



A Marketer's Gameboard for Predictive Analytics

In 1978 New York City structural engineer William LeMessurier received an odd call from a student. LeMessurier had recently unveiled the Citicorp skyscraper in Manhattan, a building with two design distinctions: a 45-degree chop at the top, as if it wore a jaunty hat, and at bottom four multistory supporting pillars placed by the sides, and not corners, of the walls. This created a remarkable view from the street — several stories above the ground, the corners of the building hung out over empty space. The engineering student, puzzled by this, had run math on what might happen when high winds hit the building, and suggested in a big storm, the entire Citicorp building might tumble down.

LeMessurier almost laughed at this kid's naivety... but later, after putting the phone down, curiously re-ran some calculations. To his horror, he discovered the student was right. If high winds hit the building from a corner angle, the pressure might destabilize the entire structure.

Call it a slight gap in predictive analytics.

If you work in marketing, your organization also will face stiff winds, and without appropriate forecasting, things may fall the wrong way. This whitepaper gives you a simple primer on how to structure media predictive analytics – including how to manage the process even if you don't have a Ph.D. in math.

The Citicorp Center skyscraper in Manhattan was designed in the 1970s with three gaps in prediction. First, NYC building codes only required estimating wind stress from the sides, not from an angle, so “quartering winds” were never modeled. Second, winds hitting it at an angle meant any 40% in windspeed could cause a 160% increase in stress. And third, contractors used bolts, not welds, in the structure's frame, weakening stress resistance. The end result was a 1 in 16 chance the building might fall down in any year due to high winds. The building was later remodeled with stronger, welded joints, and today is one of the safest buildings in Manhattan.



What is predictive analytics?

At its simplest, predictive analytics looks at patterns in past data to predict what might happen in the future. While none of us has a crystal ball, it is possible to foresee what is most likely to happen tomorrow. Any future has a range of possible outcomes, and even if some are difficult to predict (who will win an election, future fashion trends), almost all potential scenarios can be modeled.



Predictive analytics has become popular as all organizations learn to do more with “big data.” According to Statistics MRC, the global market for predictive analytics products and services is expected to grow from \$3.9 billion in 2016 to \$15 billion by 2023. And it’s already spreading through our society: Google anticipates the best search result, Amazon offers the next-best product, Netflix recommends a movie. Your credit card company tracks your past purchases to look for anomalies in the future, so if you pop up buying gas in a state far away, it may call you with a fraud alert.

And it’s likely already in your marketing organization. Your sales team has a “pipeline” of deals that may close. Your CRM database likely scores each of your customers by lifetime value, or LTV, the estimated future revenue each customer will generate over the next several years. Your finance department provides revenue forecasts. Your department heads run

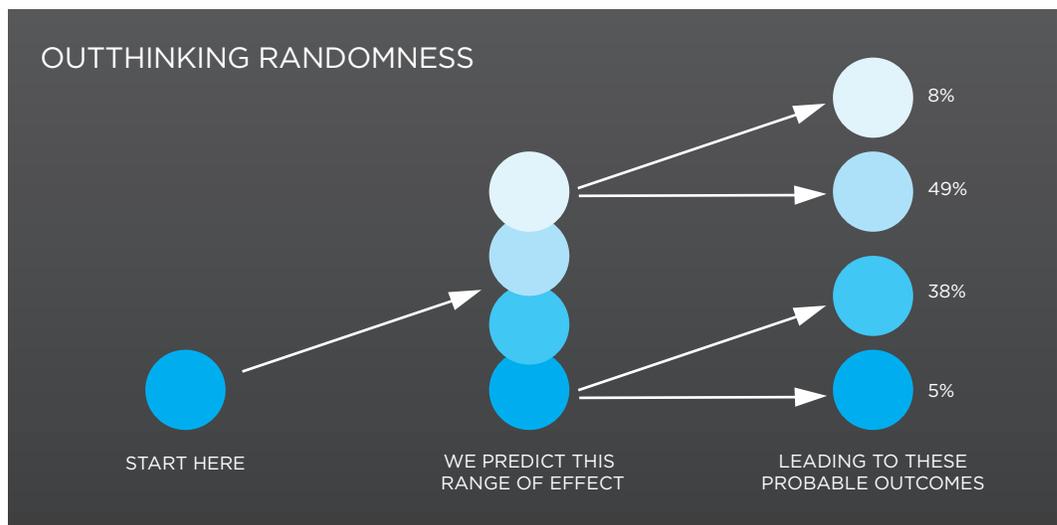
“According to Statistics MRC, the global market for predictive analytics products and services is expected to grow from \$3.9 billion in 2016 to \$15 billion by 2023.”

