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How should CFOs apply algorithmic forecasting in modern times?

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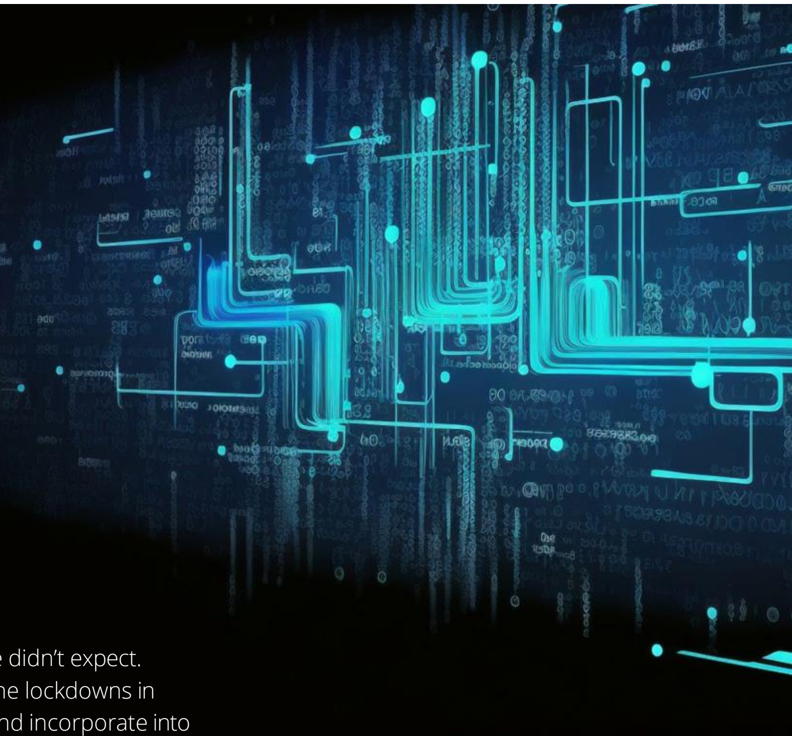
Algorithmic forecasting's relevance in a turbulent world



Within the global economy are linkages we didn't know existed, in ways we didn't expect. Impacts from unforeseen events such as trade wars, the war in Ukraine, the lockdowns in China, and, of course, the COVID-19 pandemic are challenging to predict and incorporate into business and financial forecasts. These events would've been thought nearly impossible to build into forecasting models before the pandemic, which is believed to be our generation's "black swan" event.

The pandemic and other unforeseen events have left CFOs wondering if algorithmic forecasting using predictive models makes sense in our new, turbulent world. It's reasonable for arguments on both sides of this debate—whether algorithmic forecasting has run its course or retained its relevance today and into the future.

CFOs have asked many questions. Is a predictive model's output too abstract and unreliable without foundational knowledge of historical performance and influencing factors? With so much disruption in the marketplace due to the pandemic and the war in Europe, are predictive models relevant right now, given these models apply statistical algorithms using ***historical*** data patterns to predict ***future*** events? Why do we need machines to forecast when people do it just fine? Why does algorithmic forecasting matter when the pandemic has skewed data anyway?

Black swan events have three properties[1]:

- It is an outlier, and nothing in the past suggests its possibility.
- It carries an extreme impact.
- Finally, despite being an outlier, after-the-fact explanations make the event appear explainable and predictable. (Read "Was Covid-19 A Black Swan Event?" for more information.)

Fortunately, the last three years gave us answers to these questions to advise CFOs looking for a path forward.

1. Nassim Nicholas Taleb, The Black Swan: The Impact of the Highly Improbable

Despite data disruptions, predictive forecasting remains relevant for CFOs when the enterprise leverages data effectively and appropriately considers internal and external factors. Health care-related issues and geopolitical factors that affect the economy should make us think outside the usual framework of policy (monetary, fiscal, and regulatory), demographic indices, and currency values.

A good grasp of what's occurred within the enterprise and resultant drivers allowed algorithmic forecasting to evolve in usage and approach. We're now much smarter about how and where algorithmic forecasting is applied, leveraging data science techniques more surgically to forecast volatile data and considering new approaches to driving human-centric interactions and processes for better adoption of model outputs.

