Crunch time 6

Forecasting in a digital world

Prediction is very difficult, especially if it's about the future.

—Niels Bohr
Nobel Laureate in Physics

Forecasting in a digital world

Human fascination with the future is part of our evolutionary heritage. Those who can foresee and navigate risks have always been more likely to survive than those who can't. That's just as true in business, where the ability to see ahead continues to separate performance leaders from everyone else. That's what forecasting is all about, yet it's surprisingly difficult (and often expensive) to do.

Companies have different motivations for improving their predictions. For some, the ability to deliver reliable guidance to analysts and markets might drive the decision. For others, being able to trim production waste by predicting consumer demand is what matters most. Still others want to improve cost management and streamline the forecasting process.

Traditionally, forecasting has been a mostly manual process with people gathering, compiling, and manipulating data, often within spreadsheets. With more and more data available, old-school forecasting has become an unwieldy, time-consuming process that makes discerning what's important next to impossible. As a result, humans often resort to their own intuition and judgement, which opens the door to unconscious biases and conscious sandbagging.

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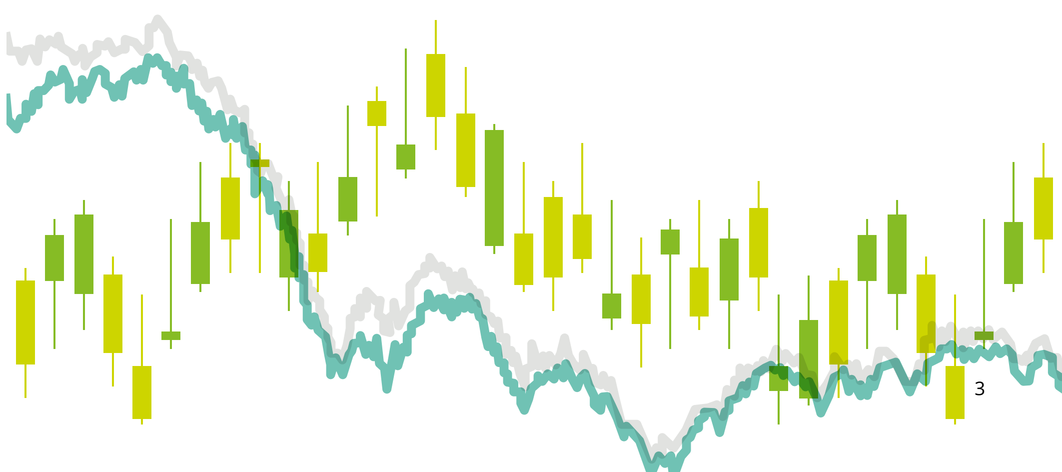
For an introduction to the digital capabilities that make data-powered forecasting possible, read *Crunch time 1: Finance in the digital age.*

There's another way. Organizations are shifting to forecasting processes that involve people working symbiotically with data-fueled, predictive algorithms. It's all made possible by new technologies—advanced analytics platforms, in-memory computing, and artificial intelligence (AI) tools, including machine learning.

Similar digital tools are common in our consumer lives. We use a mapping app to predict when we'll arrive at our destination. A real-time weather app can tell us precisely when a rain shower will start or stop. So, it's reasonable to expect predictive capabilities when we're at work.

Today, these technologies in the hands of expert forecasting talent give companies the ability to discover things they've always wanted to know—as well as things they didn't know they didn't know—with more confidence and speed.

CFOs are in a prime position to challenge the way their enterprise looks at and consumes data. In the area of forecasting, they can champion an innovative, data-driven approach that will help people project the future of their business. By modeling the potential impact of important decisions, they can help generate smarter insights and stronger business outcomes.



Algorithmic forecasting

Machines and people working together to see what's next

You can hardly turn around these days without bumping into a vendor claiming to have software that can predict the future. As is often the case, the hype outstrips the reality. Here's how we see things.

The basics

Algorithmic forecasting uses statistical models to describe what's likely to happen in the future. It's a process that relies on warehouses of historical company and market data, statistical algorithms chosen by experienced data scientists, and modern computing capabilities that make collecting, storing, and analyzing data fast and affordable.

Beyond the basics

Forecasting models offer more value when they can account for biases, handle events and anomalies in the data, and course-correct on their own. That's where machine learning comes into play. Over time, forecasting accuracy improves as algorithms "learn" from previous cycles.