budgets of anticipated expenditures. Whether you like math or not, you already live in a predictive analytics world.

What all of these models have in common is that data from the past (your historical sales results, invoices sent last month to clients) are modeled into the future. In mathematical terms, the future at first seems a stochastic, or random, process — but with probability analysis, we can define a range of potential future scenarios, some more likely than others, which can be “predicted” out of that randomness. Like Blackjack, you’ll never know the next card to be dealt, but if you count the past card patterns, you can make a better guess.

Trouble is, most marketers still have not deployed true predictive modeling to where it matters most: predicting and controlling your return on advertising spend (ROAS). You may invest \$20 million in an advertising campaign, but will it really drive \$35 million in sales, or only \$15 million? The only way to improve the odds of your future success is to model it — but while marketers may forecast sub-elements of their campaigns, they rarely stitch all the pieces together. A recent study of global C-suite executives found that only 19% of companies use predictive models to optimize marketing activity.

Outthinking a stochastic, or random, process



Marketers, lost in the math

Um, yeah. This is the point where marketers usually give up. “Ah, outthinking stochastic processes, let’s break out the statistics...” and eyes glaze over, heads nod, they head for the next meeting on branding. While you know you need better forecasts in marketing, the math may seem insurmountable.

This is a missed opportunity — because if you can dramatically increase the odds of success, why have you not invested in marketing predictive analytics? Here are two simple solutions.