We know now that CFOs should consider inserting various data points driving the economy into algorithmic forecasting models, such as the global supply chain and demand pressures when creating predictive models.

Our new world requires new data sources and driver structures to explain volatility.

CFOs know the forecasting process is not all about the data; it's about the people who make it happen and the connections they drive within the business. Human input is more vital than ever. The pandemic allowed finance to work whether employees were in the office, at home, or in another state. While humans can forecast with relative accuracy, we cannot process large data sets at the same speed as algorithmic forecasting. This limits the CFO, finance, and the enterprise. Per Philip E. Tetlock in ***Superforecasting—The Art and Science of Prediction***, "Although bad forecasting rarely leads as obviously to harm as does bad medicine, it steers us subtly toward bad decisions and all that flows from them—including monetary losses, missed opportunities, unnecessary suffering, even war and death." Given rapid changes to the external environment and the volume of data in the internal environment, algorithmic forecasting is better suited to understand patterns, identify drivers, and clarify "noise" in the data. (For more information, explore *Superforecasting* from Broadway Books.)

Various factors are crucial to forecasting—speed to analysis, driver relationships, and multi- variate, driver-based concepts.

Speed-to-analysis considerations result in situations when market shifts outpace enterprise cycle times for gathering data from which to glean insights. Driver relationships depend on proper structure and definition, including lead and lag timing. Multi-variate, driver-based concepts should be incorporated to leverage driver relationships to inform scenario modeling. Taken together, all are important and valuable to align technology with human business intelligence to translate feelings into facts appropriately.

Consistent data is also integral to insightful forecasts. Essential in forecasting is how we view data and its availability, define forecasting approaches, and develop reasonable metrics for effectiveness and the crucial human element, whereas, without people within enterprises, forecasts would not provide a robust understanding of the current landscape. Predicting the next black swan event is nearly impossible; however, CFOs can plan accordingly by employing the correct data, asking the right questions, and challenging historical and anachronistic assumptions.

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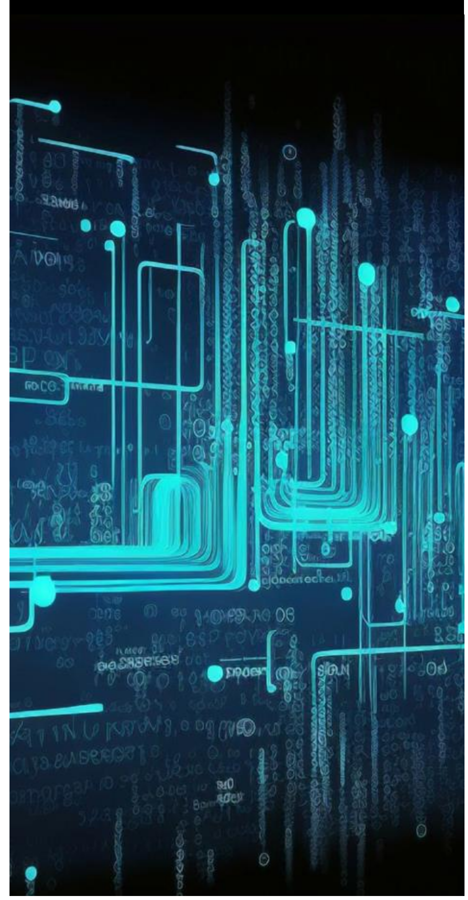


Living data/ New world data

Data can make or break a model. Its consistency is crucial in creating a useful predictive forecast during financial planning. Data consistency is good, but that alone is insufficient. What's also needed is data quality, accuracy, completeness, integrity, and conformity along with this consistency. A predictive model's output may be deemed unreliable without a strong understanding of an enterprise's historical data patterns and the internal or external factors influencing them. Thus, organizations must also implement strong data governance in our increasingly AI-driven world. CFOs will find that data governance is essential to the success of AI-enablement efforts. (To learn more about data governance for AI, see "The AI Era Is Here. Is Your Data Governance Ready?")

