Predictive Analytics:
The future of Business Intelligence.

"Until the turn of the century, knowledge was limited by access to a library or university. Now because of the increasing power and storage capacity of computers — and the amount of data published — knowledge is limited only by your ability to process it."

Contemporary Analysis
Work smart.

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What is Predictive Analytics?

In the simplest terms, Predictive Analytics uses historical data to determine the probability of future events. It is a form of Business Intelligence that goes beyond just reporting past events (reporting) and showing what is currently happening (dashboards). Predictive Analytics gives insights into what is likely to happen next — it's the closest thing business has to actually being able to predict the future.

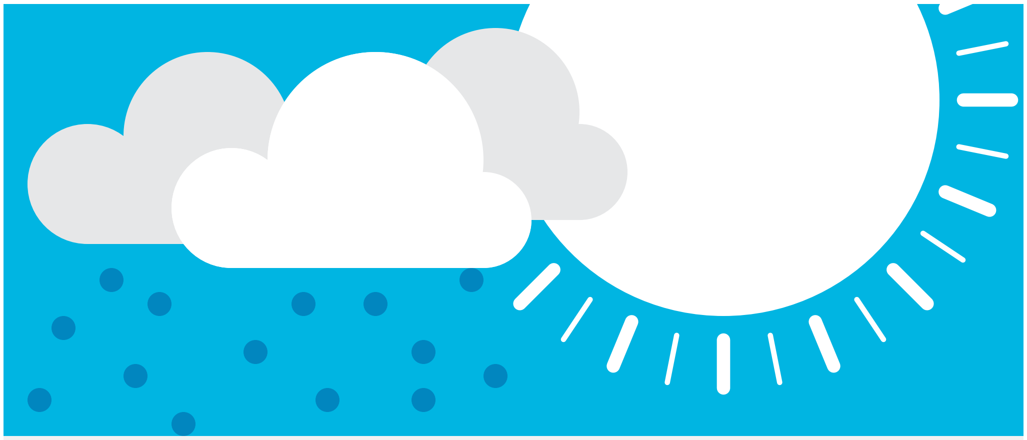
Set up a meeting to learn how we use your existing data — and the knowledge and intuition of your team — to identify your ideal clients.

Schedule a meeting!

When you use Predictive Analytics, you are able to improve almost every aspect of your business — from determining which employees are most likely to leave (and when), to figuring out which of your customers are most likely to need another product, to selecting which business opportunities your organization should pursue — simply by using your existing data to make better, more informed decisions.

In fact, you have probably used Predictive Analytics without even realizing it. For instance, have you ever checked your credit score? It is a "prediction" of your future credit worthiness based on your past payment history, how much credit capacity you have available, and a number of other data inputs.

Google's suggested search functionality, Amazon's product recommendations, and even Facebook's news feed all use Predictive Analytics to serve up the content you are most likely interested in reading, seeing, or purchasing. The possibilities are unlimited — if you have a business problem, you can most likely solve it using Predictive Analytics.



You're using Predictive Analytics without even realizing it.

While Predictive Analytics may seem like a recent development, the technology is already being used by a number of industries. And you have likely encountered it without realizing it. Here are a few real-world applications of Predictive Analytics:

1. **Weather Forecasting.** Combining historical data and trends with current conditions, weather forecasting is perhaps the mostly widely known and used application of Predictive Analytics in everyday life.

2. **Google Suggested Search.** Using their massive amount of past search data, Google is able to determine the most likely terms and results to complete your search activity.

3. **Amazon Product Recommendation.** Using your past search history, and the reviews and purchases of other users, Amazon is able to tailor product recommendations to your unique interests.

4. **Facebook Content Promotion.** Your Facebook news feed is populated using algorithms based on the content you have interacted with in the past. Using that data, Facebook determines the information that you most likely want to see.

5. **Spam Email Filtering.** Every time you mark an email as spam, you are helping your email provider better predict which emails are spam in the future.

6. **FICO Credit Scores.** Your credit score is a prediction of future credit worthiness and risk based your past payments and loan history.

The evolution of Business Intelligence.

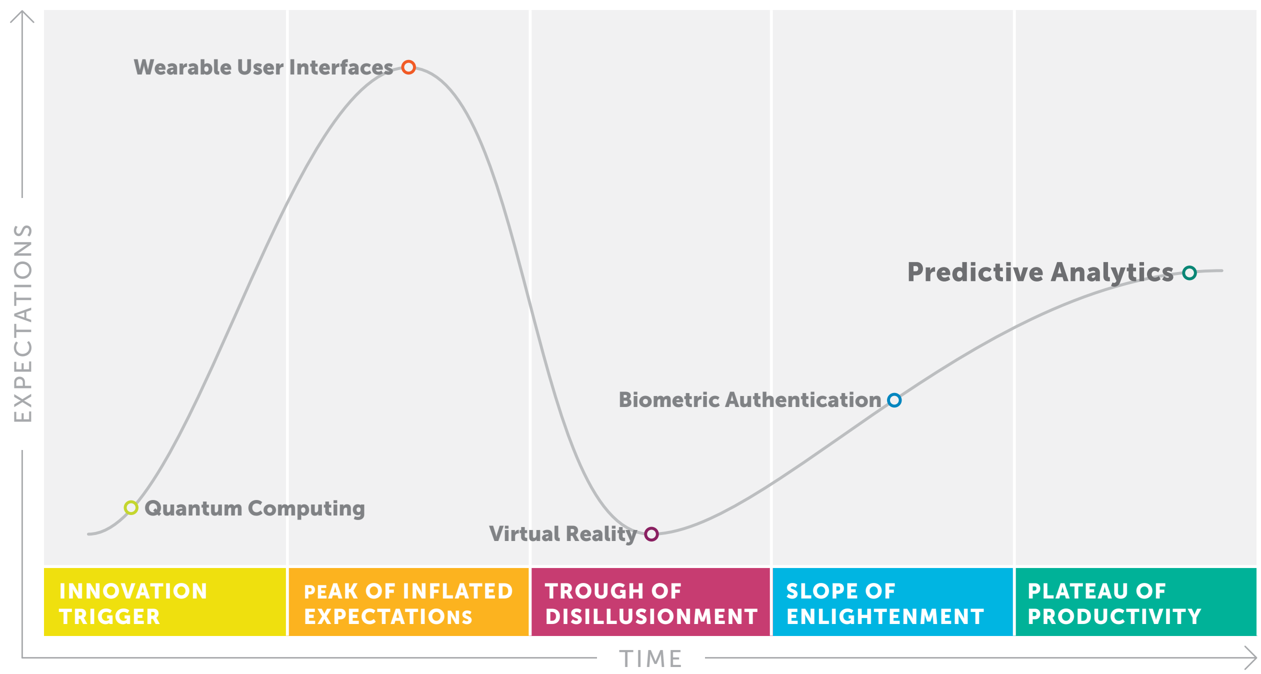
Predictive Analytics is the next step in Business Intelligence, and when used correctly is a powerful decision making tool. While traditional Business Intelligence provides information based solely on what has happened or what is currently happening, Predictive Analytics gives you the advantage of making decisions based on knowing what will happen, and guides your decision making process to maximize for the future.

