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A Glimpse into the Future of Forecasting Software

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The impact of poor planning can be devastating. In 2022, McKinsey estimated that approximately $600 billion worth of food is wasted every year, accounting for 33%–40% of overall world food production (Borens and colleagues, 2022). The ability to accurately predict future trends in a timely way has become more important than ever in the face of scarce resources, supply chain disruptions, and sudden changes in demand patterns. At the same time, energy prices hover near an all-time high, and providers must find ways to optimize their processes to cut costs while meeting demand without disruptions.

These are just some of the challenges that forecasting software companies across the globe are working to address. For years, organizations have been using forecasting software to plan more effectively for the future and to make better-informed decisions, although the impact of improving forecasting accuracy can vary. *Foresight*'s special feature "Does Forecast Accuracy Even Matter?" (Issue 68) challenged the assumption that improving accuracy *always* results in tangible benefits (such as improved customer satisfaction and increased profitability). However, the McKinsey Global Institute (Chui and colleagues, 2018) did find, in the consumer packaged goods industry, that an accuracy improvement of 10%–20% can lead to a 5% reduction in inventory costs and a revenue increase of 2%–3%.

The unique global disruption and variability stemming from the COVID pandemic have brought a new urgency to the debate. Not only must forecasts be accurate and grounded in historical data, but they must also be quick to adapt to continuous shocks and provide probabilistic distributions to manage uncertainty and mitigate risks (see, among many sources, Nikolopoulos and colleagues, 2021; Rostami-Tabar and colleagues, 2023; and O'Trakoun, 2022). As a result, the mission of forecasting software companies is to continuously innovate for their customers, offering them the right tools to generate trustworthy, high-quality forecasts that should be reliable, stable, and intelligible, and should align with users' needs (Spavound and Kourentzes, 2022).

As technology continues to advance, forecasting software is expected to become even more sophisticated, though at the same time more intuitive and accessible. Being able to generate accurate and reliable forecasts quickly and automatically and to adapt to change will help organizations become more resilient and thrive.

With these challenges to face and opportunities to capture, the future of forecasting software is promising. In this article, we present an overview of several exciting developments that are already taking shape.

DEMOCRATIZATION OF FORECASTING

The data science talent supply is stretched thin. According to one source, there will be as many as 11.5 million jobs in data science available by 2026 (*The Economic Times* HRWorld, 2021). We expect that forecasting software will focus more on visual process flows and enhanced automation driven by artificial intelligence (AI) so that multiple personas can generate accurate results. Even though the forecasting process has already been simplified by automated tools that can produce reliable forecasts at scale, such as SAS® Visual Forecasting software (SAS Institute Inc., 2023), many organizations still struggle with a lack of consistent and high-quality source data and the inability to effectively incorporate forecasts into their decision-making processes. As a result, forecasting software companies will need to focus more on providing end-to-end solutions, with composite AI in mind, so that organizations are provided with forecasts as well as recommended actions

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and automated processes based on those forecasts. Examples of automated decision making include using forecasts as inputs to an optimization model for airline crew scheduling or for setting optimal inventory policies.

DATA-CENTRIC AI

Most forecasting software can compare various forecasting techniques and select the most accurate methodology based on the chosen criterion. However, less importance has been placed on automated feature engineering to improve the accuracy of the algorithms that are deployed. The AI industry is already moving from a model-centric to a data-centric approach, with AI pioneers such as Andrew Ng strongly advocating this shift (Brown, 2022). Therefore, we believe that forecasting software companies will invest more in automating data engineering pipelines that focus on data quality and feature generation techniques.

OPENNESS AND EXTENSIBILITY

Recent years have seen a lively debate about the superiority of machine learning (ML) over statistical methods, spurred in part by the results of the M4 and M5 competitions (Makridakis and colleagues, 2020, 2022).

Both methodologies have pros and cons, and their effectiveness depends on factors such as dataset size, the complexity of the relationships among variables, and the availability of computational resources. Traditional statistical methods rely heavily on assumptions about the underlying distribution of the data but suffer from limitations in capturing nonlinear relationships between variables. On the other hand, machine learning models tend to require larger training sets and can struggle to produce interpretable results. However, they excel at finding patterns in complex data and adapting to changes over time.

More recently, the line between the two approaches has become increasingly blurred. Models that combine machine learning with probabilistic aspects, such as DeepAR (Salinas and colleagues, 2020), are now available, enabling a single model to have the best of both worlds. Similarly, adaptations of AI models that are specifically designed for forecasting continue to evolve rapidly (see, e.g., Nie and colleagues, 2022).

In parallel, a related debate has emerged on the benefits of local versus global models (Januschowski and colleagues, 2020) that look beyond the distinct model types. Local models, also known as individual models or series-specific models, focus on building separate forecasting models for each time series in a dataset. Each time series is treated as an independent entity. The forecasting model is trained exclusively on the historical data of that particular series, and the model parameters and characteristics are specific to that series. Conversely, global models, also known as pooled models or group models, take a broader perspective

Key Points

- With the ongoing advancements in technology and driven by market demands, forecasting software is anticipated to undergo further refinement, offering increased sophistication and flexibility while simultaneously becoming more user-friendly and intuitive.
- Forecasting software is expected to shift its emphasis toward enhanced automation, feature engineering, and end-to-end solutions powered by artificial intelligence (AI).
- Software architecture will be designed to offer greater flexibility, enabling the integration of emerging technologies and algorithms that use diverse programming languages.
- Forecasting as a service in the cloud will be enriched with more options, and ModelOps frameworks will evolve to accommodate the forecasting process irrespective of the specific modeling techniques being applied.

by considering multiple time series simultaneously. Instead of a separate model being built for each series, a single forecasting model is trained on the entire dataset or on a subset of related series. The model parameters are estimated using the combined information from all the series.