Models are also more valuable when they're grounded in richer, more granular data. In some cases, that might involve using natural language processing, which can read millions of documents—including articles, social posts, correspondence, and other text—and feed them directly into the algorithms.

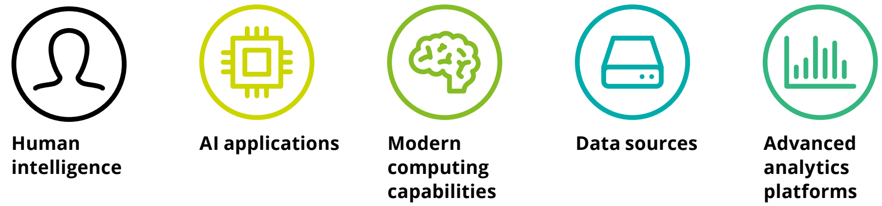
The magic

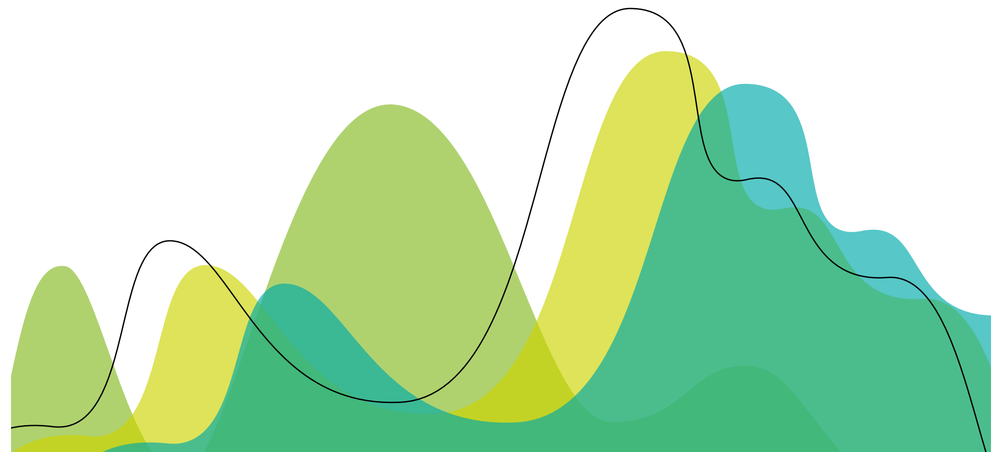
The real lift from algorithmic forecasting comes when it's combined with human intelligence. Machines help keep humans honest, and humans evaluate and translate the machine's conclusions into decisions and actions. It's this symbiotic relationship that makes algorithmic forecasting effective—especially when humans are organized to support and share their findings across the enterprise.

The bottom line

Algorithmic forecasting doesn't create anything out of thin air, and it doesn't deliver 100 percent precision. But it *is* an effective way of getting more value from your planning, budgeting, and forecasting efforts. We've seen companies substantially improve annual and quarterly forecast accuracy—with less variance and in a fraction of the time traditional methods require—while building their predictive capabilities in the process.

Algorithmic forecasting depends on these elements working together





Don't we have bigger fish to fry?

CFOs are continually weighing the relative ROI of potential investments that vie for their attention. Here are a few reasons why many leaders are moving algorithmic forecasting up their priority list:

Competitive advantage
Leaders who can more accurately predict future performance based on the underlying business drivers—both internal and external—are better positioned to recognize and respond to early warning signals.

Increasing disruption
As companies' business and operating models change in response to disruptive competition, historical patterns and trends used in traditional forecasting are becoming less and less relevant.

Growing complexity
Global market and supply chain complexity, along with increasing volatility, means that organizations should harness the agility that algorithmic forecasting can deliver to help make sense of new realities as—or even before—they emerge.

The ripple effect

While some aspects of forecasting using algorithmic models are fairly straightforward, others can be trickier. Changing processes. Building trust and transparency. Creating partnerships between people and machines. These are tougher challenges.

How work changes

With algorithmic forecasting, Finance does more insight-development work and less manual drudgery. Instead of spending their time grinding through spreadsheets, humans get to bring their expert judgment to the process. Leading finance organizations are already using automation tools to help with manually intensive work like transaction processing. Automating routine forecasting tasks is another area ripe for improvement.

How the workforce changes

Your finance talent model should evolve to keep up with changes in how work gets done—and that will likely require a different mix of people than you have in place today. Algorithmic forecasting depends on collaboration among Finance, data analytics, and business teams.

