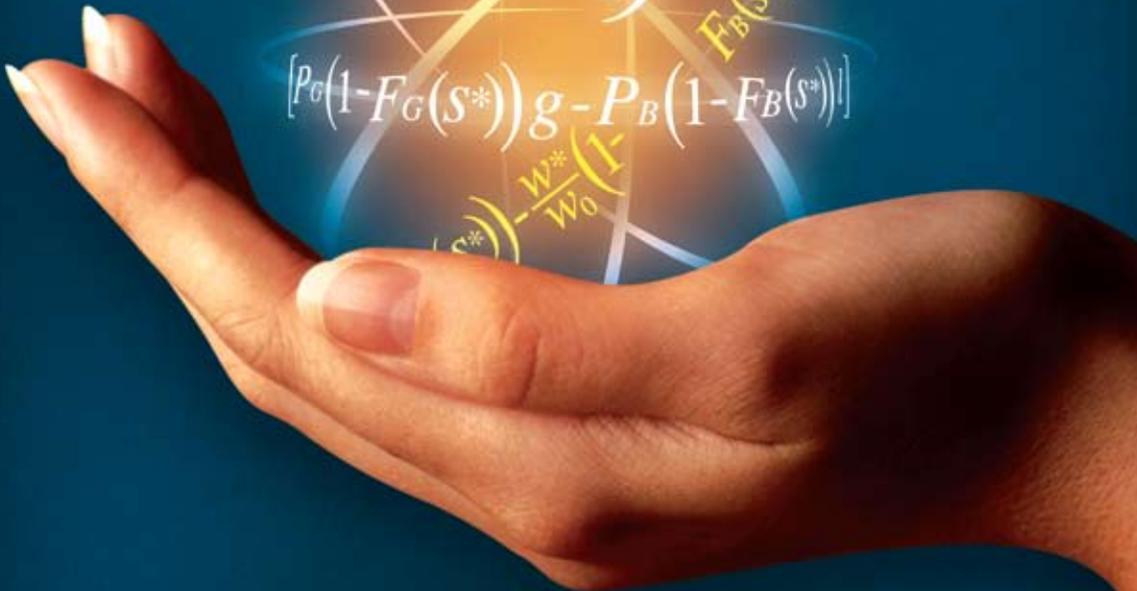


UNDERSTANDING PREDICTIVE ANALYTICS

A hand is shown from the bottom, cupping a glowing, spherical orb. The orb is filled with various mathematical formulas and symbols, including $g p_G [(1 - F_G(s^*))]$, $F_B(s^*)$, $[P_G(1 - F_G(s^*))g - P_B(1 - F_B(s^*))]$, and $\frac{w^*}{w_0}(1 - F(s^*))$. The formulas are rendered in a glowing, golden-yellow color against a dark blue background. The hand is lit from below, creating a warm, golden glow that matches the color of the formulas.
$$g p_G [(1 - F_G(s^*))]$$
$$F_B(s^*)$$
$$[P_G(1 - F_G(s^*))g - P_B(1 - F_B(s^*))]$$
$$\frac{w^*}{w_0}(1 - F(s^*))$$

YOUR GUIDE TO THE SCIENCE THAT MAKES
CUSTOMER DECISIONS SMARTER

FICOTM

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SMART, FAST AND INVISIBLE



YOU PULL OUT YOUR CELL PHONE AND DIAL.

While the beeps sound, packets of data whiz through the provider's network, not only to connect you but to feed algorithms that ask: Is this really you? Should the call be connected? Are hackers interfering with the call?

The cashier swipes your card and smiles. Before he hands it back, complex mathematical models hundreds of miles away crunch the data: If you've hit your credit limit, should it be extended? Is it really you using the card?

These are everyday examples of predictive analytics at work.

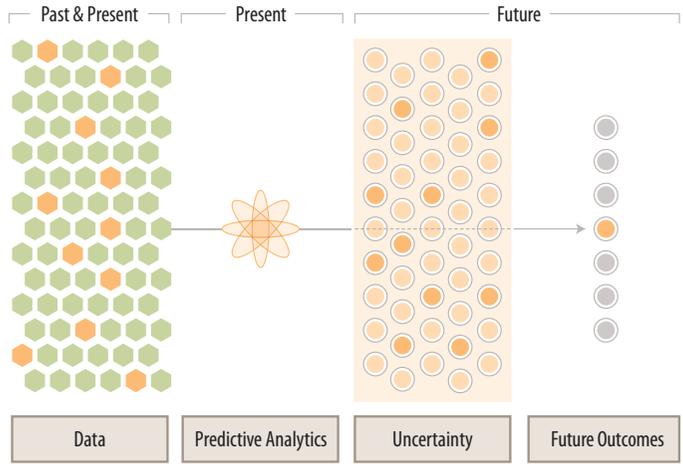
Organizations of every size are using predictive analytics to unlock value in data and make smarter decisions about their customers.