As market disruptions affect financial data, CFOs may seek mitigation strategies to lessen impacts, causing historical data to be unusable in predictive forecasting. Fortunately, data engineering techniques such as restating actuals and outlier treatment are useful data manipulation tools that help mitigate this risk by removing unanticipated or unicorn events that we don't expect to be repeated in the future. Data proxies are another means CFOs may use to bridge gaps in data and lessen disruptive impacts.

Restating actuals is the process of replacing financial periods containing volatile data points considered unrepresentative of the enterprise outlook with a historical period or periods that more accurately reflect the enterprise's expected performance. Disruptive financial periods stemming from highly uncommon macroeconomic events may be removed altogether because they deviate from business as usual if future impacts from these events are unanticipated. Feeding an algorithmic model with such periods may not produce predictive forecasts with insightful results. Instead, restating actuals allows CFOs to utilize authentic data in their algorithmic models and derive predictive forecasts based on actual data, leading to better results.

Outlier treatment, on the other hand, is the process of identifying strange events in the data through statistical methods and replacing the abnormal data points with alternate data that fits within acceptable thresholds. Unlike restating actuals, only select data points would be manipulated, rather than entire periods. For example, if the cost of an input drastically increased for a brief period because of an uncommon occurrence, this data point can be removed or manipulated to align with business as usual. As a result, algorithmic models wouldn't produce forecasts that accounted for this aberration and would still produce results based on more typical occurrences.

Both restating actuals and outlier treatment techniques help alleviate data inconsistencies caused by unexpected market disruptions. However, these techniques alone don't consider other market factors. Understanding the internal and external factors within an enterprise and the global economy is required to assess drivers that might enhance a model's output.

Including macroeconomic indicators along with the organization's internal levers can help inform an algorithmic model and make forecasts more robust against unexpected fluctuations in the forecasted account's historical data. These indicators are commonly referred to as drivers or features within the context of AI modeling. In situations where the indicators exhibit data anomalies, similar techniques as the ones stated above can be used to first treat the historical data of the indicators and then generate a forecast for them.

"Both restating actuals and outlier treatment techniques help alleviate data inconsistencies caused by unexpected market disruptions."

When there's a lack of or inability to obtain data associated with a significant driver, a data proxy can be used. Data unavailability or misrepresentation is common with large-scale data sets spanning multiple years, but a data proxy may serve as a substitute internal or external driver when the true driver data is unavailable or unreliable. Proxy drivers will provide similar signals to the AI model as the original driver so that the forecasts can be based on similar information patterns even without the original driver data. With their use, potential insights into predictive forecasts aren't lost due to the prominent driver's absence. An example is the Consumer Price Index, which can be a data proxy for the inflation rate since they historically link and fluctuate in parallel. Another example of a data proxy is the inversely negative correlation between interest rates and bond yields, whereas one can be a proxy for the other. Additionally, by incorporating more driver data sets into the algorithmic model, CFOs can uncover previously unidentified linkages.

Expanding and testing new driver data sets allows the CFO to discover insights about significant relationships between internal or external factors and enterprise financials.

If continually incorporating the same list of drivers into algorithmic models, CFOs may miss broader connections that are unforeseen until evaluated. Testing new relationships will likely result in CFOs becoming more aware of influences affecting their financials and enable CFOs to prepare accordingly.

Although predicting black swan events is nearly impossible, preparing for atypical events is a way for CFOs to safeguard their enterprise against harmful downturns. Developing artificial drivers is a means to prepare for these downturns by inputting analysis or a hypothesis from outside the model to influence financials, like scenario planning. CFOs can test impacts by using the artificial driver as a proxy for an event's potential data patterns, then incorporate the artificial driver within their models as they would a real one. CFOs could also manipulate a known driver's actual data patterns to create a hypothesis or what-if scenario.

Using a hybrid approach to increase predictive forecasting effectiveness

Historically, CFOs could leverage standardized techniques within everyday forecasting cycles. With the external events affecting the economy, CFOs realize that their organizations' must carefully craft alternate, hybrid forecasting approaches to meet modern needs and architect a best-in-class, end-to-end approach. Leading companies are taking a meticulous financial line-item-by-line-item approach, which utilizes a hybrid of algorithmic forecasting with various traditional planning methodologies. Hybrid approaches, which account for a mix of forecasting methods, help increase overall end-user and stakeholder model adoption.