Once they hit stride, these teams can move across the range of forecasting needs, embedding capabilities in the business and driving integration. These teams are integral to establishing an algorithmic solution that can work for the business, bring insights to life within the organization, and support continued business ownership of the outcomes.

Our experience has shown us that some finance professionals are simply better at forecasting than others. They've learned to set aside their biases and look at the bigger picture objectively—and they have a knack for understanding algorithmic models and uncovering flaws that others may miss.

"Foresight isn't a mysterious gift bestowed at birth. It is the product of particular ways of thinking, of gathering information, of updating beliefs. These habits of thought can be learned and cultivated by any intelligent, thoughtful, determined person."

—Philip E. Tetlock in *Superforecasting: The Art and Science of Prediction*

You'll need storytellers, too—folks who really understand the business and can translate analytical insights into compelling narratives that trigger appropriate actions.

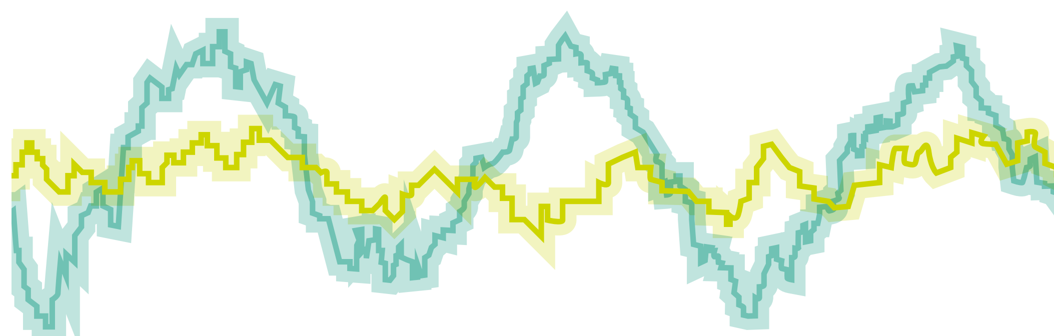
How decision-making changes

Making choices becomes a more interactive process with advanced forecasting techniques, resulting in smarter, more informed decisions, even on the fly. In-memory computing, predictive analytic software, and visualization tools enable management to easily and quickly ask "what if" questions and produce a range of scenerios to help them understand potential impacts on the business.

How the workplace changes

Forecasting isn't limited to Finance. Functions from marketing to supply chain to human resources all have needs for predicting the future to drive important decisions. While CFOs may not lead function-specific forecasting, they should help shape these forecasting initiatives since Finance will inevitably use the outputs they generate.

A shared forecasting infrastructure—even a physical Center of Excellence (CoE)—can help improve collaboration and coordination while providing efficiencies in data storage, tool configuration, and knowledge sharing. And once the organization develops the forecasting muscle to solve one problem, the capability can quickly be extended and applied in other areas.



It's happening now

Many of the companies we work with have begun their digital finance journeys by investing in cloud, in-memory computing, and robotic process automation. Others have broadened their ambitions to include advanced analytics, with an emphasis on forecasting. They want to create forecasts that enable faster and more confident decision-making. This is where those digital investments can begin to pay off. Traditional approaches to forecasting can take far too long, cost far too much, and generate too little insight about potential future outcomes.

Common applications for algorithmic forecasting

Top-down planning

- Target setting
- Integrated financial statement forecasting
- Working capital forecasting
- Indirect cash flow forecasting
- Demand forecasting
- Competitive actions and implications
- Tax tradeoffs and revenue/profit implications

Bottom-up forecasting

- Product-level forecasting
- Market- or country-level forecasting
- Direct cash flow forecasting

Function-specific forecasting

- Customer retention
- Inventory optimization
- Employee retention and attrition modeling

External reporting

- Market guidance
- Earnings estimates

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Case study

Is fast growth a financial problem?

Yes, if you can't explain it.

The FP&A team for a global consumer product manufacturer frequently outperformed their guidance to market analysts. Problem was, they couldn't explain the unanticipated growth, and holding credibility with the executive team, board, and industry analysts was a key priority.

The team suspected sandbagging was the source of their headache. Individual business unit (BU) leaders made their own bottom-up forecasts as part of the target-setting planning process, which was used for performance incentives. Finance had no objective way to verify or push back on the BU leaders' numbers.

