Machine Learning for B2B Pricing

The strategy for optimizing pricing and maximizing profits

The article discusses

- Top 5 trends driving AI/ML adoption in B2B Pricing
- Data and modelling challenges in the B2B space and their solutions
- A 3-step machine learning modelling framework for B2B pricing
- The need to bring together people, process and technology to realize ML potential

The adoption of machine learning started in the consumer space almost a decade ago, but B2B organizations have been rather slow in embracing machine learning algorithms for their pricing. However, the scene is changing.

Trends driving AI/ML adoption in B2B Pricing

B2B companies are realizing the potential of machine learning (ML) in making right business decisions including pricing. There are several trends driving adoption of ML in B2B Pricing (See Figure 1).

- **The evolution of pricing from the shadows of sales and marketing to a separate function:** Most organizations have realized the impact of pricing in profitability and revenue management. Add to this, they have understood that pricing is necessarily cross-functional and relies on inputs from enterprise strategy and finance in addition to sales and marketing. This has resulted in organizations making investments in creating dedicated pricing teams.

- **A clear shift towards value-based pricing:** Pricing strategies traditionally revolved around cost and competition. This has changed and more and more sellers are keen on determining buyer's willingness to pay, which in turn depends on the perceived value the customer is deriving from the consumption of goods and services. Each customer perceives the value differently and therefore goods and services need to be priced differently for different customers. Organizations have realized that through value-based pricing they are able to position themselves differently and command a premium.

- **Focus on price optimization:** Traditionally, pricing in B2B has been linked to deal size. Incentives of the sales people were mostly calculated on the deal size not on profitability. This resulted in sales persons offering deep discounts where it may not have been essential. There has been a growing acknowledgement that bad discounting practices have prevailed and money has been left on the table. This acknowledgement has brought the focus on pricing optimization.

- **Shift towards dynamic pricing:** The demand in B2B space is derived from the demand in the consumer space. Technology disruption such as e-commerce, collaborative consumption platforms like Uber etc. and the growing geo-political uncertainties have created enormous volatility in the consumer space and this in turn affects the volatility in B2B demand. Competition from a global market place also have added to this volatility. B2B businesses have realized the need to respond to the market better and faster. This called for an opportunity to find the right price at the moment to exploit the volatility in your favor and outsmart competitors.

- **Increasing adoption of AI/ML in areas that required human judgement.** Data science and ML based decisioning have become more visible in areas that traditionally depended on human centered interactions. Most organizations have shown keen interest in acquiring these capabilities and adopting it. The success of ML based decisions in multiple industries including pricing in consumer space helps to reduce some of the inherent skepticism towards AI/ML.

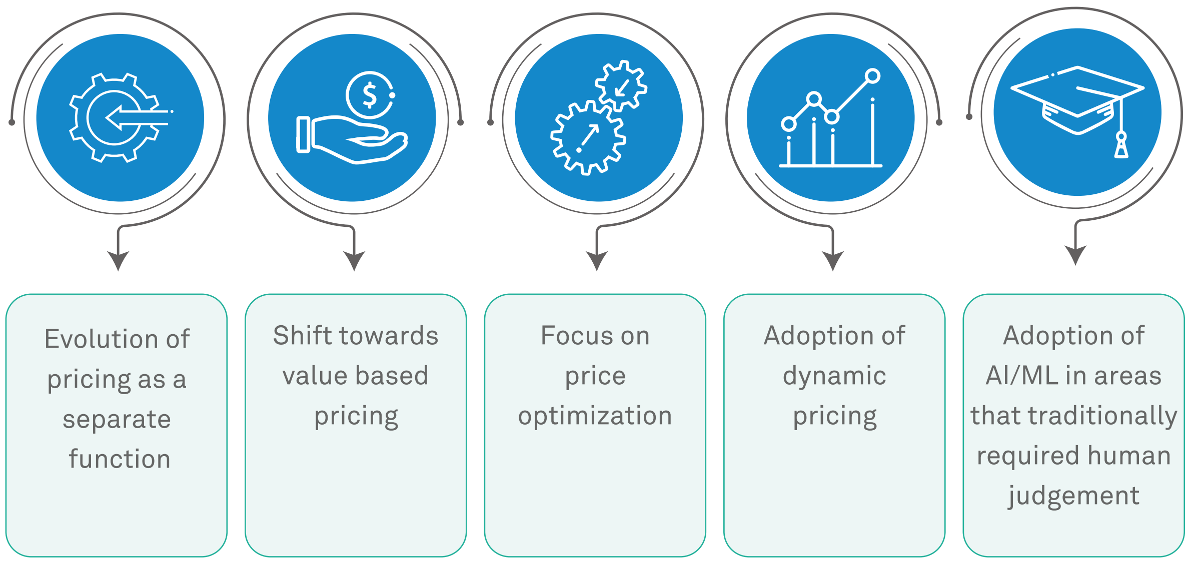

Figure 1: Trends driving AI/ML adoption in B2B Pricing

Data & modelling challenges in the B2B space and their solutions

Reluctance to adopt ML-based pricing originates from two main sources i.e. data related challenges and the complexity surrounding the pricing as a business process (See Figure: 2). In this section, we have tried to address some of these.