With the amount of volatility revealed through unforeseen recent events, leading enterprises are taking advantage of driver-based models that leverage internal and external business drivers.

Driver-based forecasting can take the form of simple ***Price x Quantity (PxQ)*** equations through to multi-variant algorithmic forecasting models to predict income statements, balance sheets, and cash flow line items, which consider financial and operational data. This model allows business leaders to react faster to levers driving the business, such as macroeconomic, enterprise-specific, and the industry, to make more timely business decisions. As part of the design of these models, we recommend a thorough analysis to determine the drivers across the business, and then algorithmic forecasting methods are applied to test the predictive power of the drivers and select the best fit for the model. CFOs can fine-tune these drivers and introduce new drivers to respond to macroeconomic events. For example, supply chain teams have used statistical models to create a starting point for a demand volume forecast for decades. By extension, applying this methodology to other financial line items and business areas is understandable.

Algorithmic forecasting can also help finance understand new relationships within the data. This could take the form of forecasting relationships between different line items over time, pressure-testing sensitivities around known relationships between various products, services, and markets, or proving out leading indicators and timing relationships, which can then support forecasting and business partnering.

Sometimes, a more simplified, traditional approach may be appropriate. These approaches include trend-based and zero-based budgeting. Trend-based models allow enterprises to analyze trends over a specified duration and use these trends as the starting point for a system-generated forecast. Predictability within a forecast improves significantly with historical data as the level of accuracy and precision is refined over time. Zero-based budgeting uses activity and driver-based bottoms-up analysis, allowing each function to think critically about the minimum viable and incremental spend required based on strategic choices. Zero-based budgeting has shown to be effective for tracking cost categories and business units with a high level of granularity to create more efficient synergies with commercial needs. While finance has used those traditional approaches, the companies leveraging best and leading practices use algorithmic models selectively by considering market, geographic, volatility, and materiality to make decisions.

CFOs should react quickly and efficiently to provide data to make business decisions that align with enterprise strategic objectives. Thus, defining a forecast's level of detail and granularity is key to structuring the perspective in which information is available for a specified decision-maker.

> Evaluating the strategic goals and levels at which decisions are made within the organizational hierarchy is required to determine the right amount of data that end users and stakeholders need to validate the outputs of these models.

By answering these questions within the leadership team, each finance user group can receive the most important data, leading to increased accountability over the forecast. Technology and systems integration can help allocate the forecast to the right reporting level. Companies often attempt to explain variances at the reporting level based on higher-level drivers irrelevant to their decision-making, which causes unnecessary rework and churn.