This booklet tells you how predictive analytics works to improve customer decisions. It can help you see how much value this technology can add to your business—and to every customer interaction.

WHAT IS PREDICTIVE ANALYTICS?

Five signs you can benefit from predictive analytics

1. You need to make fast decisions while weighing many variables.
2. You know more about what your customers have done than about what they will do.
3. There's a risk associated with poor decisions—and a reward for making better ones.
4. You want a consistent decision process that helps you differentiate customer treatment.
5. You use a large number of rules to guide customer decisions.



Predictive analytics simplifies data to amplify value

Predictive analytics can navigate overwhelming complexity to give you a clearer view of the future and help you chart your course.

While new to many industries, predictive analytics is a proven technology that's been used successfully for decades. It encompasses a variety of mathematical techniques that derive insight from data with one clear-cut goal: find the best action for a given situation.

Why use predictive analytics in business? Because making the right business decision, especially when it involves customer behavior, requires the ability to navigate overwhelming complexity. When considering hundreds or even thousands of factors, and a universe of thousands or millions of customers, people just can't "connect the dots" to make the ideal decision. Predictive analytics connects the dots scientifically, guiding each decision to greater success.

Predictive analytics increases the precision, consistency and speed of the decisions you make about your customers and prospects

Simply put, predictive analytics is the science that makes decisions smarter. It increases the precision, consistency and speed of the decisions you make about your customers and prospects.

Predictive analytics can help you:

Know your customers—and act on the insight. Predictive analytics provides insight on future customer behavior that can help you identify the best action to take on every customer or transaction. And analytics guides other strategic action, such as placing accounts at collection agencies that will maximize collected dollars, or detecting fraud, abuse and error in healthcare claims.

Work smarter and faster by replacing guesswork with science. Analytics answers complex questions and processes transactions with empirical precision and at incredible speeds, often during “live” transactions. Decisions that used to take hours or days can be reduced to minutes or milliseconds—from “instant” credit offers to insurance underwriting to approval for new phone service to real-time fraud detection.

Reduce costs with a clear gauge of risk and uncertainty. With analytic insight, businesses can more accurately measure business risks and reduce losses. This includes losses due to fraud, since predictive analytics can detect the subtlest abnormal patterns in application, purchase, claims, transaction or network data.

Add consistency to business decisions, improving compliance and customer service. Predictive analytics operates consistently and dependably, relying on mathematical technique. This is critical to the risk control and consistent treatment required by regulators in banking, insurance, pharmaceuticals and other industries. Consistent, unbiased decisions meet the fairness test better than decisions based on human subjectivity.

Become more competitive. The end result of faster, smarter and more consistent decisions is a more agile business that can respond quickly to market conditions and regulatory changes, improve customer service and profitably grow into new markets.

Predictive analytics can tell you:

- What is the best action to take on this applicant, claim, account or prescriber?
- Which product best matches this customer's needs?
- What actions can I take to reduce point-of-sale fraud without delaying too many genuine transactions?
- What actions will optimize my marketing spend while keeping credit losses even?
- Which accounts should I drop into collections queues and how aggressive should treatment be on each, given resource constraints?
- What is the impact on revenue if I raise my brand drug pricing by 5%? By 10%?

WHO USES PREDICTIVE ANALYTICS AND HOW?

An industry transformed by predictive analytics

Over the past 40 years, predictive analytics revolutionized the credit card industry, changing the speed, consistency and objectivity of all types of customer decisions. The technology is now used in every phase of the customer relationship—from marketing and pre-screening, to approving applications, to managing relationships with existing customers, to collections and fraud, to the securitization of loans.

Because analytics works almost instantaneously, lenders now make much faster—and sometimes instant—decisions on revolving credit. And decisions are more objective. Issuers' systems base decisions on facts that have a proven relationship to credit risk, rather than human subjectivity.

Similar ground-breaking transformations in the airline, transportation and other industries show that predictive analytics can not only improve a single company's bottom line, it can make an entire industry more efficient.

Predictive analytics is widely used to solve real-world problems in business, government, economics and even science—from meteorology to genetics. Here are some examples of predictive analytics applied to customer decisions.



Financial services: A large credit card issuer saw a \$6 million profit boost for every million active accounts by using predictive analytics to assign an optimal credit line for each customer.