BUSINESS INTELLIGENCE →

What has happened	What is happening	**Predictive Analytics**
Most money spent on Business Intelligence is focused on: • learning what has happened, or • on knowing what is happening.		THE NEXT STEP What will happen and how to maximize for the future.

In 2013, $14.4 Billion dollars was spent on traditional Business Intelligence and analytics software, an 8% increase from the $13.3 Billion spent in 2012. In our current competitive landscape of limited resources and limited budgets, Predictive Analytics gives your organization the edge it needs to stay on the frontline.

An industry ripe for adoption: Gartner's 2013 Hype Cycle for Emerging Technologies.



And this is just the beginning for Predictive Analytics — it has only just reached the plateau of productivity on Gartner's Hype Cycle for Emerging Technologies. It has climbed the mountain of inflated expectations, transversed the valley of disillusionment, and is ready to become a standard route on your Business Intelligence roadmap.

Learn how you can stay ahead of the competition — incorporate Predictive Analytics into your business plan today.

Schedule a meeting!

Metrics vs. Analytics.

While metrics and analytics work together to provide you with the insights necessary to grow your business, metrics and analytics are not synonyms. To date, metrics have dominated the Business Intelligence field in the form of dashboards and scorecards. Dashboards display metrics as the measurement of key variables. For this reason, they are very useful for monitoring current business activities and results. And while metrics are important, analytics go beyond measurement to provide explanations of the deep relationships behind business metrics.

Instead of reporting that something happened, analytics seeks to explain why something happened, and while using Predictive Analytics, when events can be expected to occur or to occur again — while giving insight into how to act now to shape future outcomes.

The shift towards Predictive Analytics is growing in importance because today's executives need to scale their decision-making in an increasingly complex world with little room for error. While many executives understand the value of data-driven decision making, decision-makers can become overwhelmed when faced with the volume and complexity of the available data provided by metrics and dashboards. Predictive Analytics provides value by cutting through complexity and providing decision-makers with access to only the most important variables, the relationships between them, and the insights needed to make the best decisions for future outcomes. When using Predictive Analytics, executives are able to focus on the information which drives their best decision-making.

Focus your decision-making abilities with the assistance of Predictive Analytics.

A Brief History of Predictive Analytics.

Though there have been great advances in the last few decades — as computer processing and data storage capabilities grow — the initial application of Predictive Analytics was in 1688, by Lloyd's of London. One of the first insurance and reinsurance markets ever established, Lloyd's was a catalyst for the dissemination of key information needed to assess risk on overseas shipping and trading.

Founder Edward Lloyd was able to use the reliable shipping news and information gathered from his popular coffee house to assist sailors, merchants, ship owners, and bankers in their business dealings, including insurance and underwriting. Over the next two centuries, the Society of Lloyds would become the world's leading market for specialty insurance, primarily because they used historical data and proprietary knowledge to quickly and efficiently identify risk.

In fact, the term underwriting itself came from the Lloyd's of London insurance market. Financial bankers that accepted the risk on a given sea voyage in exchange for a premium would write their names under the risk information that was written on a Lloyd's slip created for this purpose.

Exponential growth.

Even with a long history of use, Predictive Analytics didn't experience exponential growth until the dawn of the computer age in the 1940's. At that time, the United States government began predicting the outcome of nuclear chain reactions and other events using computer simulations.

From that time, as computer technology has advanced, so has the ability to model even more complicated situations using Predictive Analytics.

By the 1950's, technology had increased enough to perform the great number of calculations needed to create the first numerical weather forecasts. By the 1960's, FICO scores had became prevalent in the financial services industry to predict consumer credit worthiness. By 2000, Predictive Analytics had started to gain mainstream adoption. By then, Google had begun amassing its trove of search data, and Amazon had started using its data to personalize the shopping experience on its site.

Today, we are experiencing an explosion of Big Data and Data Science. The Internet, social media, and ever-increasing advancements in technology have created a surplus of information — all of which and be mined and repurposed to gain insights about your business using Predictive Analytics.

A surge of data.

- By 2007, more computer data had been created then all data created in the previous 40,000 years.
- The world's amount of data is doubling every two years.
- The total data supply in 2012 was 2.8 zettabytes (ZB) or 2.8 trillion gigabytes (GB).
- Volumes of data are projected to reach 40ZB by 2020, or 5,247 GB for every person on the planet.
- It is estimated that 25% of data currently held could yield useful insights if properly analysed.
- However, only 3% of the world's data is ready for manipulation, and just 0.5% is being used for analysis.

The current state of affairs.

In a reflection of the first use of Predictive Analytics, its use as a tool for underwriting and risk management is still the backbone of the insurance, banking, and real estate industries. However, access to new and better information has given way to other types of Predictive Analytics, including applications in customer retention, upselling, and cross selling.

For example, a bank can take the same information it uses to underwrite loans, including capital, collateral, and credit history, as well as demographics, geographics, and psychographics gathered from their CRM, to generate a model that can predict who has the highest propensity of taking on a new mortgage loan. So not only can you qualify who the best mortgage loan candidates are, you can also predict who is ready for a loan or to refinance their current mortgage. This not only saves time with your underwriters, but also optimizes the efforts of your marketing, customer service, and sales teams.

Although relational databases, faster computer processing units, and new tools have paved the way to bring Predictive Analytics to the masses, it is important to remember its history and that there is still a human element involved in the process. Like the sailors, merchants, and shipowners of Lloyd's Coffee House, experts in your business must provide their knowledge and experience to validate your predictive models — whether you're underwriting risk or analyzing the propensity of purchase for your current customers. Without validation, you cannot trust the models to reflect reality, and therefore you cannot trust them to make the best decisions.

