 600
Model B	$2,200,000	35%	14:1	$ 750

As shown above, based on the results for sum of the available credit saved, the performance of Model B appears superior to the performance of Model A. However, an issuer who decided to choose Model B based on these results will be disappointed to find out that actual fraud losses will rise. In fact, Model A has superior fraud detection performance, detecting 55% of fraud (vs. 35%) at lesser impact on customers (lower account false positives). It also detects more fraudulent dollars earlier, leading to a lower average fraud loss per case of confirmed fraud. This example makes it easy to see how the wrong metric selection can lead to an erroneous model selection and may in fact result in inferior performance and more fraud.

Best practice success measurements

The correct statistical measures to compare fraud detection models should be based on industry best practices, as well as reflect your particular business strategy (e.g. reduction in fraud losses vs. improvement in account false positives). In order to assess how effective a model will be in practice, it is useful to understand what different measures evaluate and how to translate this information into results that are meaningful to your organization. In addition, you should measure and evaluate these metrics in conjunction, rather then independently, in order to have a complete picture of model performance.

Value Detection Rate (VDR)

The most common metrics used in the industry for assessing model performance on historical data are value detection rate (VDR) and account false positive rate (AFPR). The goal is for the VDR to increase while the AFPR remains stable or decreases.

VDR is computed by establishing the percent of all fraudulent dollars that the model saved to the total amount of fraud that was attempted. For instance, if a fraudster attempted to charge $2,000 to an account in several transactions, and the model identifies the account as fraudulent in time to prevent $1,000 of those charges, then the VDR is 50%. VDR shows not only whether a model catches fraud, but also how fast. Faster and earlier fraud detection will lead to lower average fraud losses per occurrence, and lower overall losses to the issuer.

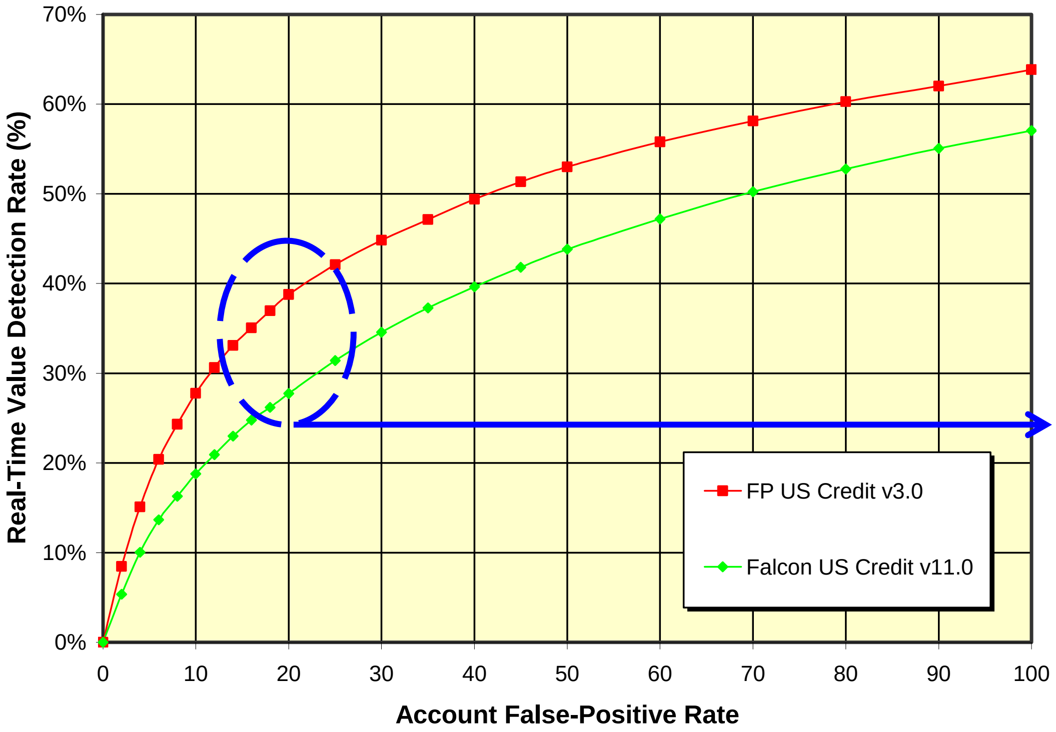
Real-time deployment (RTVDR)

In a real-time mode, a score is produced for each transaction before the transaction is completed, thereby allowing you to prevent a fraudulent transaction right at the point of sale. In comparing model performance, we look at the value detection rate (VDR) in respect to the account false positive rate (AFPR). The goal is for the VDR to increase while the AFPR remains stable or decreases.