What happened next
Finance leadership asked Deloitte to help them develop an objective, data-driven forecasting approach. Within 12 weeks, Deloitte's data scientists designed a top-down predictive model that incorporated the company's internal historical actuals and external drivers for each global market, including housing starts, local GDP metrics, commodity prices, and many additional variables.

The model enabled the FP&A team to deliver a second-source forecast based on external macro drivers that aligned to market expectations and provided insightful, accurate projections across the P&L, balance sheet, and cash flow statements. Planners also gained the ability to quickly create growth, recession, and other scenarios using desktop visualization software.

The toolkit
The Finance team received the fully functional predictive model built on an open source platform, which enables their CoE to manage and model forecasts on an ongoing basis. Leadership gained an objective, transparent, and visual conversation starter for discussions with business units about new opportunities and upcoming challenges for their markets.

Looking ahead
Leadership sees this as a game changer, and not just for their top-down financial forecasts. The business segments do, too. Following the successful delivery of a prototype focused on corporate FP&A, Finance has added data scientist capabilities to its talent model. Socializing the results with the business has created significant demand to dive deeper and extend the solution to the business segments and regions. Additionally, the client has taken steps to industrialize the model and to provide business users greater visibility into the driver assumptions and relationships to the financials.

The company continues the journey to scale the solution within the organization on their own. The client's FP&A leader reports, "This is a good-news story. We made an investment [to prototype algorithmic forecasting], proved the concept, and got the business interest. We created significant demand for a new Finance-developed forecast capability that will help the organization improve forecast accuracy and efficiency."

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Roadblocks

When you start having conversations with colleagues about replacing traditional forecasting processes with algorithms, you'll quickly discover that people have preconceptions about what it is, how it works, and what it means for the organization. That's what happens when change is in the air.

Fear and loathing

People are often scared of the unknown. Even though Finance is a discipline grounded in numbers, some will resist the idea that algorithmic forecasting might enhance their own methods. Help them see that machines can handle the tedious number-crunching work while enabling people to spend more time uncovering valuable insights.

Small thinking

Some people won't take time to see the bigger picture. They'll go along with algorithmic forecasting if they have to, but they'll start small and stay small, looking for what's wrong instead of what might be workable—all while refusing to give up the old ways of thinking and acting.

Black boxes

There's a myth that algorithms are black boxes where magic things happen. While not true, some complicated models may seem that way. To help build trust across the organization, consider using easier-to-understand algorithms with transparent inputs in the beginning. As comfort grows, so will the willingness to accept more complex approaches.

Turf battles

Is algorithmic forecasting a CIO thing that needs to be brought into Finance, or is it a CFO thing that needs IT's help? And when it comes to bottom-up forecasting, who's on first—the business or the business partner? The reality is that effective algorthms require data, computing power, *and* business insight—so collaboration is important. Making accountability and ownership decsions up front can improve collaboration and value generation.

Engagement matters

It's important to involve end users to help conceive, design, build, and implement algorithms. After all, they know the sandtraps that need to be avoided, and their acceptance is key to effective implementation.

Silver bullets

Algorithmic forecasting often gets introduced with a lot of hype. Don't do that. It's just a tool. That said, when this kind of powerful tool is combined with human intellect, the impact can be transformative.