Insurance: A large Brazilian insurer grew net profits by 130% using predictive analytics in its underwriting to reduce risk and grow revenue from profitable customers.



Telecommunications: A major global carrier saved \$70 million and decreased net bad debt by 25% in its first year of using an analytics-based collections solution. Collectors can pinpoint which accounts will repay the most.



Retail: A mid-size specialty retailer generated an additional \$250,000 in revenue per campaign and increased retention, using an analytics-based marketing solution to target customers and find the right marketing mix.



Healthcare: A major commercial payer saw more than \$20 million in annual savings using an analytics-based fraud solution to detect provider fraud and abuse, overpayment, and policy and system errors.

HOW DOES PREDICTIVE ANALYTICS HELP AUTOMATE DECISIONS?

Predictive analytics helps automate “decision strategies”—the decision logic or ruleset that defines the steps, in order, that will be applied in making a given customer decision.

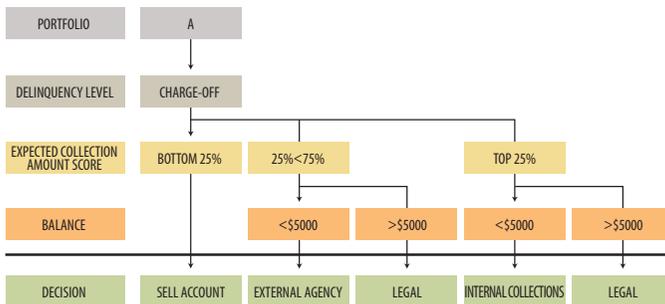
For example, one step in a collections strategy may be to use analytics to segment customers by their expected collection amounts and vary treatments accordingly. Automating decisions leads to greater speed and consistency.

SMARTER, SLEEKER BUSINESS RULES

Businesses that automate customer decisions using rules-based systems can gain added benefits from predictive analytics. Predictive analytics augments rules by:

- Improving the precision of customer segmentation, leading to more targeted actions
- Vastly simplifying rulesets, replacing dozens or even hundreds of rules
- Bringing empirical data analysis to business decisions, producing actions that are literally calculated to succeed

Rules management systems make decisions faster and more consistent. Predictive analytics also makes those decisions more precise and relevant. This helps you not only increase efficiencies but also take action to boost revenue.



Decision strategy

This recovery decision strategy uses balance and analytics that measure expected collection amount to segment customers for targeted treatment.

Applying mathematics to business problems

Predictive analytics applies diverse disciplines such as probability and statistics, machine learning, artificial intelligence and computer science to business problems. It's often aligned with operations research, defined by the Institute for Operations Research and the Management Sciences (INFORMS) as “applying advanced analytical methods to help make better decisions” (www.scienceofbetter.org).

HOW DOES PREDICTIVE ANALYTICS DIFFER FROM DATA MINING & BUSINESS INTELLIGENCE?

DATA MINING EXPLORES, PREDICTIVE ANALYTICS ANSWERS “WHAT NEXT”

Predictive analytics and data mining both apply sophisticated mathematics to data in order to solve business problems. But when people talk about data mining, they are usually referring to an analytic toolset that automatically searches for useful patterns in large data sets.

By contrast, predictive analytics is an analyst-guided (not automatic) discipline that uses data patterns to make forward-looking predictions, or to make complex statements about customers by evaluating multiple data patterns. If data mining searches for clues, predictive analytics delivers answers that guide you to a “what next” action.

Data mining is often one stage in developing a predictive model. Automated data mining techniques can isolate the most valuable data variables within a vast field of possibilities. The analyst uses those variables, and the patterns those represent, to build a mathematical model that “formalizes” these relationships and predicts future behavior consistently.

BI DELIVERS INSIGHT, PREDICTIVE ANALYTICS DELIVERS ACTION

Traditional business intelligence (BI) tools extract relevant data in a structured way, aggregate it and present it in formats such as dashboards and reports. Like data mining, BI tools are more exploratory than action-oriented, but the exploration is more likely driven by a business user than an analyst. BI helps businesses understand business performance and trends.

Whereas BI focuses on past performance, predictive analytics forecasts behavior and results in order to guide specific decisions. If BI tells you what’s happened, predictive analytics tells you what to do. Both are important to making better business decisions.

Predictive analytics also focuses on distilling insight from data, but its main purpose is to explicitly direct individual decisions. Many BI suites now include some analytics, ranging from report-driven analytics that synthesize past performance data to predictive analytics used in forecasting. However, BI analytics almost always aggregates past customer data in a collective sense—for example, how have my customers behaved so I can forecast product sales by quarter?