Make the best decisions for your organization — utilize your data, and the knowledge and wisdom of your team.

Schedule a meeting!

How does it work?

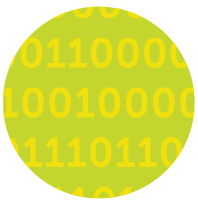
Finding patterns in historical data.

Predictive Analytics finds patterns and trends in your existing data, and then uses those insights to determine what is most likely to happen next. A combination of data and mathematics, the outcome is called a predictive model. Because this model is created using the historical trends found in the analysis of your data, it is able to more accurately determine what is likely to happen in your organization.

To get started, you need data to "train" the model. For example, a set of input fields — name, gender, zipcode, number of items purchased, etc. — representing a customer, is assembled into a customer record. When multiple records are combined together they become a dataset that can be mined for insights into your organization using predictive modeling techniques, or mathematical algorithms, that identify and "learn" the patterns hidden in your data. These patterns can then be applied to incoming data to predict the most likely outcome.

The necessary elements of Predictive Analytics:

Predictive analytics is both an art and science. It requires a combination of both empirical and subjective experience to verify the accuracy of a model. There are three main aspects to take into consideration when building predictive models: data, theory, and math. Your predictive models will not reflect reality if all of three of these aspects are not properly considered.



Data.

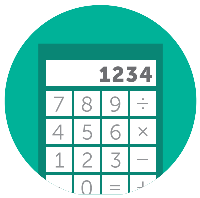
Data is the underlying foundation of Predictive Analytics. If your data is bad, the patterns you uncover and the generalizations you make are not likely to hold up. You will need to take the appropriate steps to clean and process your data — a process often referred to as ETL, or extract, transform and load.

In business, there will always be outliers or situations you've experienced infrequently. To account for these situations you must update your assumptions and models frequently so you're continuing to capture changes in your competitive environment, customers, and data. If the scope of your data doesn't allow you to generalize reliable patterns, Predictive Analytics will do you little good. In these cases it's best to use a combination of empirical and subjective experience to rationalize your decision.

Theory.

Theory is the experience you can append to the patterns in the data. Without solid experience — the knowledge, wisdom, and intuition of your team — you cannot understand the patterns in your data. Engage your company's subject experts to understand what patterns and variables are important to analyze. This also allows them to validate your predictive models.

For example, knowing that young males in college are usually the least loyal to your bank allows you to pinpoint that age, gender, and educational attainment are important variables when building a predictive loyalty model. There is also the chance that this empirical evidence may refute what some experts think, which is why it's important to facilitate discussions beyond what the typical "rule of thumb" may be. Its not uncommon to find surprises in your data.



Math.

Math is the engine that allows you to scale the patterns in your data and theory. This is the process by which we choose the best predictive models. Data and theory provide the context for which mathematical algorithms to apply. However, focusing on the math alone will lead you astray.

Using the previous example, if you decide to build a predictive model using age, gender, and educational attainment as predictors you may find that the mathematical results indicate that age and gender are not significant predictors of loyalty. Normally at this point you would decide to remove these variables from the model and work with what remains. However, if you had the knowledge before hand that a specific relationship may exist, such as the trend with young males, you could try creating a single variable that takes into account both age and gender (i.e. 19-25 year old males). Knowing this allows you to build a better predictive model, but requires having the context to back it up.

What is data? And what makes it valuable?

"Data" is a term used to describe facts, processes, or events that can be recorded and measured. Whether descriptive or quantitative, nearly anything can be converted into data. Facebook profiles, sales metrics, demographics, transactional information, interest rates, zip codes, tweets, emails, DNA sequences, and flight tracking information are all examples of data — and we have a lot of it. Data is collected from many different places, and while humans can collect data, machines and technology can collect far more and do it faster. Computer systems are designed to collect massive amounts of data on the processes they observe or facilitate, yet most of this is never used.

Thanks to these advances in computer processing power and storage capacity, 90% of the data available to humankind was nonexistent only two years ago — data is this age's most abundant raw material.

Consider data on a customer, such as what, where, when and how much they buy of something. This can be converted further into information, which when cleaned up, and presented in a fashion that allows us to ask more questions of it, allows us to obtain knowledge by using it to figure out answers to different business questions. Questions like: what are customers most likely to buy, how often, and how much? — which gives a company actionable information. Converting data into knowledge requires using advanced mathematics and modeling techniques to uncover patterns and connections within the data to make predictions of future behavior.

A hierarchy of data:

Data
(raw material)

Information
(refined data)

Knowledge
(actionable insights)

Judgments vs. Calculations.

Before a decision can be made, most organizations spend an inordinate amount of time researching, looking at forecasts, and interviewing wisdom. Many people assume that the more data they get, the better decision they can make. They believe decisions are calculations. Calculations require data. The more data you have the better the decision. But this is in accurate.

Making the correct decision is not selecting the right answer from hundreds of wrong answers. This fundamental flaw leaves most data-driven decision makers unhappy using data to make a decision. More data doesn't make the decision clearer, it makes it more complicated. But how can that be?

> Instead of a single right answer and hundreds of wrong answers, there is a spectrum of less wrong answers.

This is because business decisions have no right answers. They are not calculations at all, they are judgments. It only when framed correctly — when using data to choose the least-wrong decision — does Predictive Analytics make sense.

Understanding this, you need to ask different questions. You need to know what decisions you need to make and what work you have to do. Using Predictive Analytics and Data Science allows you to create predictive models that provide not just information, but actionable insights about why things are happening, and what steps you need to take today to prepare for what is likely to happen tomorrow. And there-in lies the value in data-driven decision making — spend time executing, not researching.

Data and Intuition.

No amount of data will make the "right" decision obvious. Data is not enough. Intuition and experience is required. Without a complete understanding of your unique situation, the Data Scientist creating your model will not be able to grasp the complete picture of your organization.

By using your data — and your team's knowledge and intuition — you will be able to determine the variables that make Predictive Analytics work the most effectively for your organization.

Once you have incorporated your data, and your team's knowledge into the predictive model, you can now run an organization where everyone has a more accurate decision-making engine. Everyone will be able to build on the experience, knowledge, and intuition of the company's top performers and your most experienced executives. Instead of repeating the past, you can build a better future.

How much data do you need?