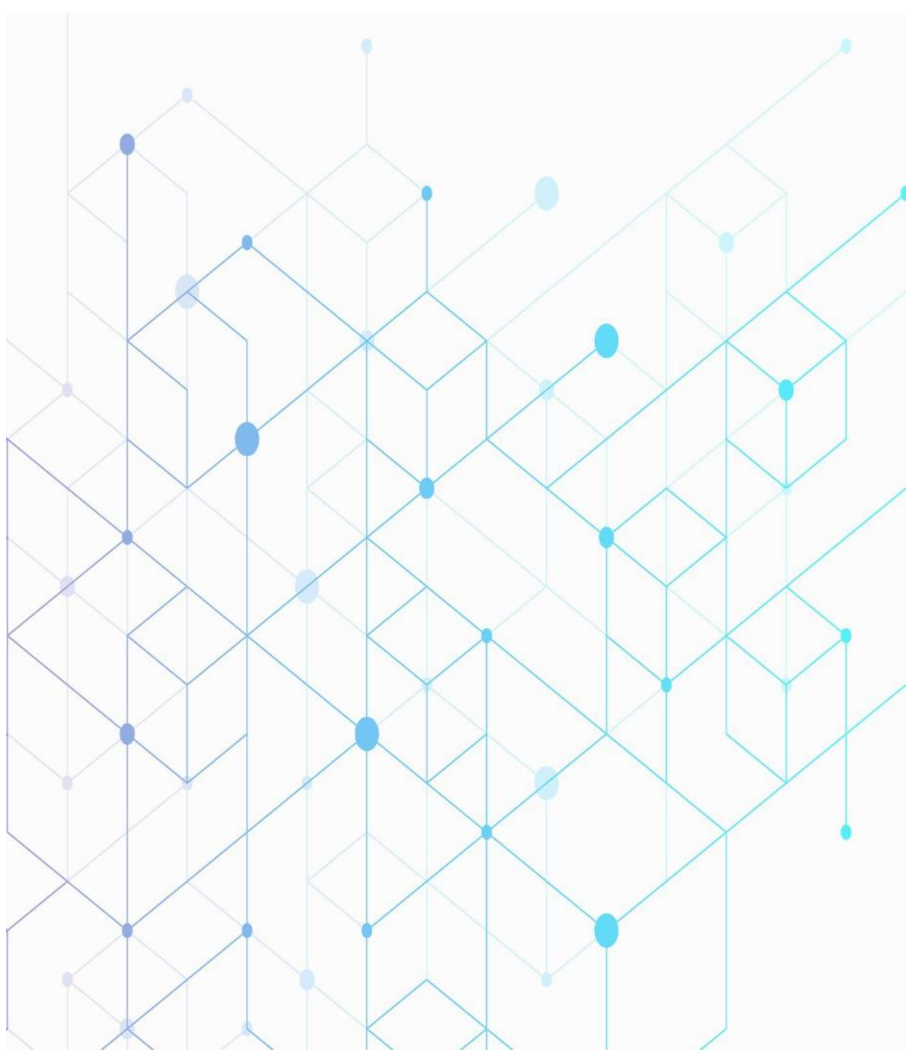
Adopting hybrid models and changing levels of detail and granularity depend on an enterprise's maturity level. An enterprise's ability to align on the right model and approach that best suits its business needs and determine the right level of detail and granularity needed for each user group are imperative to the probability of successful adoption of the forecasting approach. This results in finance having an end-to-end vision of how forecasting aligns with broader enterprise objectives and clear direction from leadership regarding the level of detail needed for each forecast cycle. Enterprise culture plays a role when changes are communicated from the top down but are being adopted from the bottom up. In designing the optimum planning approach and methodology, finance should consider both top-down and bottom-up requirements and the business's culture and behavior. This comprehensive approach will help land a connected process that alleviates work instead of disjointed capabilities and processes that only create more work.

Leadership must consider several questions when determining the proper forecast:

What critical business decisions need to be made, and how do we match data granularity, drivers, and data availability to support those decisions?

What level of detail do we need to materially plan and forecast the business? Where does the business accountability reside?

What is the best strategy to reach that forecast to maximize effectiveness (effort vs. accuracy)? How can the organization effectively overlay human insights upon machine capabilities to derive and create a plausible and reliable forecast?



The human element

While predictive forecasting algorithms have proven beneficial in identifying multi-scenario outcomes, human intervention is indisputably vital in building meaningful predictive forecasts. Although predictive modeling's benefits are widely known, some enterprises have been slow to adopt it because of an unwillingness to disrupt old-fashioned forecasting or because learning new methods has not been established as the standard. In many cases, enterprises need to see the value of predictive forecasting before fully investing funds and time. However, enterprises can only derive the actual value and potential of predictive forecasts when they fully commit to leveraging forecasting across lines of business continuously, overcome data literacy issues within their teams by appointing data translators, and invest in learnings and the appropriate people to fit business needs.

Integral to the full adoption of algorithmic forecasting is for finance to "meet in the middle."