- **ML models need huge volume of data and in B2B, the volume of data is less to build an effective model.**

  Solution - This stems from the common perception is that ML models need a large data set. While it is true that some of the more sophisticated models like deep learning cannot be trained without large volumes of data, there are multiple algorithms in ML e.g. Decision Tree or Generalized Linear Models (GLM) that do not really need huge data sets. In fact, the first few areas of applications of statistical modelling were clinical trial and agriculture where data volume is even less compared to some of the B2B organizations.

- **High cost of an error:** A typical B2B deal size runs into millions of dollars and losing a deal can have a significant impact on the company's revenue. Therefore, B2B deal pricing is a much riskier endeavor to be left to algorithms.

  Solution - We advocate ML models to be a supplement to human decisioning and not a substitution of the same. The human amendments to the model's recommendation should be sent as a feedback to the model. It should be captured as an insight that can be leveraged in subsequent pricing decisions.

- **Data quality issues:** Poor data quality is a reality and good models cannot be built on these data.

  Solution - Over the years, most organizations have made significant investments in their applications like ERP, CRM as well as enterprise data warehouse. Additional checks like multi-level reconciliations across systems, investing in a master data management systems will just not help pricing but the overall organization. Ultimately a good model needs good data. It is strongly recommended to treat data enrichment as a continuous process to reap benefits from any analytics initiative.

- **Sparse data:** Some stakeholders in B2B organizations feel that most of the deals are unique and an ML model can hardly learn from the past data during model training.

Solution - Techniques like Bayesian Hierarchical Models or Decisions Trees can be leveraged to model such scenarios. Let's say, you are selling a product in a territory and you don't have any past history of selling the same product in the same territory, hierarchical models intelligently roll up the data to the next level in hierarchy where you have available historical data and generalize those insights.

- **Complexity in B2B sales process:** B2B buying decisions are complex and often the price may not just be a function of quantity but the terms and conditions of contract as well. This makes the calculation of price elasticity extremely difficult.

Solution - The focus of the modelling should be to compute the Bid Price vs. Win Probability and not estimation of price elasticity i.e. demand as a function of price. The outcome in a B2B sales cycle consists of multiple phases but the advantage here is the seller has the option to revise the quote according to the response from the buyer. The different stages in the B2B sales life cycle can be modelled as state transitions that can be factored as an input to the model so that accurate prices can be determined earlier in the flow. One advantage while modelling pricing in B2B is the buyers and sellers in a B2B environment are expected to behave rationally compared to their consumer counterparts, and models need not really factor in the behavioral pricing that are frequent in the consumer space.