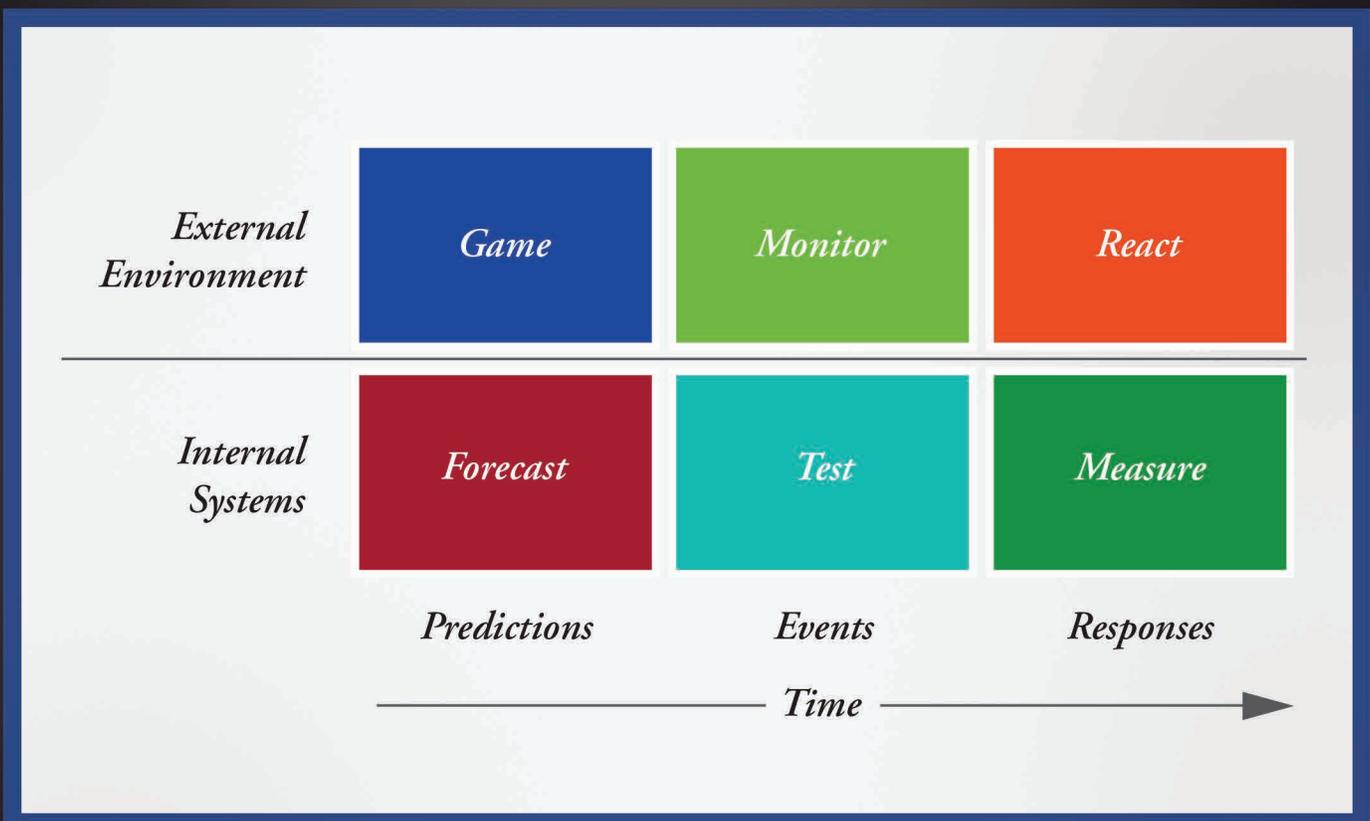
First, it’s important to note this is not necessarily an expensive technology investment. Yes, companies such as Google and IBM are doing incredible things to advance AI predictive modeling. Under the hood of their gleaming artificially intelligent, “machine learning” systems is a bunch of deeper math that few understand — clustering algorithms, decision trees, linear regression, random forests. While these are important and useful platforms, especially for modeling complex future systems such as weather or stock market trends, most marketers can fare well with simpler, more intuitive models.

Second, you can build predictive models with the tools you already have in-house. There are a few core questions marketers must answer about the future, and all of them can be easily modeled in Excel or Tableau with a little guidance:

- **Consumer demand.** When is consumer demand highest or lowest for products and services? With this model, you can put your message in market at the optimal time to drive highest response.
- **Media mix.** What is the optimal mix of creative, media, offer, and response channels to drive sales response? Using this, you can plan your campaign components for best results.
- **Funnel response.** If you invest \$XX million in marketing over Y period of time, how many Z sales will you achieve? With this, you can accurately forecast revenue and profit.
- **Brand vs. DR.** How do you balance the mix of branding communications and direct response (DR) tactics? With this, you can plan multiyear budgets for both branding and real sales results.

A simple gameboard for predictive analytics in marketing

To help marketers understand how to build and connect these models, we've designed a little gameboard. It has six squares, and if you can put models in place that connect them all, you'll be on the path to predict and control your marketing outcomes.



Let's start at the left side. There are two categories you must model in marketing to predict future results: Internal systems and your external environment. These two factors flow over time, as seen in the graphic above, across predictions, events and responses.

Our agency Mediassociates calls this the Predictive Analytics Gameboard.

FORECAST: This is the most obvious square, in which your organization predicts how your internal marketing activities of A will drive sales results B. Typically marketers model this off of historical performance — but the key gap is they often model only the effect of what they will do internally. For example, if you spend \$100,000 in paid search this quarter, at a past \$4.00 cost per click, you can predict you will get 25,000 respondents to your website. At 2% conversion, that's 500 sales. So far, so good. But you're missing the “game” square...