Before beginning any Predictive Analytics project, it is essential to investigate the breadth and depth of data needed and how much is available. However, at what point is it acceptable to say you have enough data to start?

The correct answer is: it depends. Certain types of Data Science and Predictive Analytics require more specific data requirements. Extreme cases, such as predicting survival rates of people or machines, may require data spanning the entire lifespan of a large population.

However, in most cases, data requirements are less stringent, and chances are you have the ability to perform intensive Predictive Analytics with the data you currently have. In fact, taking a snapshot of three to five years worth of data can yield a breadth of patterns surrounding consumer and business behavior. But why?

Consumer and business behavior is influenced by short-term and long-term economic outlooks. Your short-term economic outlook is what happened to you yesterday and what you think will happen tomorrow. Long-term economic outlook is your expectations for what will happen in the future, in most cases three or more years.

In the short term, behavior in consecutive time periods will be more volatile when compared relative to the next. However, in the long-term, there are cyclical patterns in consumer and business behavior relative to certain economic cycles. The goal is to capture at least one side of an economic cycle — boom, bust, or both.

How long is an economic cycle? From 1945 until now, there have been 11 economic cycles. From peak to peak, the average cycle lasted 66 months or 5.5 years with the last cycle lasting 81 months or 6.75 years. As a general rule of thumb, there should be at least 3 years and preferably 5 worth of data before beginning any predictive analysis project.

Determine if you have the data needed to preform Predictive Analytics.

Schedule a meeting!

By analyzing a snapshot of data spanning an economic cycle, you can develop a more comprehensive understanding of how consumers and businesses behave and better predict what they are likely to do next.

Does this mean you need the foresight to plan this analysis 5 years previously? Not at all. In fact, you've been gathering customer data since your business started. As explained, data often contains more information than is presented at face value.

A wealth of knowledge:
The hidden gems in your data.

Your data contains more information than you think. By changing your mindset and taking your data at more than its face value, you are able to mine important insights into your business. Consider simple transactional sales data from your customers. With simple analysis it is possible to extract a great number of potentially significant variables.

For example, you could extrapolate the following variables:

Total Purchase Price

Product(s) Purchased

Product Relationships

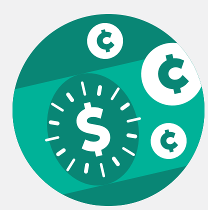
Time & Date of Purchase

Salesperson Responsible

Location of Purchase

Length Between Purchases

Bill-to/Ship-to Addresses



Payment Type

What can you do with Predictive Analytics?

So now that you know what it is... What can you do with it?

The reality is this — your competitors are most likely already using Predictive Analytics to gain market share as you remain on the sidelines.

Consider the undisputed king of retail — Wal-Mart. What's their secret? What has given them the edge for so many years over their competitors? Data analysis. They have lived and died by their data for decades. Wal-Mart knows their customer data better than anyone, and they have the market share to prove it.

Recently Dollar General took on Wal-Mart by providing cheap essentials like toiletries and medicine. Their strategy started to see success and Wal-Mart started to lose market share. But the retail giant went back to their data for a solution. The data said that many Wal-Mart customers started pinching pennies at the end of each month and needed a few basic items to tide them over until payday. As a result, they began stocking shelves with thousands of items under $1 at the end of each month. Customers lured to the Dollar stores for such items were back in the Wal-Mart fold.

Despite the hype and the proof that Predictive Analytics can give companies a competitive edge, the sidelines are full of businesses that are still not sure about getting in the game.

Predictive Analytics is about being better, and that starts with using what you have to improve what you can, and if necessary, collecting the data that will help you improve more as you get better.

The New York Times reported that a handful of universities are using their data and Predictive Analytics to help them find students who are about to drop out of school. These schools know that higher enrollment means more money. These early adopters are reaping the benefits and aren't afraid to tell everyone. Why? The vast majority of their competitors haven't given this type of data analysis a second thought. Just like Walmart, a few colleges will charge ahead and reap the benefits of higher enrollment while other universities sit on the sidelines.

You can find the same thing happening in the health care industry. The Wall Street Journal published an article by Dr. Marty Makary of Johns Hopkins pleading with hospitals to make better use of their data to save lives. You can almost hear the frustration in his voice when he writes, "Medical mistakes kill enough people each week to fill four jumbo jets." Even though there are 98,000 deaths due to medical errors in the United State, most hospitals and medical facilities are slow to adapt any type of data analytics.

A few forward thinking hospitals and healthcare facilities will see the opportunity and do what Dr. Makary suggests. Using data visualization and Predictive Analytics, the trend setters have improved patient care, are keeping costs down — and most importantly — are saving lives in the process. But just like the universities, the majority of hospital will remain on the sidelines.

Why are so many still sitting on the sidelines? The Harvard Business Review may have the answer. In an an eye opening survey they reveal the source of the bottleneck. Interestingly, the study shows that awareness about data analytics is at an all time high:

- **85% of organizations reported that they have Big Data initiatives planned or in progress.**
- **70% report that these initiatives are enterprise-driven.**
- **85% of the initiatives are sponsored by a C-level executive or the head of a line of business.**
- **75% expect an impact across multiple lines of business.**
- **80% believe that initiatives will cross multiple lines of business or functions.**

But here is where the rubber meets the road. The same HBR report also stated that:

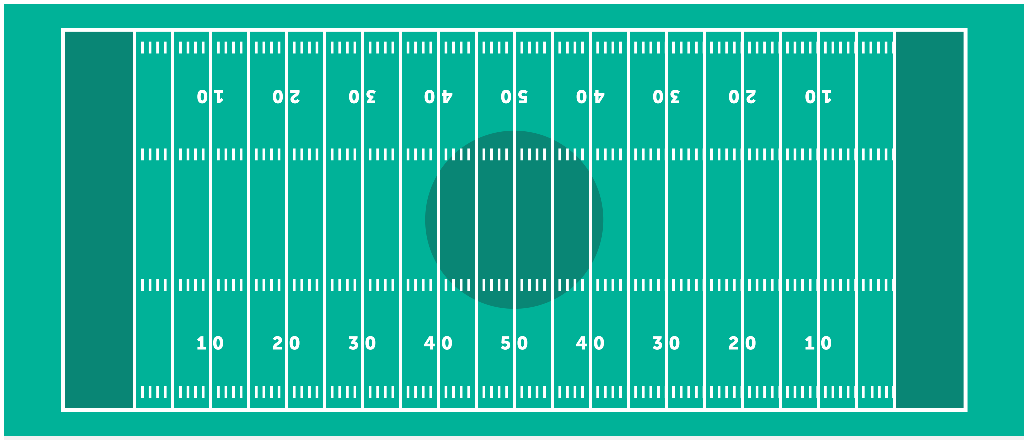
- **Only 15% of respondents ranked their access to data today as adequate or world-class.**
- **Only 21% of respondents ranked their analytic capabilities as adequate or world-class.**
- **Only 17% of respondents ranked their ability to use data and analytics to transform their business as more than more than adequate or world-class.**

The majority of companies are on the sidelines because they think they can't readily access the data they have, they don't have the in-house tools or talent to analyze it, and they don't have the ability to put the data to use anyway. In other words, they don't think their data is good enough, they don't have enough of it, and they don't have the right data.