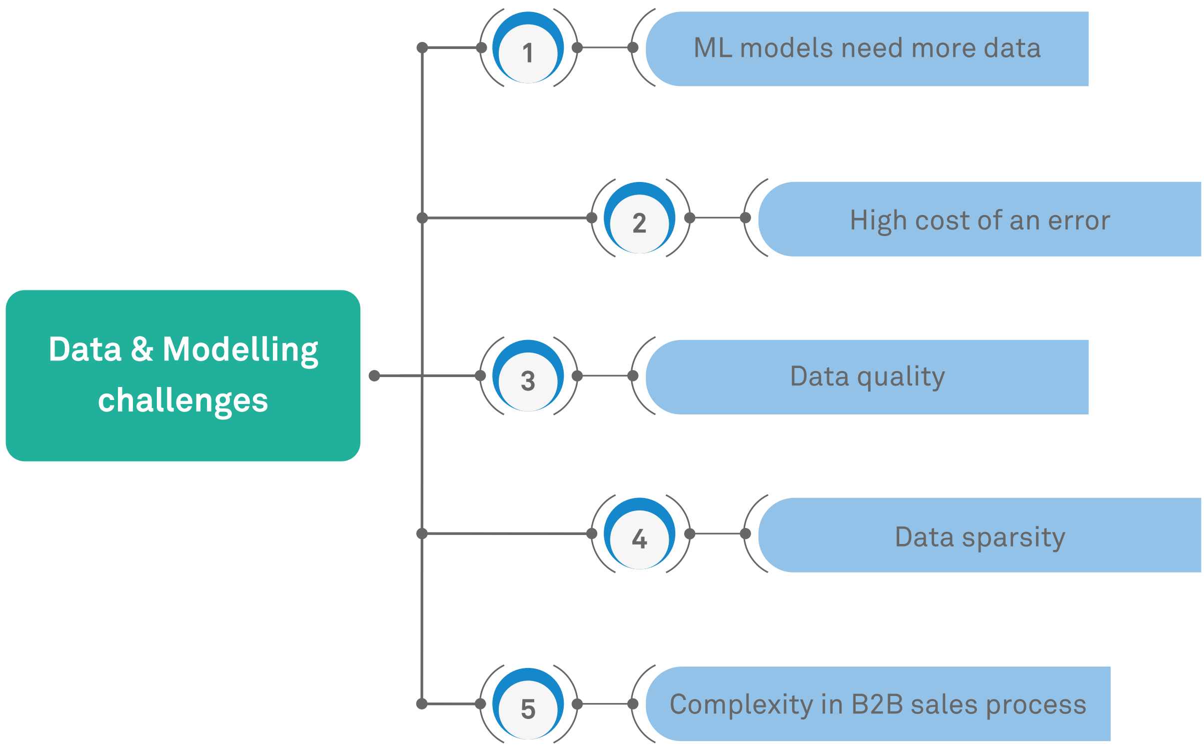

Figure 2: Data & modelling challenges in B2B pricing

ML framework for B2B pricing recommendation

Pricing can have several objectives beyond winning the bid. One of the most important being profit maximization. In addition, based on the strategy, an organization would like to maximize the revenue through cross-sell or up-sell. Elsewhere, increasing the customer trust to maintain long-term relationship with the customer may be the priority (See Figure 3).

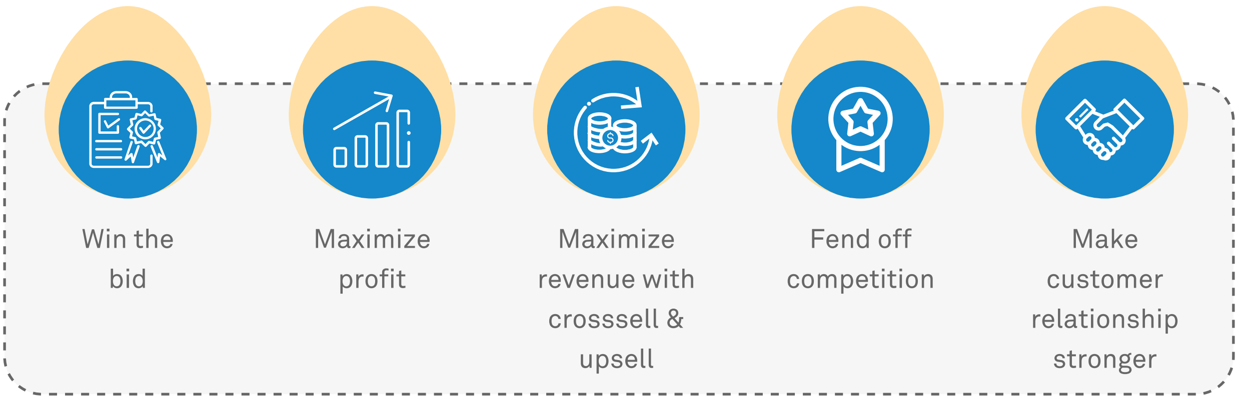

Figure 3: Objectives of pricing

The various objectives in pricing require trade-offs which directly impact the revenue and profitability. The pricing analytics team should factor the expectations of the concerned stakeholders i.e. senior leadership, Finance as well as the field sales force and work towards the common organizational objective.

In 2010, Robert Philips of Columbia University proposed a modelling framework for customized pricing. An adaptation of the same is presented in Figure 4 which comprises of 3 key steps with profit maximization as the objective. The modelling approach can be extended to include other objectives.

