Comparison of Predictive Models
Versus
Fraud Decision Rules

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### Predictive Models – Overview

Predictive modeling is a process used in analytics to create a statistical model of future behavior. A predictive model is made up of a number of predictors, which are variable factors that are likely to influence future behavior or results.

In predictive modeling, data is collected for the relevant predictors, a statistical model is formulated, predictions are made and the model is validated (or revised) as additional information becomes available. The model may employ a simple linear equation or a complex neural network, mapped out by sophisticated software.

Predictive modeling is used in industries such as Financial Services, Insurance, Direct Mail, Utility Companies and Retail for multiple applications:

- Profitability Scoring Model Assessments
- Underwriting/Pricing Applications
- Retention Models
- Elasticity Models
- Cross-sell Models
- Lifetime Value Models
- Target Marketing
- Fraud Detection and Prevention
- Customer Segmentation
In Financial Services, issuers typically utilize an automated system, with predictive neural network models, to evaluate individual consumer accounts and identify potential fraudulent transactions. They utilize innovative proprietary attributes along with fraud models to evaluate individual consumer accounts and identify potential fraudulent transactions based upon “learned” relationships among known variables.

Model evaluation consists of the following key steps:

- Sort data by score range
- Break the dataset into 10 equal segments:
  - Best “decile”: lowest risk score
  - Worst “decile”: highest risk score
  - Difference: “Lift”

The larger the lift the model has the more economic benefit to the business. Predictive models are used because this technique provides a dramatic improvement in fraud detection, especially at low false-positive rates, where a real-time referral strategy is most effective. The objective is to identify only those accounts with the highest probability of fraud.

From consumer, resource and return on investment perspectives a business wants to identify and queue the smallest percentage of their transactions/population with the highest probability of fraud.
Predictive Models vs. Fraud Decision Rules

Predictive Models – Use

Predictive models can be utilized where multiple parameters in combination are complex, either linear or non-linear. In situations such as this, rules tend to:

- Include large groups of consumer accounts
- Exclude large numbers of consumer accounts
- Obscure the false-positive rate or detection rate

When utilizing a predictive model, a business can manage their false-positive rate associated with their economics to maximize their return on investment. A predictive model has the ability to segment the top 2% of score range, with an 80% fraud rate.

A simple rule, such as $ > 3$ transactions and $ < 2$ inquiries and $ > 3$ years at an address, might include hundreds of thousands of consumers, while a rule that is very specific might only include three consumer transactions. A rules-based approach is inefficient and might flag 30% of a population with a low fraud rate.

Many business users who adopt scoring sometimes have a rules “mentality”. They believe that they need only to score a portion or subset of the total population (“screened”) of possible accounts or transactions. This is dangerous to a business, because rules used “with” a scoring model almost always cause the model performance to degrade, either in detection rate or, more often, in false-positive rates. This approach limits the power of the fraud solution and lowers the overall return to the business. As an example, if this approach was taken historically in the Financial Services industry, the following would not have occurred…identifying the riskiest credit card transaction – one that is for less than $10$ at a gas station. If the logic of not scoring all transactions prevailed in credit card scoring, this small dollar amount transaction would most likely have never been scored or detected.
Predictive Models vs. Fraud Decision Rules

Rules-Based Methodology – Overview

Historically, the most common approach to fraud detection was to apply rules-based methodology and technology. The rules were intended to imitate and automate human judgment. They were for events where transactions matched known types of fraud. This approach has several weaknesses.

1. A rules-based approach is based upon human judgment:
   a. Judgmental, based upon subjective (life) experience
   b. Inconsistent
   c. Manual, labor intensive
   d. Parameter and policy driven
   e. Impossible to track performance based upon original decision

2. A rules-based methodology is either:
   a. Too general – excludes large segments of potential consumers (i.e. high insult rate) or,
   b. Too specific (i.e. isolate 3 high risk accounts, low detection rate)

3. A rules-based approach cannot screen for new, unknown, types of fraudulent behavior

4. A rules-based approach does not recognize that each consumer account has a history of transactions and that some consumers have demonstrated a greater or lesser degree of atypical activity.

5. Impossible to monitor and track results based upon decision:
   a. Which rule caused the fraud to be detected – cannot track performance by rule
   b. Many rules can “fire” during an event – don’t know which rule is most important
   c. Determining threshold for rules is difficult and typically anecdotal – fraudsters learn threshold values quickly
   d. Rules are easily copied or reverse engineered – fraud perpetrators often discover the rule strategy by multiple purchase or transaction attempts to circumvent the rule
   e. Rules do NOT scale - as business and fraud patterns get more complex, effort required to “maintain rules” increases exponentially
   f. Rules continuously expand – rule “explosion”

6. Rules are extremely expensive to develop and even more costly to maintain
Predictive Models vs. Fraud Decision Rules

In certain cases, the use of rules-based methodology is legitimate. In other situations, it puts an organization at an economic and competitive disadvantage.

**Rules-Based Methodology – Legitimate Uses**

- Implement corporate or compliance policy – for example a consumer must be at least 18 years old to be issued a credit card, or must be a female to get ob/gyn reimbursement
- Rules are binary “either/or” criteria
- Rules are used to:
  - Implement strategies and business policies
  - Manage processes
- Rules are used with deterministic issues, versus probabilistic forecasts

**Rules-Based Methodology – Limitations**

- Rules have very high maintenance, are cumbersome and error prone to implement and if numerous, can slow the processing system down
- Parameters coded into the processing system tend not to change over time, even though the fraud pattern does change – sometimes within days
- Rules can be difficult to modify, when hard-coded in system – become outdated
- Each rule is a judgmental policy directed at controlling one aspect of fraud
- Ability of rules-based methodology to RANK risk:
  - If ONE rule is violated, is that less risky than if 5 rules are violated?
  - With predictive model scoring, a score of 900 is riskier than a score of 800
  - A business can rank the scores from high to low and track the performance
  - If highest score is highest risk, then retrospective analysis of past transactions should demonstrate that the highest scoring accounts had the most confirmed frauds
Predictive Models vs. Fraud Decision Rules

- Rules-based methodology cannot allocate resources:
  - Human review work load or caseload
  - Predictive model scores can be adjusted up or down to increase or decrease the number of accounts queued and presented for review
  - Scores can be used to maximize return on investment or optimize the percent of frauds detected

Fortel Analytics – Analytic and Predictive Modeling Data Needs

We will use advanced analysis and predictive modeling to:

- Categorize each transaction for potential modeling
- Capture and model a behavior pattern of good versus bad consumer, provider and claim transactions
- Identify fraud perpetrators with atypical purchase and transaction patterns
- Impute performance where necessary - we have the intellectual property to impute performance in cases where fraud history doesn’t exist

Our analytics and predictive model development requires an extract of recent transactions paid or declined. We typically require 12 or more months of data. Examples of attributes we require include, but are not limited to:

- claim #, date service performed, diagnosis code, procedure code
- practitioner ID code, claimant ID#, age of claimant
- type of work performed, total amount billed, total amount paid

A formalized list of attributes will be requested once a project is formally launched.