Additionally, a 2013 Survey of Big Data by SAS shows the following reasons that companies are not implementing or planning on implementing Big Data:

- **21% Don't know enough about Big Data**
- **15% Don't understand the benefits**
- **11% No reason**
- **9% Lack of business support**
- **8% Poor data quality in current systems**
- **6% Lack of executive commitment**
- **6% Cost/financial resources**

Don't let this kind of thinking keep you on the sidelines. Predictive Analytics is about being better, and that starts with using what you have to improve what you can, and if necessary, collecting the data that will help you improve more as you get better. Your organization should have more than enough data to get started. Don't be one of crowd still sitting on the sidelines. Use the data you have to make better decisions. Be better at selling a product, servicing a customer, finding savings for your company, or even saving lives. Be an early adopter in your market space; use Predictive Analytics to jump ahead of your competition and see that the future is brighter from the front of the pack.



Data Science in the NFL: Finding the right players & strategies.

Who are the best NFL players and why? NFL teams spend a lot of money on scouts to find the best future players, and on staff to determine if their current players are up to par. So why are some teams beginning to hire data scientists to analyze a players stats to determine his value? How does data science help determine whether a player is good or not?

With football being perhaps the most popular, talked about, and drama filled sport in America, NFL teams invest a lot of money to become the team that everyone talks about, pays to watch, pays to be endorsed by, and generally just pays. The best way to do this is to win a Super Bowl.

So… how do you win a Super Bowl?

To win you have to get the right players on your team. Not the best, but the right players. This has been a proven strategy. Contrary to popular opinion, it's more about how well a team plays together to execute effective plays, even if one man's role is to perform a glory-less block that no one sees. This makes finding players more difficult than it might seem. If your goal is to make a cohesive team, full of players who complement each other — rather than sign the players with the most star studded track record — you have to consider several different categories of not just a few future players, but of all your current players.

How does data science fit in with recruiting?

Good staff and good scouts are priceless, because they have rare abilities and experiences. However they are limited to evaluating only what they remember seeing. They are limited to finding simple patterns. Using mathematical models allows teams to find more complex patterns. The models not only tell them what traits the team needs, but also the players that exhibit those traits.

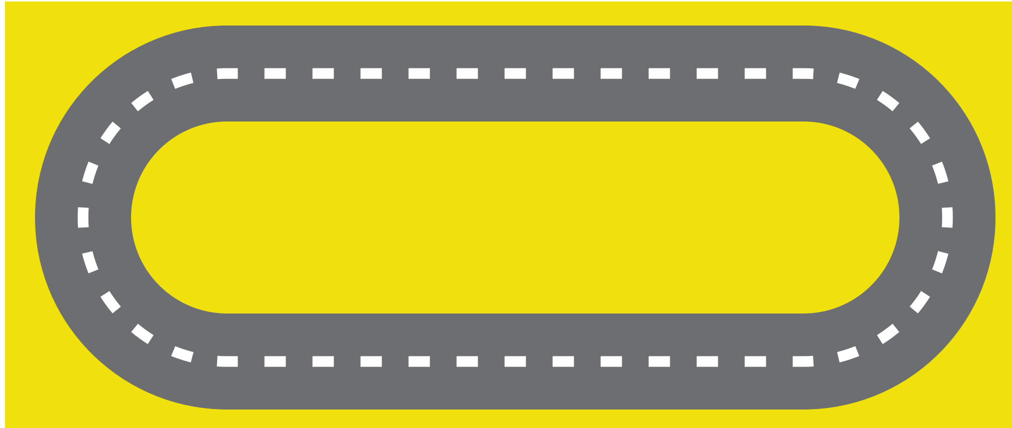
This would be similar to a business trying to find who they should hire next, based on who is currently on the team and what clients they want to work with. Imagine working at a place where people are selected because their skills compliment the other members of the team.

Data Science in the game

Where else could the NFL use this kind of analysis? Any football fan will hear at some point in time that the most prolific and successful quarterbacks in the NFL study game film, in order to find weaknesses in defense. They see patterns in certain players, such as: every time Troy Polamalu plans to blitz he nearly goes offsides because of impatience to take out the opposing QB.

The only problem with this method is that it takes a long time to see with the human eye…hours in fact. What if you could generate a report showing the areas of weakness in every player on the defense, based on the patterns that their mathematical model highlighted? Predictive Analytics does this, only more efficiently, and without the mental strain on your most valuable player. Imagine predicting how the defense will react to the types of plays and schemes your offense will run.

It's similar to predicting how consumers might react to the kind of marketing you produce, or how your current customers might react to a new product launch.



Formula One Racing & Predictive Analytics.

Formula One is to many the pinnacle of motorsports. It has the most technologically advanced cars, the most skilled drivers (some are compensated at $50+ million per year), and the most exotic race locations. Formula One is a closely sanctioned "space race" creating and refining innovative and groundbreaking technologies including traction control, anti-lock brakes, direct injection, synthetic oil, kinetic energy recovery systems (KERS), carbon fiber, and computational fluid dynamics (CFD). Many advancements made in technology by F1 teams have contributed to the efficiency and safety of everyday vehicles.

With team budgets around half-a-billion dollars, Formula One racing is big business. Similar to most businesses, teams are scratching and clawing for any advantage. F1 is a ruthless take no prisoners game where at seasons end, 10 of the top 20 drivers can be separated by less than five championship points. Each championship point can be worth millions. Teams are always looking for any competitive advantage to get as much of the $700+ million season purse as possible.