Predictive analytics can help you identify the best action to take on every customer transaction

Predictive analytics guides *individual* customer decisions, based on calculations of future customer behavior. It is often embedded in operational processes, allowing for real-time decision making where required.



BI AND PREDICTIVE ANALYTICS: A NATURAL FIT

Customer-focused predictive analytics complements traditional BI, allowing businesses to extend their data-driven insight into front-office applications and processing systems. An organization hoping to refine its pricing decision strategy could leverage BI to view past pricing trends, then use predictive analytics to simulate potential pricing outcomes and optimize a new strategy.

How can I improve my marketing decisions using...

DATA MINING?

Identify attributes associated with purchase (age, gender, etc.)

HOW?

Run an automated search through historical transaction data

BUSINESS INTELLIGENCE?

Break out customers by gender and age to see which groups are buying which products

HOW?

Examine cross-tabulations using an OLAP tool on the historical data warehouse

PREDICTIVE ANALYTICS?

Predict future "customer lifetime value" and response patterns to determine appropriate marketing treatment

HOW?

Build a statistical model of value using historical purchase and promotional data

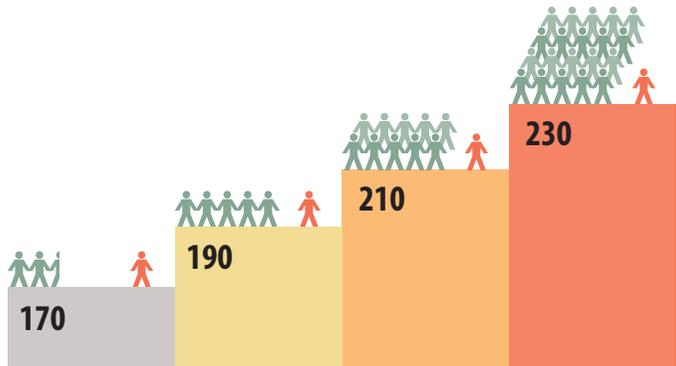
WHAT ARE THE TYPES OF PREDICTIVE ANALYTICS?

Predictive analytics is often used to mean predictive models. Increasingly, people are using the term to describe related analytic disciplines used to improve customer decisions.

Since different forms of predictive analytics tackle slightly different customer decisions, they are commonly used together. The models are built using a similar methodology but different mathematical techniques.

PREDICTIVE MODELS

Predictive models analyze past performance to “predict” how likely a customer is to exhibit a specific behavior in the future. For example, an attrition model measures the likelihood of a consumer to attrite or churn. This category also encompasses models that “detect” subtle data patterns to answer questions about customer behavior, such as fraud detection models.



Predictive model

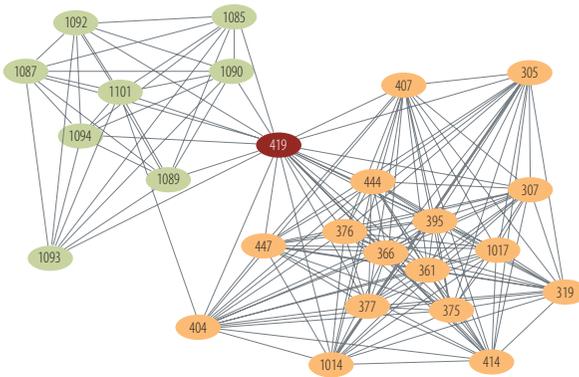
Predictive models predict how likely a customer is to exhibit a specific behavior. The risk model in this example predicts payment performance—there are many more “good” customers (green) for every “bad” customer (red) at higher score ranges.

Predictive models are often embedded in operational processes and activated during live transactions. The models analyze historical and transactional data to isolate patterns: what a fraudulent transaction looks like, what a risky customer looks like, what characterizes a customer likely to switch providers. These analyses weigh the relationship between hundreds of data elements to isolate each customer’s risk or potential, which guides the action on that customer.

Predictive models analyze past performance to “predict” how likely a customer is to exhibit a specific behavior in the future

DESCRIPTIVE MODELS

Unlike predictive models that predict a single customer behavior (such as attrition risk), descriptive models identify many different relationships between customers or products. Descriptive models “describe” relationships in data in a way that is often used to classify customers or prospects into groups.



Descriptive model

This model describes the purchase patterns that connect numerous products a retailer offers. This kind of analysis helps retailers “guide” consumers from one set of products to the next.

For example, a descriptive model may categorize customers into various groups with different buying patterns. This may be useful in applying marketing strategies or determining price sensitivity.