Data, data, everywhere

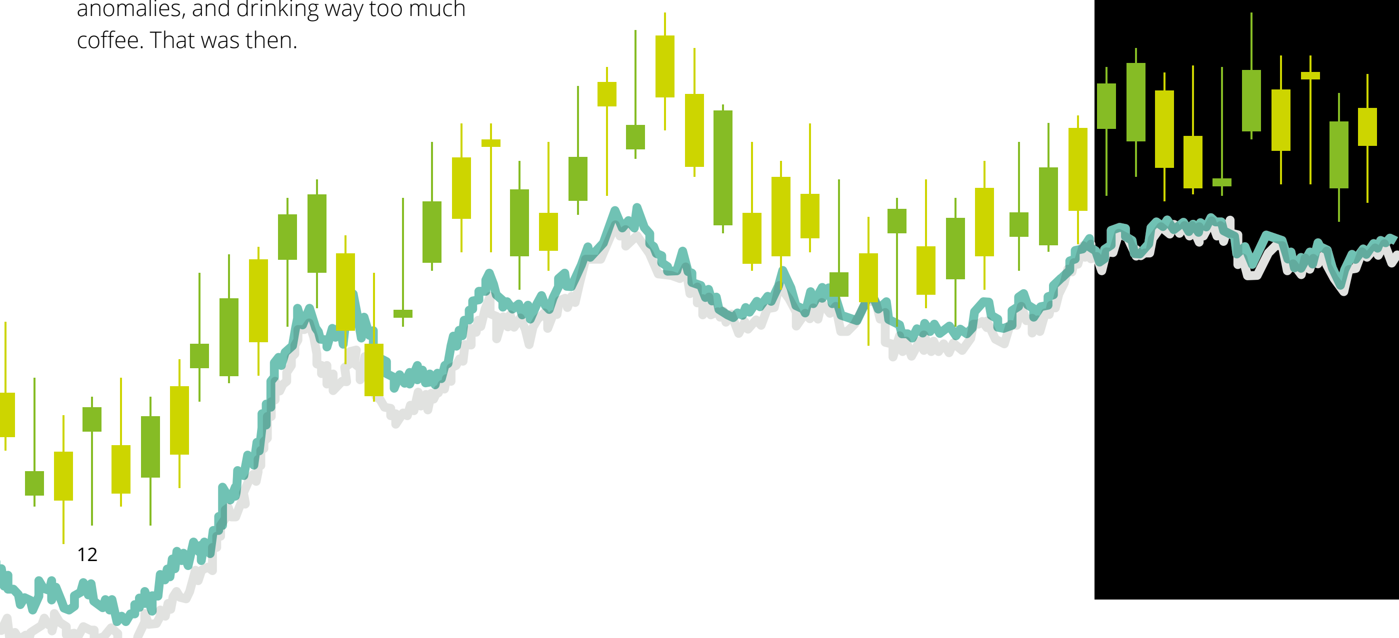
Some companies want to try new approaches to forecasting, but they're worried their data problems will stymie them. Whether those problems are the result of mergers and acquisitions, a history of poor data management, disconnected systems, or all of the above, you're not alone. The first step toward improving forecasting for many companies is getting their data house in order—sometimes even one room at a time.

Algorithmic forecasting in action

It's 7:00 a.m., and you're thinking about the day ahead. By noon, you have to settle on a forecast about how your business will perform over the next quarter. And at 2:00 p.m., you need to tell that story to a dozen board members on a conference call.

In the past, your forecasting team would be pulling all-nighters for days before your meeting. They'd be grinding through spreadsheets, calculating growth percentages, chasing down anomalies, and drinking way too much coffee. That was then.

Today, your forecasting function is a well-oiled machine, with more than 80 percent of the work happening automatically. Every piece of financial data you could want is available on your tablet. All you have to do is ask—literally. *Display the impact on profits if the cost of steel goes up 20 percent in the next month.* You can drill down, roll up, set aside exceptions, and run a dozen more scenarios before your conference call. And you can do it all without an army of analysts scrambling to help.



What changed?

Almost everything.

More and better data
Your organization now uses data of all types—financial, operational, and external—to train your forecasting model. Once the model is set up and evaluated, machine learning kicks in. The model gets better over time through constant and automated iterations. It is always up-to-date, evaluating and determining which of the latest inputs add the most insight and value to your predictions.

Improved accuracy, more confidence
Where are you going to land this quarter? This year? Do you need to update your guidance to the Street? If so, by how much? Algorithmic forecasting answers these questions in real-time, without having to aggregate bottom-up analysis from every corner of the globe. Your communications with investors are more informed and more efficient.

A clearer view of performance drivers
Scenario modeling also gives business leaders visibility into performance drivers. For example, you can easily see how to manage existing markets by building out price, product mix, and volume analytics.

More models, more options
With better models analyzed more quickly, you have the opportunity to understand the impact of unforeseen trends in the market and factor them into your planning. How are unemployment and disposable income trends going to affect the business? How much of that cut in trade spending should I expect to fall through to the bottom line? Scenario modeling done in collaboration with business units gives them advanced capabilities to work smarter, not harder, along the forecasting journey.

No sandbagging, no rose-colored glasses
Algorthmic forecasting enables you to measure—and remove—these two big human biases, giving you objective predictions you can trust.

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Getting from here to there

Most clients we work with don't attempt a wholesale change to their forecasting approach from the beginning. Instead, they select a part of their business or a specific revenue, product, or cost element to use as a pilot or proof of concept. They often run algorithmic forcasting parallel to their human-centric forecast for a period to compare accuracy and effort.