In figure 1, we see a performance graph that compares the real-time VDR versus AFPR for Fraud Predictor and Falcon Fraud Manager. At an AFPR of 20:1, Fraud Predictor detects about 38% of fraud, while Falcon Fraud Manager detects roughly 27%.

Therefore, by using Fraud Predictor in place of Falcon Fraud Manager, an issuer experiencing $1,000,000 in attempted fraud every month would be able to prevent an additional $110,000, or 11%, in fraud while holding AFPR constant.

FIGURE 1



At a 20:1 AFPR, Fraud Predictor detects 38% of fraudulent value in real time versus 27% of fraudulent value detected by Falcon Fraud Manager.

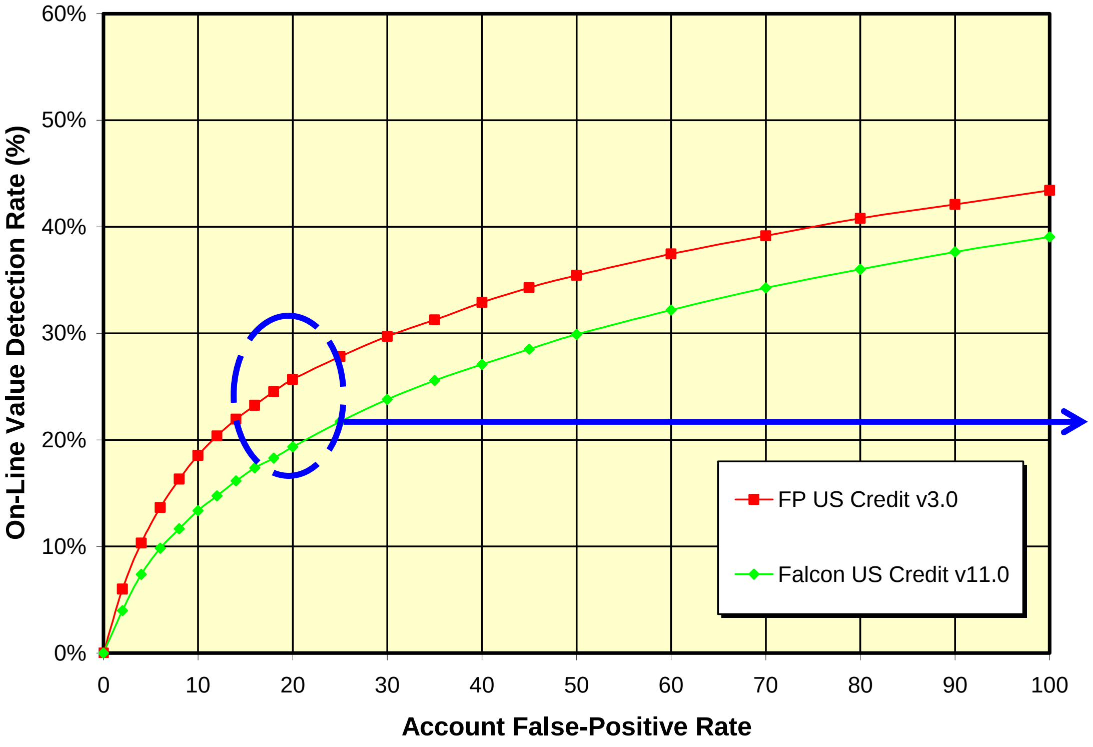
Online deployment (OLVDR)

Online mode is when a fraud score is generated after completion of a transaction. This allows the fraud analyst to take action on a case after the transaction has occurred.

In figure 2, we see a performance graph that compares the online VDR versus AFPR for Fraud Predictor and Falcon Fraud Manager. At an AFPR of 20:1, Fraud Predictor results in an online VDR close to 26%, while Falcon Fraud Manager delivers an online VDR of roughly 19%.

Therefore, by using Fraud Predictor in place of Falcon Fraud Manager, an issuer that was experiencing $1,000,000 in attempted fraud every month would be able to save an additional $70,000, or 7%, in fraud, while limiting AFPR to the same value.

FIGURE 2



At a 20:1 AFPR, Fraud Predictor detects 26% of fraudulent value in online deployment versus 19% of fraudulent value detected by Falcon Fraud Manager.