GAME: No one runs marketing in a vacuum. In the “game” square, marketers must assess their external environmental factors and run scenarios on what could happen out there in the future. If you run a hotel resort on the Gulf of Mexico, if a hurricane blows through in August, your tourist counts will decline. If you're a technology startup and Apple launches a similar tech gadget in November, your market share is going to be squeezed. Building out



these scenarios requires “gaming” hypothetical actions your competitors, suppliers, market entrants, market substitutes, and environmental movements such as weather and the economy will take. Not everything can be gamed out, but you should start by mapping the past two years of your business and defining the external factors that influenced your marketing — and then gaming similar scenarios in the future.

TEST: This is what you should do when your marketing is happening, right now. Testing is a real-time refinement approach of offer, message, and media, seeking to learn rapidly to feed optimization. An important point on testing is it does not have to be expensive or risky. New digital services allow rapid prototyping of creative messages to learn consumer receptiveness for as little as a few thousand dollars, and social media paid advertising can also be a forum for speed-testing creative or audience targets on small percentages of your total campaign spending.

MONITOR: This is how you look outward when your marketing is happening, right now. In today's economy, external environmental factors are shifting more rapidly than ever before. Social media sentiment, competitive tracking, news monitoring, and evaluation of how you perform in search vs. competitors are all urgent requirements to make sure an asteroid-type-event is not striking your marketing campaign when you least expect it.

MEASURE AND REACT: The last two squares are obvious, but often poorly designed by marketers. One common error is to measure only a portion of your campaign in detail, typically digital marketing, given the plethora of data available. A simple test of how well you measure is to build a chart of your entire media mix that reaches your desired audience across their “customer journey” from awareness to acquisition to conversion to loss to winback — and then overlay what percent of each activity you really measure.

Also be careful to cull down what you measure as well. In their classic HBR article “Prepare Your Organization to Capitalize on Predictive Analytics,” Brian McCarthy and Walter Frick recount the story of a retailer who measured 52 data elements at the local store level — but

“A fun but challenging exercise is to play angels and apocalypse against your own marketing plans.”

eventually found that only a handful of these metrics had any real impact on sales volume, revenue and profit. Before you measure every indicator, be sure to set up a “data dictionary” and evaluate the few key elements that really give you signal on future performance. These, and only these, key performance indicators are what you'll need to plan and react.

Top marketing predictive models

Marketers can start by setting up models for the forecast and game boxes. Here are the broad strokes for how to start:

Consumer demand models — These models anticipate the ebbs and flows of consumer interest. As the 1to1 strategy guru Don Peppers once said, “consumers are not on-off switches, they are volume dials.” To build these, you'll need to collect data from the past several years on weekly consumer demand, past marketing activity, media mix history, offers, and external

factors such as competitor moves. Statistical modeling then pushes these demand cycles forward 12 months to see how consumers desire your various products or services on a weekly basis.

External game models — This refers back to attempting to control the stochastic or random process of the future, and is more subjective. We typically start by assessing past external factors that influenced a marketing client's business, and then conducting ideation sessions on



“what if” scenarios. A fun but challenging exercise is to play angels and apocalypse against your own marketing plans (or entire business) and imagine anything big that could give your marketing a kick or crater. What if a new market entrant emerges? What if a giant incumbent fails? What if your top competitor doubled their ad spend? Then prioritize these “gamed” scenarios to the likely odds of each happening, and estimate the impact on your marketing campaigns.

Funnel, media mix and brand-DR predictive models — We can't give away all our secrets, but we do suggest building predictive models for how each sub-element will perform through the customer response model. Then, like a child playing a game of chess, you can move marketing elements around in these tables to see how different mixes drive better outcomes.

Conclusion

Predictive analytics in marketing provides two benefits: better arguments to take to your CEO or board if you need to justify marketing investments, and better advance campaign planning to foresee what will really happen to responses and sales. The only way to influence the future is to try to predict it.