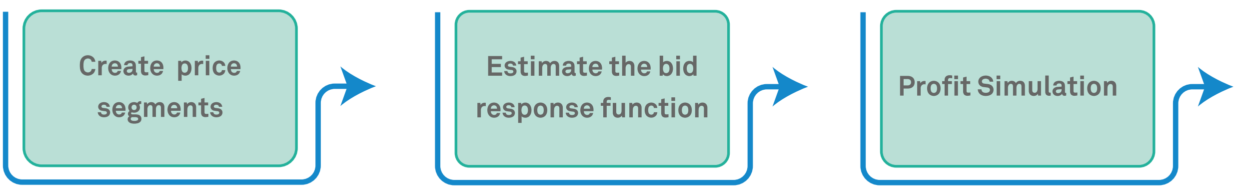

Figure 4: B2B Pricing Modelling framework

- **Create price segments:** The objective of this step is to identify the groups of quotes where different pricing strategies have been adopted. In B2B settings, the pricing strategies adopted by the seller varies from customer to customer. For a large customer, where the seller sees substantial future potential, it may go for aggressive discounting. But for small or medium scale customer, similar discounts may not be offered. Pricing varies for product segments as well, e.g. the product categories where the organization is the leader (dominance pricing) vs. it is relatively less established and trying to capture the market (penetration pricing). There are several other criteria like deal size, market or channel where different pricing strategies are adopted. Organizations may have a pricing policy but then exceptional approvals are norm almost everywhere. Clustering algorithms can be used to identify such price segments from historical quotes data.

- **Estimate the bid response function:** A bid response function estimates the relationship between the outcome of a bid i.e. win or loss for a given bid price and other independent variables like price, product, customer, market, competitor and channel attributes. This can be modelled from the historical win/loss of quotes data. A bid-response function generally assumes the shape of an S (Sigmoid) i.e. when the price increases, the chances of winning the deal reduces and vice versa, that is, when you reduce the bid price, the probability of winning increases.

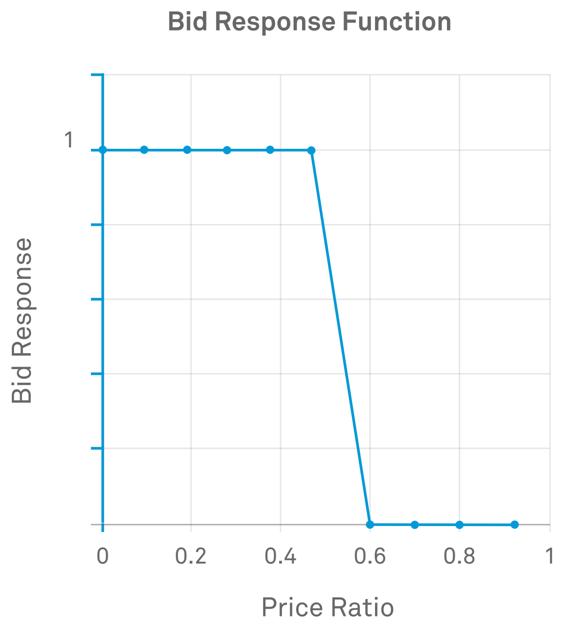

Figure 5: Bid Response vs. Price Ratio. Bid Response is depicted by 1(Win) or 0(Loss).

Price ratio in Figure 5 indicates the net price the customer will pay to the actual listed price. A price ratio of 0.2 indicates 80% discount i.e. customer pays only 20% of the listed price. Bid response of 1 indicates the win while bid response of 0 indicates a loss.

It is suggested to use probabilistic algorithms e.g. logit, power etc. while estimating the bid response function. Unlike algorithms that give a binary outcome, probabilistic models produce the probability of winning the deal at each price point. Also, they are more interpretable and the influence of price and other variables can be illustrated to the field sales force. Complex black box models which produce a binary outcome of win and loss (not probability) and not interpretable should be avoided.

Modelling process should follow the model development lifecycle comprising of exploratory data analysis, model training and performance evaluation in a holdout data. The performance of various algorithms across a set of parameters like accuracy, precision, recall, AUC, ROC etc. should be compared to choose the best performing model.

Once the Bid Response function is estimated i.e. the relative importance of the variables on the deal outcome (win/loss) is determined, it can be used to simulate the probability of win at different price points (See Figure 6).