Account False Positive Rate (AFPR)

A second major success measurement is the Account False-Positive Rate (AFPR). It measures the efficiency of a model in finding fraud, while minimizing the impact to good customers. When comparing two fraud models, the model that delivers superior value detection rates at the same (or lower) account false positive rate will generally be considered a better model.

Take for example the results that we illustrated with real-time value detection rates (figure 1). Fraud Predictor detects approximately 38% of fraudulent dollars at a 20:1 false positive while Falcon Fraud Manager detects 27% at the same 20:1 false positive. As you can see, AFPR and VDR are tied together to provide a basis for model selection. Figure 1 also shows Fraud Predictor provides greater detection at all AFPRs.

Average fraud loss per account

The third success measurement, and one that can be used in production, is the average fraud loss per confirmed case of fraud. Effective fraud models detect fraud earlier while maintaining the AFPR rate, allowing you to minimize losses on a particular account. Issuers that are able to reduce their average loss per confirmed case of fraud are able to reduce their overall fraud losses as a result. Fraud Predictor will help you achieve a lower average loss per case, while maintaining or lowering your AFPR, through better detection. The table below illustrates this by showing losses before and after the implementation of an improved fraud model, for the same AFPR.

	Average Loss per Case	Total # of Fraud Cases	Total Loss
Before	$1,000	1000	$1,000,000
After	$700	1000	$700,000
Savings			**$300,000**

Measurement Period

The performance window that you choose may affect which model validates better. You should determine an appropriate length of time for which the performance of accounts in the validation is to be observed.

The performance window used in the validation should match the practical period in which account performance can be effectively measured. For example, a model used in new account booking may have an 18-24 month evaluation period if these accounts are not expected to show their true performance until this timeframe. However, the effectiveness of fraud models can be reliably evaluated within a 3-month reporting window. This period of time is most adequate for all fraudulent accounts to be identified, including those accounts that are not detected by the system and are self-reported by cardholders after having received their statements.

Model Performance and Your Business Strategy

Be sure to examine the model performance results in the context of your business strategies, policies and operations and not just on a stand-alone basis. In reality, Falcon Fraud Manager and Fraud Predictor scores are likely to be just one of many decision elements in your strategies and in your operational queues.

Following are some considerations that you should factor into your comparison of Fraud Predictor and Falcon Fraud Manager performance.

Implementation Mode of Score (Real-time or Online)

The value achieved from your fraud scores is heavily reliant on your decision to use that score in real time or the online mode of operation. A score used in real time provides you with the ability to evaluate the transaction before the authorization decision and to use the score as an element in the decision whether to approve or refer the transaction. In online mode, you score the transaction after it has been completed and then can send that account to be reviewed by an analyst. The real-time mode will deliver better and more consistent fraud results since the decision is automated, while the online mode depends heavily on your operational capacity, staffing, scheduling and analyst experience to stop the fraudulent activity.

Since real time delivers more consistent and measurable results, you will have a more reliable comparison between Falcon Fraud Manager and Fraud Predictor during the measurement period. Since Fraud Predictor outperforms Falcon Fraud Manager in the referable higher score ranges, you can expect more bottom line benefit with Fraud Predictor in the real-time mode of operation.

Strategies and Policies

Fraud scores are probably just one element in your rules and strategies. Issuers that have highly segmented treatments of accounts or those that use the scores sparingly will probably achieve much different performance results than those indicated in the Fraud Predictor or Falcon Fraud Manager Performance reports.

You should therefore review your strategies to understand how they might affect the actual performance results.

Operational Treatment

You must ensure that there is no operational bias that is introduced into the performance evaluation. There are many caveats to be aware of:

Operational inefficiency. If the analysts are unable to get to high scoring fraud cases in a timely manner, then there will be little or no difference in performance between Fraud Predictor and Falcon Fraud Manager. If both scores are receiving no or untimely treatment, then the results of the models are negligible.

Operational Treatment differences. You should consider any other operational bias that could be introduced into the performance results. For example, if you send Fraud Predictor- and Falcon Fraud Manager-scored cases into separate queues, and contact customers according to different strategies or prioritization, it will introduce bias into the performance analysis.

Filtered Queues. If queue definitions are highly complex and have additional filters, then Fraud Predictor or Falcon Fraud Manager cases may not get worked. That will lead to inferior overall performance and benefits will not materialize as expected. You should create “score-based” queues to ensure that all Falcon Fraud Manager and Fraud Predictor accounts are worked without additional filters.

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