Teams who can translate complex math and algorithms into humanized "perspectives" delivered by machine learning can help predictive models gain widespread trust within large and complex enterprises, unlocking greater benefit. Predictive models must gain widespread trust within large and complex enterprises to fully benefit from predictive forecasting. Historically, enterprise teams were given a choice to "opt in" and leverage modeling on an ad hoc basis. With this approach, teams not leveraging predictive modeling consistently will lack forecasting capabilities knowledge and miss opportunities to gain necessary experience with predictive models. As a result, teams will increasingly grow divergent in using models due to the learning curve required for their proper use. However, teams that opt in consistently will have the opportunity to quickly gain the experience that will equip them with the expertise to handle models and generate insightful predictive forecasts. As predictive models are used more and experience is built, trust in the outputs will grow. Further, as enterprise teams move from point-based forecasts to more advanced driver-based models with a range of different perspectives and projected outcomes, they may find themselves more likely to trust the message provided by the model since it encompasses a wide range of factors affecting the enterprise. As a result, the use of outputs to drive key business decisions will increase. This all begins by opting in.

CFOs may wonder what makes one enterprise better suited than another to leverage predictive forecasting. Generally, enterprises familiar with analytics and data literacy are more likely to adopt forecasting capabilities. This is primarily because of the learning curve involved in leveraging predictive analytics effectively. Since analytics and data literacy have not historically been key components of finance and are relatively new, some enterprises may lack the correct personnel with experience or willingness to learn and apply data-based methodologies to their financials. Without the correct personnel, forecasting capabilities will be limited and underutilized. To bridge this gap, the role of a translator is increasingly important.

Translators add perspective to model outputs and connect them with real-world circumstances.

The translator role requires a breadth of knowledge across data science and finance. However, the translator may not possess deep expertise in these individual knowledge areas. With the translator's help, finance can develop meaningful insights and make decisions from market and enterprise perspectives. Data scientists and finance roles do have critical differences between them regarding forecasting. Data scientists possess the skills to process high volumes of structured and unstructured data to create sophisticated, complex forecasts. Finance professionals drive and explain the forecast to their business leaders and with leadership. Translators bridge the gap between these roles.

To help prevent this, an enterprise should build performance-based compensation plans with the complete business impact in mind, incorporating objective metrics and key performance indicators to reinforce that sound business decisions are made, unaffected by personal pressures, behaviors, and expectations.

CFOs understand that the complete modeling process, combined with assumptions, measures, and outputs, determines a forecast's success.

Forecast accuracy alone does not effectively allow CFOs to leverage models to make unbiased business decisions.

The autonomy of predictive forecast modeling removes some burden on CFOs and finance teams by quickly processing large data sets, aiding in assessing their relative importance, and measuring the impact of the information while separating the noise; however, outputs still require a "human element" to maintain the quality of a model, identify driver-specific relationships, and explain the story that the data is telling. The adoption of algorithmic forecasting is essential to bringing insightful forecasts to life. The key to successful adoption is identifying barriers and then successfully addressing and overcoming them. Change is never easy. CFOs understand the importance of empowering finance professionals to perform higher-order activities when business partnering, such as making recommendations to stakeholders and leadership, instead of spending time and effort on the mechanics of forecasting.

Therefore, barriers may be overcome when leadership understands and agrees that predictive forecast modeling elevates the finance function—from a service organization to a true enterprise partner—and drives the enterprise's strategic outcomes.

To support the successful integration of algorithmic forecasting into an enterprise's processes, CFOs must ensure that employee performance-based incentives are entirely independent of model outputs. The goal is to prevent a scenario in which the Demand target is driven by an unrealistic Sales plan, resulting in additional inventory.

For example:

- Company A has recently started using a model to help determine optimal inventory quantities.
- If the model suggests that Company A's supply planner orders 100 units, yet the planning manager insists on a higher inventory order, the planner may order 120 units to placate the manager.
- Consequently, if 100 units were sufficient, this increases inventory carrying costs, leading to waste, shrinkage, and obsolescence while it remains on the floor without selling.

Looking ahead

Predictive models are more relevant now than ever in our post-Pandemic world, despite the volatility of historical data in the past several years. Although recent macroeconomic events have significantly affected the world around us, leaving no industry or areas of business untouched, including FP&A, it is incumbent to revisit fundamentals of algorithmic forecasting design.

By investigating new approaches to the design and approach of algorithmic forecasting, implementing leading practices for balancing the level of detail with decision-making and data availability, investigating new modeling and data manipulation techniques more suitable to post-Pandemic data, and adopting new forecasting methods which adapt to the culture of the organization, the value of algorithmic forecasting can be fully realized by organizations today and into the future.