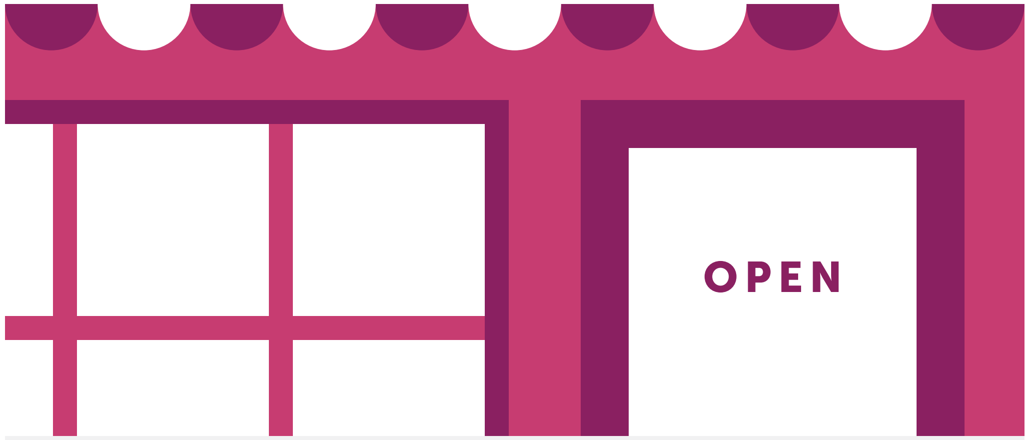
Prefecting race stategy — the key to success.

Formula One race strategy is equivalent to solving an impossible puzzle. Variables include weather conditions, tire degradation, position and speed of others on the track, safety car deployment, fuel conservation, opponent pit forecasting, and aerodynamic design. In real time, team engineers must take an impossible number of inputs and design the most efficient pit stop schedule. F1 engineers are expected to do what most believe is impossible — predict the future — which is where Predictive Analytics come in.

In the past few years, F1 teams have been working with companies including QuantumBlack to push the envelope and create predictive algorithms to optimize race pit strategies. QuantumBlack has produced predictive algorithms which they claim have assisted in accruing more than 300 championship points since 2009. These algorithms take into account current values of the variables listed in the previous paragraph and couple them with the real-time telemetry readouts from a team car to give an optimized race strategy. The process is so advanced, it allows these predictive algorithms to be adjusted and updated in less than four seconds of real-time.

These algorithms help team engineers make the most informed decisions for pitting. If an engineer is able to adjust a scheduled pit for a driver currently stuck in traffic and release that driver into a clean section of track, the payout can be valuable seconds, which equals points, which can mean millions of dollars.

If Predictive Analytics can be used to increase revenue of F1 teams by hundreds of millions of dollars, imagine the rewards your business could reap from developing your own predictive algorithms.



Diapers, beer, & Data Science in retail.

When asked specifically about legends that roam the retail world of Predictive Analytics there are many options: that milk is the most purchased item so it is always in the back of the store, that women's shoes are always on the way to mens clothes, and the fact that bananas are found at the front of stores because they are considered an impulse buy.

But the one that seems to get the most traction is the study that found that men who buy diapers most likely also have beer in their carts. It doesn't seem that far-fetched — a man coerced into buying a pack of diapers from the corner store on his way home from work picks up a case of beer as well.

The legend says that a study was done by a retail grocery store. The findings were that men between 30- 40 years in age, shopping between 5pm and 7pm on Fridays, who purchased diapers were most likely to also have beer in their carts. This motivated the grocery store to move the beer aisle closer to the diaper aisle and wiz-boom-bang, an instant 35% increase in the sales of both.

As it turns out, the study is much older than thought. It has nothing to do with analytics and everything to do with data mining. The myth relates to a study done in June of 1992 when Thomas Blischok, then VP of industrial consulting for NCR (now spun off to TeraData), did an analysis for Osco Drug.

They examined 1.2 million market baskets in 25 stores identifying over 20 different product couplings including beer and diapers, and fruit juice and cough syrup.

The story about how Osco moved beer next to the Diapers and both made more sales isn't correct though — Osco took the NCR study and identified approximately 5,000 slow-moving SKUs in its inventory. After removing those items from the shelf, consumers, now finding more items they wanted easier, actually thought Osco's selection had increased.

What Osco and the NCR study did was create a fundamental understanding that buying habits could be used to enhance the whole buying experience. Twenty years later, data mining has been upgraded to Business Intelligence and Predictive Analytics. Companies can now consider carefully how and what people buy and layout their stores more efficiently. They can offer coupons on items bought together, and have extra stock on hand when demand is going to increase.

"What Osco, and essentially the whole retail industry, began to understand, was that with the examination of data, the right amount of the right merchandise could be put on the shelf at the right time," said Blischok.

Now imagine applying those same principles to your product offerings and distribution strategies, you would be able to increase your overall revenue by predicting what your customers want, and when.

Strategic planning, Predictive Analytics, & Union Pacific.

For most, seeing a Union Pacific diesel-electric locomotive does not bring Predictive Analytics to mind. But the largest railroad network in the United States is showing the effectiveness of analyzing non-conventional data forms to increase operational efficiency.

Thinking outside the box, Union Pacific is currently using bearing acoustic monitors to identify faulty or failing bearings on trains. The acoustic detectors have been used for years, but enough data has now been collected to show the correlation between failing bearings and certain frequency spectrums. This correlation has been applied to real time acoustic readings to help predict bearing failures and ultimately decrease derailments and costly train delays.

Understanding what information can be analyzed is the most difficult obstacle to overcome when discovering new possibilities of Predictive Analytics. As soon as immeasurables are turned into measurables by quantitatively reducing uncertainty, Predictive Analytics can be applied.

Union Pacific has saved tens of millions of dollars by taking the time to understand and analyze the sound of bearings. The next time you see a Union Pacific train plowing through the countryside, imagine the competitive advantage your business would possess if you could make more well-informed decisions using Predictive Analytics.

Applying Predictive Analytics.

The best way to apply Predictive Analytics is to help automate and improve your decision making on a specific business problem. In other words, Predictive Analytics is best applied when it creates actionable insights for your company. Its application is only as valuable as the actions and changes made with the information provided. From the beginning of any Predictive Analytics initiative, the focus should be finding areas of your organization where it will allow you to take action or make change. If you are not using the insights to improve your business, then there is no value in implementing Predictive Analytics — having a GPS system does little good if you never turn it on.