Of course, all models are fallible. William LeMessurier believed his engineering design had accurately forecast the stress factors on his new skyscraper, until a young engineering student called to point out what he had missed. But armed with these new variables, LeMessurier was able to quickly respond and strengthen his structure. To increase your future odds of success, you need predictive analytics.

Whether you are a CMO seeking a multimillion-dollar investment in branding, or a marketing director trying to allocate advertising media channels most appropriately, forecasting models that anticipate how your internal choices and external factors drive results give you a path to success.

Yes, analytics is complicated math. But marketers don't need Ph.D.'s to be able to guide an actionable predictive analytics system. Simply cover the six squares on our Predictive Analytics Gameboard.

About the author



Ben Kunz is EVP of Marketing and Content at Mediassociates, a media planning, buying and analytics agency. A specialist in forecasting marketing results, Ben tracks emerging advertising and technology trends to bring new ideas to clients. He has been published or quoted in Ad Age, Adweek, The Atlantic, Bloomberg, Businessweek, Digiday, Fast Company and The Wall Street Journal.

About Mediassociates

Mediassociates is a leading independent media planning, buying and analytics agency. We see the media data behind advertising as a strategic platform for business growth. Using this, we help marketing clients plan and implement advertising campaigns — while predicting and measuring business outcomes. For more information on our services visit www.mediassociates.com.

THE BUSY EXECUTIVE'S GUIDE TO PREDICTIVE ANALYTICS TERMS

Are you an executive annoyed by predictive analytics buzzwords? Here, we put them in plain English. And to be really helpful, we show how each term is connected.

Predictive Analytics: *The science of examining patterns in past events to forecast future outcomes. If today it is raining 300 miles to the west and the wind is blowing east, you can predict it may rain at your home tomorrow. To build predictive analytics, you'll need to run patterns of past data through an **Algorithm**.*

Algorithm: *A series of steps that lead to an outcome. When you multiply 23 x 13 on a piece of paper and start with the right series 3 x 3, you are stepping through an algorithm. Recipes, your TV remote control buttons, even your innate human adrenaline that preps you for a 5k run are all algorithmic processes. Predictive analytics runs past data through algorithmic steps to forecast future outcomes. The most sophisticated predictive algorithms now use **Artificial Intelligence** or **AI**.*

Artificial Intelligence (AI): *These are algorithms that can improve themselves, recursively, without additional coding. Also called "machine learning," AI systems grow smarter over time. AI can be narrow to complete specific tasks (such as recognizing faces in Facebook photos, or beating a human at the game Go) or broader approaching human intelligence (simulating human conversation). AI modeling helps find patterns in **Big Data**.*

Big Data: *The buzzword for the plethora of data now accumulated in modern business systems. Marketers often struggle with big data, especially from digital advertising systems. One approach for finding useful patterns in data noise is grouping data to **KPIs**.*

Key Performance Indicators (KPIs). *The very few data that drive results. Typically KPIs are connected in tree-like branches, where one major goal has subordinate KPIs with each of them having additional inputs. KPIs are a form of **Descriptive Analytics**.*

Descriptive Analytics: *Looking at information in hindsight. Descriptive analytics tell you what happened in the past. This is vital, but a bit like looking in the rearview mirror. It's a big mistake if your marketing department only gets reports on the past. To understand why things happened and to peer ahead, you must move to **Diagnostic Analytics**.*

Diagnostic Analytics: *Understanding why something happened. If response rates fell in the digital ads you've been running for 8 weeks, perhaps you are facing creative "wearout" and need to refresh the ads. Or perhaps the ad frequency was too high. Or*

perhaps competitors matched your move. You have to diagnose the reason. The next step, once “why’s” are understood, is looking into the future with predictive analytics (above) and **Prescriptive Analytics**.

Prescriptive Analytics: Once predictive models are built, prescriptive analytics answers “how can we make the future happen?” If you predict paid media initiative A will drive twice the response rate as that of initiative B, you can then decide to move more investment into A. There are several tools to do this including **Classification**, regression, clustering and association analysis.