Every company will make its own unique journey from its current approach to planning and forecasting to an improved approach. That said, there are some things you'll want to consider on your path forward.

1 → 2 → 3 → 4 Prototype and scale

1 Identify the problem to solve

- Define scope and ambition
- Determine the level of business to work with
- Identify targets (geographies, products, customers, channels, etc.)
- Set a realistic time horizon

2 Think about how to proceed

- Decide if you want to build this competency in-house—or if outsourcing to a managed analytics service makes more sense
- Determine if algorithmic forecasting is a capability you want to provide as a service to the enterprise
- Make sure your organization has the talent and culture to embrace this

3 Identify the help you need

- Assess available talent and their abilities
- Determine if additional professionals are needed—financial analysts, data scientists, data visualization architects, or others—and how you'll get them
- Determine external vendor support needs
- Identify which tools you already have in place
- Ask IT what other tools may be needed

4 Prototype and scale

A Driver analysis and data cleansing

- Identify key revenue and cost drivers
- Collect and structure relevant data for analysis
- Align on an initial set of priority drivers
- Collect and clean required data inputs
- Test drivers for significance

B Predictive modeling

- Develop statistical models for P&L line items based on relevant drivers
- Consider using models that are easier for the business to understand, to build trust and adoption
- Include end users in the process of conceiving, designing, building, validating, and implementing forecasting models
- Test and validate the models
- Link P&L forecasts to the balance sheet and cash flow

C Dashboards and visualizations

- Develop dashboard views with key metrics
- Develop accompanying visualizations
- Enable scenario analysis functionality
- Elicit feedback from dashboard users
- Use A/B testing to optimize the effectiveness of dashboard displays

D Socialization

- Socialize results with key stakeholders all along the way
- Prepare detailed documentation for maintaining and managing the model
- Track results in parallel—keep score
- Train the organization to understand the value of this collaborative approach

E Ongoing

- Align on cycles required for refreshing your models
- Assess opportunities for machine learning and cognitive enhancements

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Before you go

A commitment to algorithmic forecasting is both a cultural thing and a statistical thing. Making it happen involves great people working with elegant technology. Neither is sufficient on its own. Here are some of the lessons we've learned while helping companies move forward.

People lessons

- CFOs should be the ringleaders and champions. Reading at least one book on the topic can help ground you in the culture of forecasting.
- Train your team—and yourself—on the basics of probabilistic thinking and how to spot and correct for common human biases that can derail effective forecasting.
- Management and employee engagement becomes easier when models are transparent. Choosing a less accurate model with more intuitive drivers may result in better business adoption than a more sophisticated model that people can't understand.
- Build an approach where accountability for "the number" remains local—in the hands of those closest to the business.
- Assess your workforce needs with the understanding that changing from traditional to algorithmic forecasting may create spare capacity as routine tasks are automated and skill gaps where new professionals are needed.
- Don't underestimate the value of visualization. It makes forecasting real.

Statistical lessons

- For mature and stable businesses, predictive models usually require five or more years of monthly data to train properly, with the most effective models often using 10 years of data to identify trends, seasonality, and driver correlation.
- Don't overlook the possibility that past performance may not be relevant to future performance predictions. Often the data can be used, but may need to be adjusted or filtered by human experts. Experiment with different types of modeling approaches to see which leading and lagging indicators improve the relevancy of your results, especially in a changing or disruptive industry environment.
- Aggregation across business units, divisions, groups, or the whole company generally improves predictability.
- Products with higher sales frequencies yield stronger predictability due to the greater number of data points. Long-cycle products can require additional data history for the models to mature.
- Annual forecasts tend to be more accurate than quarterly. Same is true that quarterly predictions tend to be more accurate than monthly. That's because variances tend to cancel each other out—up to a point. Over longer time horizons, predictions can become less accurate as unexpected events become more likely.

Want to learn more?
Start here.

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> "The best qualification of a prophet is to have a good memory."
>
> **—Marquis of Halifax**
> *English writer and statesman*

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Looking ahead

Forecasting is something many companies struggle with—and where business leaders say they need help from Finance. They're being asked to make predictions about what will happen in the future, and no matter how good they are, biases and guesswork come into play.

Algorithmic forecasting is a transparent way to help improve the forecasting process, while relieving Finance professionals of tedious, repetitive work. The result can be more accurate and timely forecasts—and more informed decisions. You and your people can spend your time uncovering insights and taking action, and less time grinding through mind-numbing spreadsheets. Everybody wins.

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