DECISION MODELS

Decision models predict the outcomes of complex decisions in much the same way predictive models predict customer behavior. This is the most advanced level of predictive analytics. By mapping the relationships between all the elements of a decision—the known data (including results of predictive models), the decision and the forecast results of the decision—decision models predict what will happen if a given action is taken.

What is a model? A score?

A model is a mathematical equation that takes in data and produces a calculation, such as a score. Think of it as a very specific set of instructions on how to analyze data in order to deliver a particular kind of result.

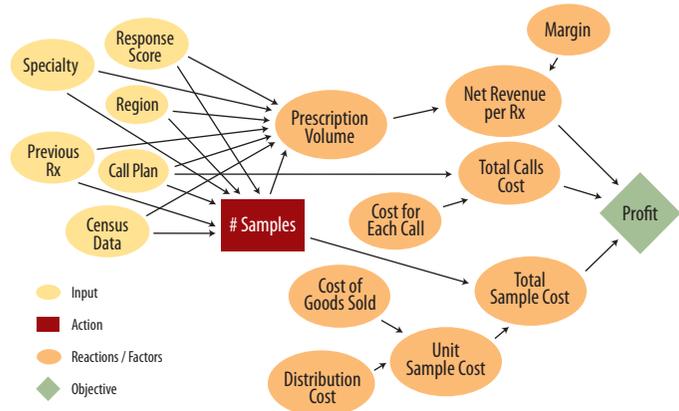
A score is the numerical value generated by a model or group of models when applied to a specific individual or account. Scores are common outputs of many types of predictive analytics—but not all models generate scores.

What is optimization?

While the term optimization is used loosely within the business community—sometimes simply to mean making a better decision—the technical definition is much more concrete. Optimization involves using analytic techniques to mathematically calculate the best action in a specific situation, given business goals and constraints.

True optimization is highly complex, able to account for uncertainty and balance competing business objectives—such as growing your customer base without overexposing yourself to risk. Its effectiveness increases when combined with predictive and decision models.

A predictive model could measure how likely a doctor is to prescribe a specific brand drug (behavior). By contrast, a decision model could determine the appropriate number of drug samples to send to each physician that would result in a written prescription (action). A decision model considers economic and business drivers and constraints that a predictive model would not.



Decision model

This decision model maps the relationship between a pharmaceutical company's drug sample distribution and profit for a given drug. Multiple underlying equations define the connections, in order to simulate the results of different actions and determine which actions would maximize profit.

Unlike predictive models, decision models are generally used offline to develop decision strategies. These strategies can be deployed in real time. Optimization (see sidebar) combined with decision modeling helps produce decision strategies that determine which actions to take on every customer or transaction, in order to mathematically optimize results and meet defined constraints.

Before you roll out a new offer or strategy, decision modeling also allows you to “simulate” changes to volume, response and risk—for example, “What would happen if I lower my pricing by 5%? By 10%?” You can run hundreds of these simulations within a short period, exploring many more possibilities than would be practical with live testing.

HOW DOES PREDICTIVE ANALYTICS WORK?

Different types of predictive analytics are applied distinctively in business. Here's how some frequently used models work.

SCORECARDS—PREDICT CUSTOMER BEHAVIOR

Scorecards are a popular form of predictive model, used in risk assessment and other areas. A scorecard produces scores that “rank-order” customers according to their likelihood to exhibit a specific behavior, from low likelihood to high. Numerical scores make it easy to set “cutoffs,” above and below which you take different actions.

Say you run a collections department, and you want to make sure your collection officers collect the maximum amount per hour. For each account, a collections model could deliver a score that would indicate the relative expected collection amount. Your system could send high-scoring (high expected collection amount) accounts to your best collectors, and sell low-scoring (low expected collection amount) accounts to an outside agency.

CHARACTERISTIC	POINTS
Length of Credit History in Months	
Less than 12	12
12–23	35
24–47	60
48 or more	75
Number of Credit Accounts with Balance > 0	
0–1	65
2	55
3–4	50
5–7	40
8+	30

Scorecards

This sample section of a scorecard shows how points are assigned for different values of a characteristic (category of information). It's easy to see how each factor relates to an individual's score.

Scorecards are often good options for industries that must explain decisions to customers or regulators. Since there's a clear relationship between the “points” assigned to each piece of data (see graphic), scorecards make it easier for businesses to understand why customers score the way they do. In addition, regulatory and business considerations can be built into the scorecard—controversial or prohibited data can be excluded, for example.

How can you use the past to predict the future?

Predictive models are built using a variety of techniques to analyze past data to predict future events. To build a scorecard, the analyst compares data snapshots for thousands of customers from “before” and “after” a particular decision—for example, before and after an offer was extended, or a loan was made. The analyst assigns values to relevant pieces of data according to which are most predictive, and this information is used to build the scorecard.