An in-depth analysis of the pros and cons of the various types of models is beyond the scope of this article. What is important is that the accelerated pace of development of new models and techniques offers unprecedented and exciting opportunities for researchers, software designers, and practitioners alike. It also underlines the necessity for forecasting software to be open, extensible, and configurable. Specialized software packages that implement new algorithms are released nearly every day, often in a variety of programming languages. No software vendor can keep up with the fast pace of development of new methodologies and incorporate them into a product rapidly. Software architecture needs to be open to provide flexibility and adapt to evolving requirements and emerging technologies, enhancing the system's extensibility and future-proofing its capabilities. Modern forecasting software can enable users to extend the built-in algorithm with custom algorithms that use heterogeneous languages. SAS Visual Forecasting, for example, supports a drag-and-drop visual pipeline, where modeling nodes can be added and removed with a click of a mouse. The code in the modeling nodes can be SAS, R, Python, or a combination of the three languages.

CLOUD-BASED SOLUTIONS

Cloud-based software is becoming increasingly popular, and this trend is expected to continue. According to Gartner, global end-user spending on public cloud services will grow by 20.7% in 2023 (Gartner, 2022); by 2026, public cloud spending will account for more than 45% of all enterprise IT spending (Gartner, 2023). Businesses want to avoid the expense and complexity of buying and installing software that uses in-house infrastructure, as well as the need for special expertise to manage it. Various analytics consumption models, such as software as a service (SaaS), platform as a service (PaaS), function as a service (FaaS), and results as a service (RaaS), all powered by the cloud, give businesses greater flexibility and scalability. This lets them focus on handling specific use cases while easily scaling their computational resources up or down as needed. We expect that forecasting as a service will be enriched with more options to suit the needs of different personas, from automated forecast generation to interactive scenario analysis, and that these options will be easily configurable for application to different scenarios and use cases.

AUTOMATION EVOLUTION

Forecasting software companies are already giving data scientists and forecasters the option to autogenerate machine learning and deep learning models, which are automatically tuned and then compared to select the best-performing model (a process also known as AutoML). While these methods are widely applied in the field of forecasting and continue to advance, there is limited guidance for choosing the appropriate methods to apply to datasets with different characteristics. Richness comes from diversity, and every method has its benefits. We believe that particular focus will be given to recommending the right family of algorithms, for the right data groups, to simultaneously optimize computational intensity and forecasting accuracy. This is particularly important in the cloud, where organizations are charged for the time they are using the computational resources. As many as 94% of organizations currently overspend in the cloud (Forrester, 2023), and they are looking for ways to control costs. Software providers are already focusing their efforts to assist customers in this goal.

MODELOPS

Model operations (or operationalization), widely known as ModelOps, emerged from the need to manage models from end to end while treating them as corporate assets. This framework will evolve to accommodate the forecasting process regardless of which modeling techniques are applied. We expect this evolution to include advancements in various areas that contribute to the successful implementation of a ModelOps framework. First, software tools will focus on improving collaboration among different personas by using enhanced visualization tools and reusability features. Another critical part of this process will be the improved explainability and interpretability of forecasting results in a clear and intuitive way. Lastly, the continuous monitoring of forecast quality and model fitness will be enhanced by automated reports and recommendations, which will be provided via natural language generation technology and chatbots.

INTEGRATION WITH OTHER TECHNOLOGIES

Forecasting software will be more integrated with internet of things (IoT) technologies and enterprise resource planning (ERP) software. Companies such as Walmart have already understood the value of collecting real-time data to make faster decisions, meet customer needs, and differentiate themselves in the market (Marr, 2022). The integration of forecasting software with IoT will enable businesses to take advantage of these new data sources. At the same time, integrating with ERP software will provide a more comprehensive view of business operations. Both developments will be accelerated by partnerships among technology providers and by advancements in edge computing that will enable data processing with advanced algorithms to provide near-real-time insights. These tight integrations will result in more accurate predictions at a more granular level, which will drive better-informed decisions and enable businesses to adapt quickly to changes in order to address current economic conditions and manage uncertainty.

To summarize, forecasting software companies have a lot of work to do, now and in the future. They must develop capabilities that will drive wider adoption of forecasts with high levels of confidence by organizations of all types and sizes. Democratization of the end-to-end forecasting process, better-quality data, and new extensible technologies will enable organizations to make more accurate predictions faster and more easily, resulting in improved efficiency, effectiveness, profitability, and competitiveness. The recent explosion in the popularity of generative AI will also bring changes to the forecasting world; this, however, is a topic that needs to be addressed separately. As we continue to explore new and innovative technologies, we are excited about what lies ahead.

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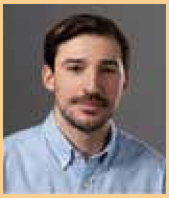

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