When applied properly, Predictive Analytics guides your organization to make better judgments based on the information you have available. By focusing on a specific business problem, you are able to create the biggest impact for your company. It is an error to apply Predictive Analytics to an entire business function such as marketing, sales, or human resources. The right way to scope a project is to try to automate and improve one routine decision process inside a business function at a time. For instance, sales is a business function. Identifying the right leads is a routine decision. Predictive Analytics is great at generating and identifying quality leads because successful lead generation depends on making unbiased decisions using hundreds of variables to select the best sales opportunities among thousands of options.

When to apply Predictive Analytics.

Though most business activities can be modeled using Predictive Analytics, there is a point where the advantages do not overcome the cost or effort to apply data science to the problem at hand.

First, predictive analytics should ***not*** be applied if:

The cost of being wrong is low.

You should not apply Predictive Analytics if reducing uncertainty does not provide enough value. Predictive models should only be applied in situations with a high cost and/or probability of being wrong and where Predictive Analytics can provide information to reduce uncertainty. To determine if Predictive Analytics is worth applying to a decision you need to calculate the expected value of information.

The relationships are obvious.

A predictive model is basically a story about why something happens and what will most likely happen in the future. With this in mind, you do not need to develop models if people are able to accurately — correctly — describe the relationships between variables well enough that they can tell stories about why certain things are or are not happening.

The model can not be reproduced.

If you develop a model, but it can't be reliably reproduced then you should admit that Predictive Analytics can not be applied to that situation. Predictive models find and tell stories that are difficult for people to discover because there are either too many variables or the events being studied are too rare. The value in knowing the story of why something happens is that you can reduce uncertainty, make better decisions, and run your organization more effectively.

Predictive Analytics allows executives to learn from the cumulative knowledge of their organization. This systematized learning has the potential to help businesses and executives to make decisions that are less wrong, so that they can work smart.

The following are situations when predictive analytics ***should*** be applied:

Too Much Information.

Over the last 30 years there has been an explosion of data, and Business Intelligence has been focused on collecting and presenting that data. Predictive Analytics is one of the Business Intelligence tools that is capable of statistically filtering out what data is most important.

Customer management is an example of when Predictive Analytics can be used to find valuable patterns in an overwhelming amount of data. It can determine how to group customers, and help develop campaigns to improve specific behaviors for each client segment.

Rare but Important Events.

When an event is rare and results in either major gains or losses, it can be very beneficial to gain a better understanding of why the event happens. Predictive Analytics can help you develop plans to encourage or discourage specific rare events.

Predicting the failure of essential business processes is an example of when Predictive Analytics can be used to find valuable patterns in rare but important events. For instance, perhaps your organization manages a fleet of large (and expensive!) machinery, with considerable lost revenue associated with unexpected downtime. Imagine being able to replace parts and equipment before it breaks down so that essential business operations continue to move forward.

Predictive Analytics allows executives to learn from the cumulative knowledge of their organization. This systematized learning has the potential to help businesses and executives to make decisions that are less wrong, so that they can work smart. However, it is important that Predictive Analytics is applied in the right applications, so that is produces the most value to your organization.

Learn if applying Predictive Analytics is right for your organization's business problems.

Schedule a meeting!

10 tips for successfully implementing Big Data & Predictive Analytics.

1. **Focus on the application not the technology.** It is easy to focus on technology. After all, companies spend millions of dollars in marketing to get you excited about their technology. Unfortunately, the only way to realize a return on investment is by applying the technology to solve a problem. Don't focus on the technology, focus on how it helps improve your business.

2. **Don't focus on data collection.** Only 3% of the 2.8 zettabytes – 2.8 trillion gigabytes – of data available in 2012 was ready for manipulation, and only 0.5% was used for analytics. While it might be fun to talk about the "big" in Big Data, your focus should be on applying your data instead of collecting more.

3. **Focus on existing data.** Many organizations delay pursuing Predictive Analytics because they think they don't have enough data. The truth is most companies have enough data for Predictive Analytics, especially if they have been in business for more than three years. Since Predictive Analytics uses patterns in the historical data, new data sources aren't bad, but stable historical data is better.

4. **Concentrate on specific business processes — not entire functions.** Predictive Analytics should focus on one routine decision process inside a business function at a time. For example, sales is a function and identifying leads is a routine decision. Predictive Analytics is great at identifying quality leads because successful lead generation requires making unbiased decisions using the hundreds of variables available.

5. **Start with familiar business processes.** It is a good idea to start automating what is familiar, and expand into unfamiliar territory only after you have had success. You are already aware of the nuances of the processes your business uses, and you can use that knowledge to test predictive models to make sure they reflect reality before using them to make decisions.

6. **The goal is to automate and improve decisions not deliver more information.** Predictive Analytics is about automating and improving routine decisions. Traditional Business Intelligence treats decisions as calculations with right answers; instead of judgments. However, most business decisions are judgments with no "right" answer, only a gradient of better answers, none of which are wrong. The power of Predictive Analytics is that it is able to merge this experience and intuition with historical data to create better decisions.

7. **Don't isolate non-technical stakeholders by using math talk.** Mostly because you need them to help create the improved decision making models talked about in #6; non-technical stakeholders have the experience and intuition required to build a predictive model. In order to avoid isolating non-technical stakeholders it is key to allow them to participate in the model development process without having to understand the math.

8. **Budget for implementation and testing.** A predictive model is a complicated series of variables, coefficients or values for each variable, and the relationships between them. If you are building a Predictive Analytics application from scratch it is important to budget three to four times the cost to develop the model for implementation and testing. You can build great models, but they are only useful if the results are applied accurately.

9. **Frame success in hours instead of dollars.** It is very common for businesses to reduce decision to dollars. However this over simplifies the impact of Predictive Analytics. Its value is in freeing people — mostly at a fixed cost — to do more valuable work by improving and automating routine decisions. The impact of making better decisions represents a significant monetary return on investment, but it is minor compared to the impact of having more time to spend on non-routine decisions, as well as better management and communication with customers, the public, and employees.

10. **Don't forget about policies, privacy and security.** Predictive models contain the knowledge, experience and intuition of the business process modeled. This makes security very important. A security breach doesn't mean just the loss of data, but also the loss of intuition and experience. Most companies need to create policies for how to use Predictive Analytics. A useful policy is that the methods should support the goal.