Neural networks are trained in development on a data set where they “learn” by example. The models initially make a number of random predictions. By assigning “penalties” to incorrect predictions, the neural net is systematically updated so that the models eventually learn to make correct predictions. Neural nets are considered artificial intelligence because their structure is based on the way the human brain processes information.

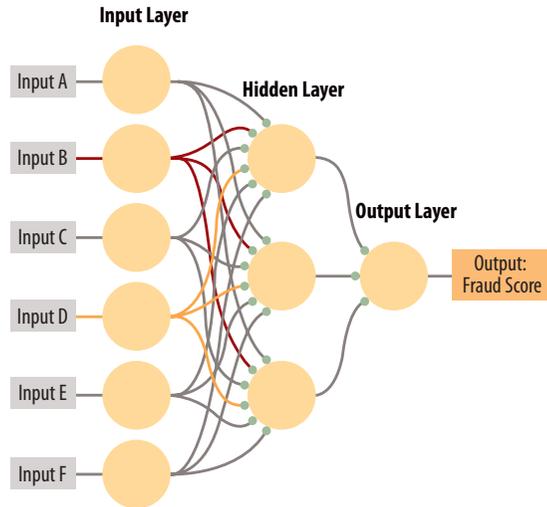
How does a model “analyze” data?

To understand predictive analytics, it’s important to know both how models operate and how they’re built. The distinction can be confusing. Model development involves analyzing vast amounts of data, and in operation a model will also analyze data in order to guide action.

Here’s the difference: In developing a model, an analyst identifies the data relationships that are important to the problem at hand and writes the equations that codify these relationships. In operation, new data runs through the model, which applies its equations to calculate a result that drives a decision.

NEURAL NETWORKS—SPOT ABNORMAL DATA PATTERNS FAST

What if data relationships are highly complex, but your profitability depends on identifying them quickly and precisely? In environments with heavy transaction volume and abnormal data patterns, like fraud, neural networks may be the answer.



Neural networks

The hidden layer is the mathematical core of a neural net. It selects the combinations of inputs (e.g., dollar amount, transaction type) that are most predictive of the output—in this case, likelihood of fraud. By “training” on a vast amount of data, the neural net can identify predictive but non-linear relationships.

When your credit card is used or a claim is processed for payment, for instance, the transaction is probably examined by a neural network model for signs of fraud. Neural nets are good at processing large amounts of transaction data at incredible speeds. They are also “trained” to identify what’s known as “non-linear” relationships in the data.

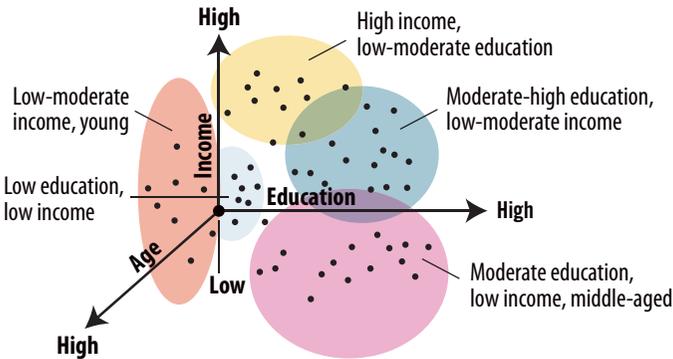
In a “linear” data relationship, fraud risk would increase as the transaction amount increases or as the distance of the purchase from home increases. But fraud patterns are not so linear—what if

Neural nets are considered artificial intelligence because their structure is based on the way the human brain processes information

a customer makes a large purchase while on vacation? Neural networks can more easily identify this non-linear situation as non-fraudulent versus models built to predict linear relationships.

CLUSTERING— SEGMENT CUSTOMERS INTO GROUPS WITH SIMILAR BEHAVIOR

“Show me how to split my customer base using demographic and customer data to create groups with different price sensitivities to our most profitable products.” This is one kind of problem tackled by clustering, a type of descriptive model that associates customers with each other relative to a certain dimension.



Clustering

Clustering models use demographic data and other customer information in order to find groups or “clusters” of customers with similar behavior, attitudes or interests.

If you needed to execute a marketing campaign against a universe of customers, for example, one step might be to vary the creative and the offer according to the customers’ needs and desires. Using clustering, you could assign each customer to a particular life stage and buying profile—for instance, young urban parents or cautious retirees. You could then build your messaging and product or service terms to appeal to each of these groups.