Classification Methods: In predictive analytics, “classification” groups future outcomes into structures such as “decision trees,” simply saying some things will go one way or the other. If you forecast 100,000 respondents to your ad campaign, decision trees might predict that 3,700 will convert, and of them 1,200 will buy the higher-priced product while 2,500 will buy lower-priced products. Think of this approach as mapping the branches of actions that happen in the future. Classification methods include “rule induction,” “K-nearest neighbor,” and “naïve Bayesian,” predicting things such as credit risks. The next step is to see how one thing causes others to happen, requiring **Regression Analysis**.

Regression Analysis: A term thrown around a lot, this simply means examining the relationship between two actions, often a cause and effect. If you double your advertising spend and also double sales, if no other factors are involved, it is highly likely advertising creates sales. Plotted on an X-Y axis, a perfect correlation of events creates a cool 45-degree line. But often the patterns are more complex, requiring **Clustering Analysis**.

Clustering Analysis: This approach shows how different groups cluster together in response. Often in marketing, for example, different customer segments may respond in different manners. If an alien marketer landed from outer space and had no idea how human shopping works, the alien could use clustering analysis to discover that women tend to buy purses and men tend to buy wallets. Using this information, the alien could with assurance run advertising for wallets only targeting men. Clustering finds the patterns that can guide future marketing efforts against specific demographic targets, geographies, psychographics, etc. Next, you’d want to see if people take actions that are also connected, using **Association Analysis**.

Association Analysis: This approach sees how actions are connected. If you buy bread, do you also buy peanut butter? If you are a grocery store manager, you’d like to know this, so you could stock peanut butter in the same aisle as bread. For many marketers, this level of analysis is fruitful in cross-marketing to consumers to increase share of wallet and **Customer LTV**.

***Customer LTV:** The future “lifetime value” of a customer. Typically this is a revenue number associated with the expected lifetime of a customer using your products or services, and is especially useful in subscription services or dynamics such as automotive sales where customers may buy several cars or SUVs over their lifetime. Customer LTV forecasting is important for the long-term health of your business, allowing you to focus marketing on customers most likely to generate more revenue and profit in the far future. LTV is typically modeled in **CRM Systems**.*

***Customer Relationship Management (CRM):** Originally a 1990s business strategy for identifying customers and treating different customers differently, the term CRM was coopted by technology sellers as a database solution. Today, CRM typically means a large database interface, powered by Salesforce.com, Microsoft or Oracle, that tracks customer interaction history and scores customers by value. Connecting CRM to marketing initiative and paid advertising can be extremely useful in improving sales to high-value prospects, or finding lookalike audiences. A relatively new subset of CRM systems are **Data Management Platforms or DMPs**.*

***Data Management Platform (DMP):** DMPs are data warehouses most often used to store and manage cookie IDs (code used to track online behavior) and then generate digital targeting audiences. Marketers and agencies use DMP technology to gather learnings from past digital advertising campaigns and to improve future targeting of digital communications. While they excel at targeting, DMPs are not as useful in modeling attribution from marketing, a task better suited for **Multi-Touch Attribution (MTA)** systems.*

***Multi-Touch Attribution (MTA):** Ah, we're back to the first question for predictive analytics — what happened in the past that allows us to model the future? MTA systems seek to stitch together the series of past events, often a sequence of advertising exposures, that caused a consumer to respond. If a person sees your online video ad and then a banner ad and then searches for your brand on Google, which of the three caused the final action? Or do all three get some credit? No MTA platform is fully automated and all require human guidance in modeling and projection, but they are extremely useful in illuminating all the causes of past behavior — necessary if you want to predict the marketing future. This will point the path to **Return on Ad Spend (ROAS)**.*

***Return on Ad Spend (ROAS):** The amount of revenue an organization receives for every dollar spent on advertising. One key goal of predictive analytics in marketing is to increase ROAS. Do this, and you can rest easy.*