The best use case of Big Data is to use Predictive Analytics to improve and automate routine decisions so that your organization can run more efficiently. Predictive Analytics is the application of Big Data.

Schedule a demo to learn how to get the most value by using Big Data & Predictive Analytics in your organization.

Schedule a meeting!

When to update your predictive models.

Everyday new data is being created, and your predictive models need to be updated accordingly. The environment is constantly changing — your customers are buying more, subscribing, or unsubscribing. While predictive models can handle a lot of new new data, overtime those environmental changes build up causing predictive models to lose their effectiveness. As these new patterns emerge its important to periodically take time to investigate your data, update your models, and challenge your assumptions about your business. But how often should you do this?

To answer that question, consider the following:

- **How often is my data changing?**
- **How often do I plan on making decisions with the data?**

To understand how often your data is changing, its necessary to understand what type of data you gather and how often. The average number of customer transactions per year is often a good place to start. For example, if on average your customers purchase from you once a month or once a quarter, it may be possible to identify new patterns in their behavior on an annual basis, which would only require you to update your models and assumptions annually. Models primarily based on customer demographics, including gender, age, income, geography, etc., tends to change little over time, often times not even annually.

Set up a meeting to discuss the unique requirements necessary to implement Predictive Analytics in your organization.

Schedule a meeting!

Contrastingly, if your customers have more frequent transactions (i.e. daily, weekly, bi-weekly), your customer data is quickly growing in size and complexity. The patterns created as a result of this new data are also more dynamic. This means you need to update your models and challenge your assumptions more frequently — often monthly or quarterly.

Knowing how often you plan to make decisions with the results of your predictive models also helps you determine when to update your predictive models.

For example, if it only makes sense to focus marketing efforts or strategic initiatives quarterly, quarterly updates are sufficient. However, if you or someone in your company uses the outputs daily, weekly or monthly, you may need to update your predictive models monthly. In extreme cases where new data is created by the minute, such as commodities trading, daily updates are required.

Obtaining political buy-in and support for your Predictive Analytics initiative.

The decisions you make in business may never be perfectly right, but you can strive to become less wrong. Predictive Analytics provides decision makers with a system to continually improve decision-making, while eliminating some of the inefficiencies of non-analytical trial and error.

However, the ability of Predictive Analytics to systematize an organization's cumulative knowledge can be threatening to experts who value their accumulated knowledge. When beginning a Predictive Analytics initiative, the most vital key for gaining political support is to maintain focus on the business problem, and never the technology.

There are many people who rely on their accumulated knowledge as a competitive advantage, and job security, against their fellow team-mates. In light of this situation, quite possibly the most effective method of gaining support, is to focus Predictive Analytics on a specific, defined business problem. Your initiative must be dialed in on solving a vital, business critical issue. This way, dissenters to implementation will be seen in the light of hindering the future success of the organization.

Learn how Predictive Analytics can grow your organization — and the reasons you need to move forward with your initiative as soon as possible.

Schedule a meeting!

Consider the following case study: a client had a division that was responsible for sourcing materials for production. They had a group of commodity traders responsible for sourcing materials at the best price possible. While the company had made significant investments into Business Intelligence, the amount of data required to make an informed trade had been growing exponentially for the last ten years.

The future of the organization required developing a system that made learning from the cumulative knowledge of the organization easier. However, implementing Predictive Analytics was politically challenging, as it could be threat to both Business Intelligence and the company's best commodity traders. To overcome that perceived threat, the focus was placed on the business problem and a case was made that eliminating the problem was essential to the continued success of the organization.

The key to gaining political support is to define the business problem in the context of its importance to the continued success of the organization. If solving the business problem is not essential to the success of the organization, it may not be worth addressing. But if it truly is important, and Predictive Analytics is the best candidate for the job; internal opposition will be seen as opposition to the continued success of the organization.

Presenting Predictive Analytics for the greatest impact in your organization.

The nature of forecasting the future makes presenting Predictive Analytics unique and challenging. There is no magic bullet that will make presenting analytics any easier. There is only a model that tells a story about the future of users' business, customers, non-customers and competitors. To produce a meaningful return on investment you need to translate the details of the story into results that can be applied to a specific business question.

Select an Audience.

Who you are presenting to determines what information you present and in what order. When presenting to generalists you want to start with the conclusion and then explain how you reached that conclusions. By starting with the conclusion, you provide generalists, who are typically decision makers, a filter to understand and develop questions during the rest of your presentation.

When presenting to experts, you want to start your presentation by providing background information, and then explain step by step how you reached your final conclusion. This is useful because the experts want to know that you know what you are talking about, and presenting background information before you reach conclusions will help you establish trust.

Set Expectations.

When presenting Predictive Analytics your audiences expectations should be set on becoming less wrong, instead of finding the perfect solution. There are no perfect answers in complex sciences, such as Data Science and Predictive Analytics, only less wrong answers. The goal is to reduce the uncertainty of making the wrong decisions, not thinking uncertainty will be eliminated.

Justify Each Element.

The key to success is to curate your presentation by justifying the existence of each sentence, graph and data table. If you can not provide a good explanation for something you included in your presentation, you must take it out.

Focus on Results.

After a successful presentation, your audience should know exactly what the next step is; who they need to call, what they need to buy and what they need to do. If there is no clear action they must take after hearing your presentation, then your research and presentation have been wasted.

Set up a meeting to learn how to get the most value by using Big Data & Predictive Analytics in your organization.

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Work smart.

We use Predictive Analytics and Data Science to solve business problems — sales, marketing, customer service, management, and strategic planning — and to help businesses work more efficiently.

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Why choose CAN?

We believe that Contemporary Analysis has several unique benefits that will give your organization a competitive advantage. We strive to make Predictive Analytics simple and affordable because all companies, not just the largest, should be able to benefit from Predictive Analytics and Data Science.

Our principles:

1. **We care about business.** Each business deserves a custom solution. Problems are our passion.
2. **We solve core business problems.** We make a big impact quickly. Value is our focus.
3. **We help you make better decisions.** Less wrong is the goal.
4. **We are technology agnostic.** We focus on the solution. Technology is just a tool.
5. **We create simple solutions.** Our job is to solve problems, not introduce more complexity.

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Set up a meeting to learn how you can use your existing data — and the knowledge and intuition of your team — to your business run more efficiently.

Schedule a meeting!