As a result, clustering can be used as a precursor to predictive modeling. Once clustering identifies key customer segments, predictive models can help tailor action for each segment.

HOW ARE MODELS DEVELOPED?

How much data do I need?

As a general rule, the more data, the more powerful the model. With enough data, you can build “segmented model” systems, which use multiple models for different customer segments with different predictive patterns.

Depending on available data, business goals and other considerations, here are some options:

Custom models—based on your company’s customer data. When you have sufficient historic data, custom models are built specifically to predict how customers will perform for you. They can incorporate your knowledge of customer patterns or important variables.

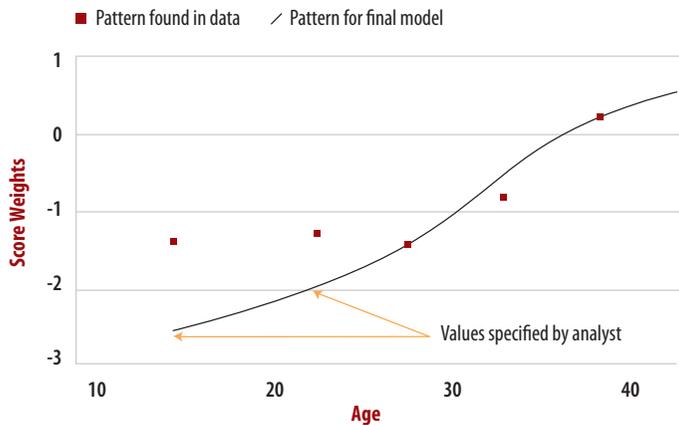
Pooled-data models—based on many companies’ data. Pooled-data or “consortium” models draw on a wide range of customer experiences in your industry. As a result, they often identify patterns not yet present in your customer population. Credit bureau scores and the leading fraud scores are based on pooled models.

Expert models—built judgmentally using analyst expertise. Expert models can be built quickly and cost-effectively when you don’t have enough data. They are a good alternative to custom models when no pooled models are available.

While advanced modeling tools are essential, the real power in modeling comes from the analyst. Model development is equal parts “art” and “science.” The analyst must know both what to look for in the data and what will work for a particular client in a particular industry. An analyst who doesn’t understand your business goals will not produce the model you need.

By and large, effective model development requires five key steps.

1. Define the business problem
2. Build the development sample with relevant historical data
3. Analyze the data for predictive patterns
4. Develop the model, fine-tune it and validate it
5. Deploy the model and evaluate it in practice



Expertise builds a better model

A good analyst will shape the model based on the data and how the model will be used. In this application scoring example, the analyst has adjusted the score weights for young credit applicants, because the lender’s youngest customers had been carefully selected and were therefore lower risk than the young population as a whole.

The real power in modeling comes from the analyst

Here are a few of the things a good analyst will excel at:

Dealing with data bias. Many modeling data sets have biases, missing data on some percentage of customers or an inadequate sample size. For instance, a data sample may be biased toward—that is, predominantly include data on—the kinds of people you currently have as customers. For the model to help you evaluate a broader range of customers, the analyst may have to employ techniques such as reject inference (or performance inference), which statistically infers the behavior of customer types that aren't in your data set.

Finding predictive data patterns. The more experienced the analyst, the more capable he or she is to interpret the nuances in the data and find the best predictive characteristics for your desired performance outcome. A good analyst will also know which technique to use for your data set and business problem.

Engineering the model. Modeling includes both letting the data speak and interpreting what the data says. During model development, the analyst often needs to “engineer,” or fine-tune, the model to ensure it will address the identified business goal. The analyst’s knowledge of your business problem and industry comes into play. The analyst could substitute or remove any predictive characteristics that may be contentious, in order to address regulatory requirements or customer concerns. When necessary, an analyst can make the output of the model more transparent so businesses can communicate decisions to customers.

Validating the model. There are many techniques used to rate a model’s strength, such as divergence, K-S (Kolmogorov-Smirnov statistic) and ROC (receiver operating characteristic). The analyst must examine the right measures to see how well the model performs on an independent data sample—one that was not used to build the model. This indicates how the model would perform in practice. A good analyst can also prevent “over-fitting,” which occurs when a model is so tuned to the specific data patterns in its development sample that it would not work as well on other data.

Are there legal issues in using predictive analytics?

Many countries and industries have legal restrictions on data use, sharing and privacy. Some also have restrictions on how to segment customers for marketing treatment to prevent preferential treatment or discrimination.

In the US, for example, lenders cannot use race or gender to make decisions on credit applications. Healthcare providers, pharmaceuticals and insurers face constantly changing regulations that vary state-by-state.