Acknowledgements

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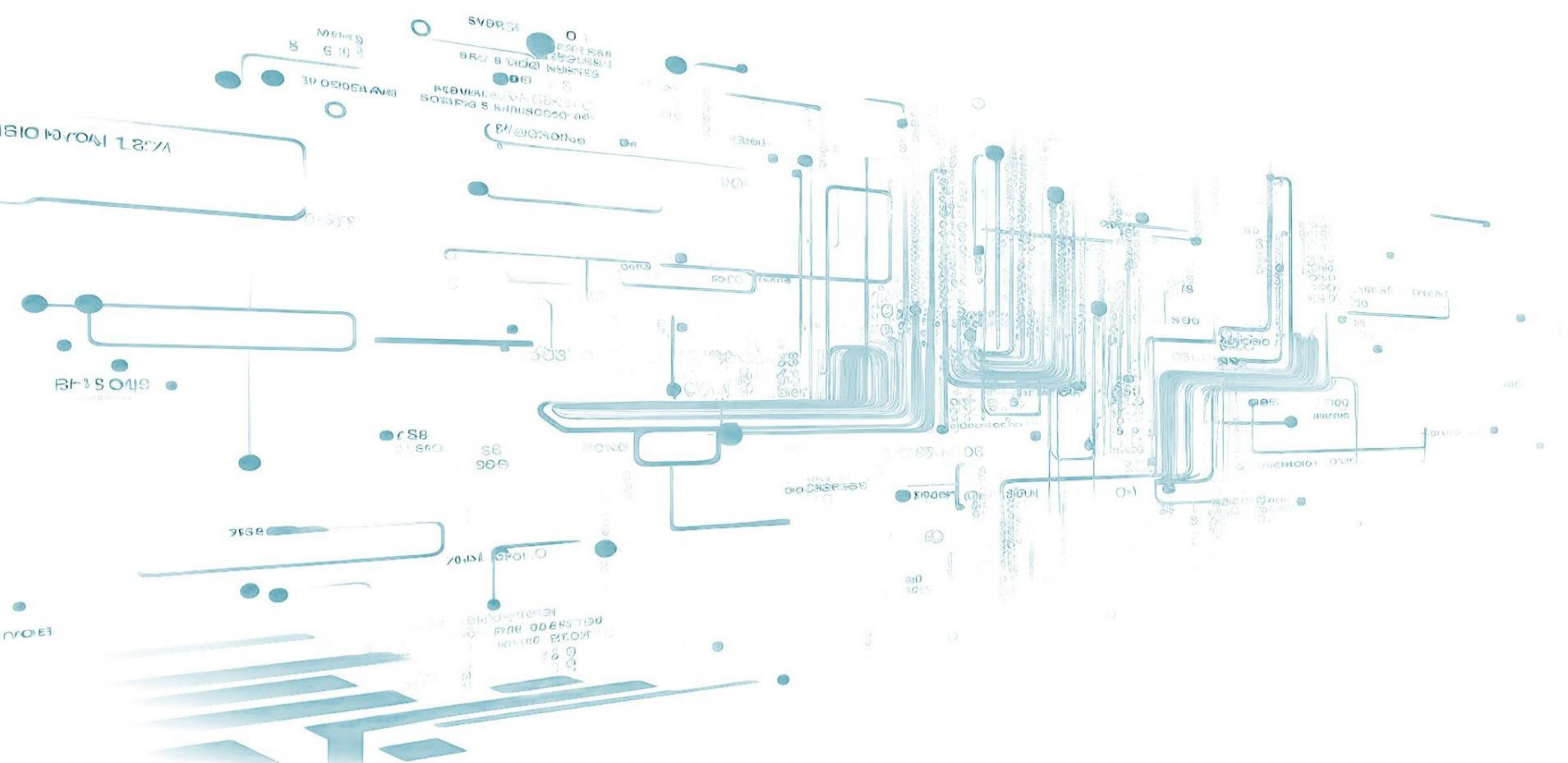

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