Look for an experienced model developer who knows how data and models can and can't be used in your industry and your region.

HOW DO I CHOOSE AN ANALYTICS PROVIDER?

FICO predictive analytics include:

- Credit risk models and scores
- Fraud models and scores
- Product preference models
- Response models
- Churn / retention models and scores
- Propensity-to-buy models
- Collections models and scores
- Next-product models
- Customer lifetime value models
- Product sequence models
- Profitability models
- Clustering models
- Decision models for the full customer lifecycle

Whether you're using scores for the first time or selecting enterprise-class modeling systems, choosing the right analytics provider is critical. A good analytics provider has both experience—in analytic technique and building models that work in practice—and the ability to deliver long-term business value.

Here are five key questions you should ask any provider:

HOW BROAD IS YOUR EXPERIENCE?

FICO has 50 years of applying predictive analytics to customer decisions. We pioneered the development of commercial scoring systems and are recognized as the leader in predictive analytics.

With thousands of clients in 80 countries, FICO's expertise and solution set span a wide mix of industries, enterprises and client problems. We have experience building industry consortiums, so individual companies can leverage broad industry data in their decisions.

HOW ADVANCED IS YOUR TECHNOLOGY?

Many analytic providers excel in one technique, which may not suit all problems. FICO's analytic toolbox contains dozens of proprietary and innovative modeling technologies, from genetic algorithms and neural networks to Bayesian algorithms and experimental design, which we have successfully used on client projects.

As a result, we extract more value from multiple data sources and are continuously refining techniques. Our solutions do a better job of accounting for business rules, legal and operational constraints, and biased or missing data. And our modeling tools enable analysts to shape results using their expertise—marrying analytic “art” and “science.”

WHAT KIND OF PROBLEMS DO YOU SPECIALIZE IN?

While superior techniques produce a sharper model—one that's built to last and offers greater ROI—technology alone is not enough. Models must be built to meet business objectives. This requires a provider that has succeeded with a variety of industries and types of client implementations.

FICO introduced the first commercial scoring systems, and we are the leader in predictive analytics

FICO offers a wide range of analytic applications for specific business processes, such as fraud detection, customer management, marketing and collections. We have unparalleled experience in the assessment of customer risk and potential. Our experience spans financial services, retail, telecommunications, insurance, healthcare, pharmaceuticals and the public sector.

HOW WILL YOU IMPROVE MY BUSINESS USING ANALYTICS?

With experience comes the ability to implement quickly, so you see results fast. FICO develops solid implementation plans, has the resources to deliver in your timeframe, and can give you the support to make the most of your analytic investment.

We offer solutions, custom projects, modeling software licenses and expert consulting to tackle your business goals and maximize ROI. We have battle-tested methodologies that help estimate business impact before deployment, and a proprietary model development platform that drastically reduces deployment time.

Our support doesn't stop once the model is deployed. We offer post-implementation guidance so you continue to see improvements with your models, including clear procedures for evaluating model performance. And we help you manage change across your enterprise, which can make or break success with analytics.

FICO has worked at length with regulators worldwide to ensure our models meet legal requirements. Our clients not only see better results, but they get clear insight into every decision and can handle customer questions more easily.

CAN YOU HELP COMPANIES AT MY STAGE OF ANALYTIC EXPERIENCE?

FICO has helped hundreds of companies get started with predictive models, and we're the analytic partner to some of the most sophisticated companies worldwide. As your analytic needs grow and change, we know how to take you to the next level of success.

To learn more about how predictive analytics can help you, visit our website at: www.fico.com. You can also call us at 1-888-342-3663 or email info@fico.com.

FICO—five decades of analytic innovation

- First commercially available scoring systems in US and Europe
- First scoring systems for retail, insurance underwriting and credit card
- First application of neural nets to payment fraud, now used to protect two-thirds of cards worldwide
- World's most widely used credit bureau risk score—the FICO® score, the standard metric of US consumer credit risk
- First commercial small business scoring systems
- First “adaptive control” system for account management, now used to manage 65% of the world's credit cards
- First multi-country credit bureau score
- Exploratory R&D for US intelligence and defense agencies, from anti-money laundering applications to bioterrorism countermeasures
- First analytic offering for prepayment detection in healthcare
- First suite that integrates business rules management, model development and optimization for Decision Management

**Explore the technology that's changing the way
businesses make billions of decisions about their customers:**

What is predictive analytics and what value does it provide?

How does this technology differ from data mining and business intelligence?

How can predictive analytics help my business?

What are the types of predictive analytics?

Who uses predictive analytics and how?

How do the models work and how are they developed?

How do I choose an analytic provider?