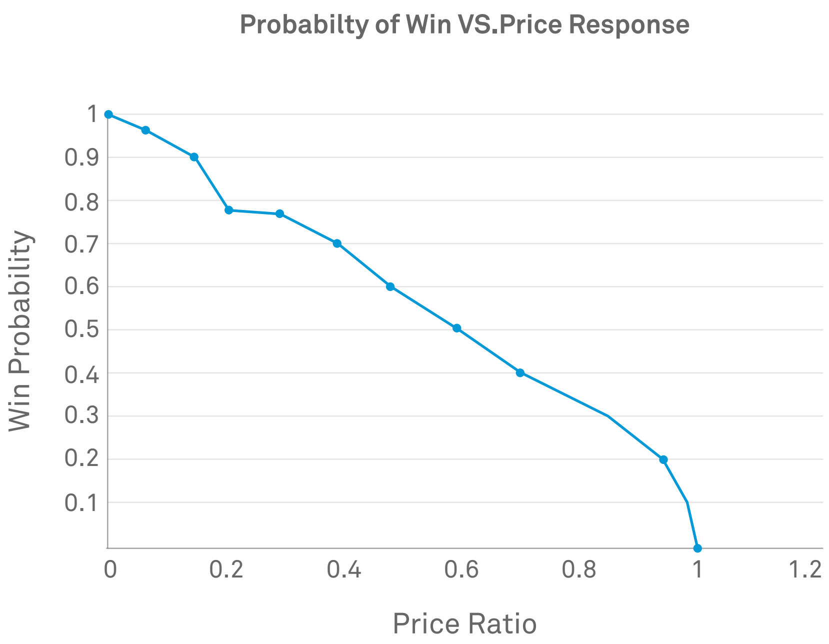

Figure 6: Win Probability vs. Price Ratio at different price points

Bid response functions should be estimated for each pricing segment separately if estimating individual functions gives performance advantages compared to a single model across pricing segments. However, due consideration should be given to the availability of data in a particular pricing segment. If the number of records are significantly less for a given pricing segment to effectively train/test the model, a single model across pricing tiers may prove to be a better option.

- **Profit maximization:** The objective of profit maximization is to simulate the profits at different price points. This can be arrived by working with the finance team from company's internal cost data.

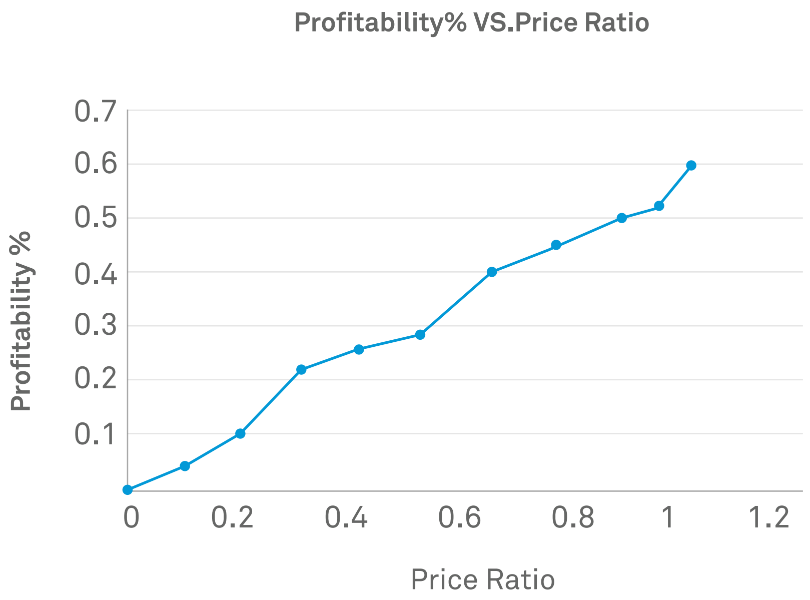

Figure 7: Profitability % vs. price ratio to depict the profitability % at different price points

Once the probability of win and profitability, both are determined, the profit can be estimated at different price points.

Estimated Profit = Probability of winning the deal * profit

The price point that generates the highest estimated profit will be recommended to the field sales persons.

Bringing together people, process and technology

In order to reap the benefits from the implementation of an ML-driven pricing program, organizations should ensure they have the people, process and technology policies aligned to:

- Incorporate the organizational intelligence and contextualize the insight to a specific deal
- Assimilate the judgement of the sales person and bring it as a feedback to the pricing models
- Be responsive to changes in key variables that determine the outcome

People

- **Identify the right sponsor:** It starts with identifying the sponsor for the pricing analytics program. Because pricing has a very significant impact on revenue and profitability, ideally someone in the C-Suite needs to be the executive sponsor of the program with the head of pricing function championing it. The role of the project sponsor will also be critical in setting up the objective and preamble of the solution , building consensus as most pricing decisions need trade-offs and driving the change management to increase adoption of the pricing recommendations by the end users.

- **Align the sales force:** It should be very clearly articulated that pricing analytics is aimed at augmenting the human judgement and not substituting it. The benefits of the pricing recommendation e.g. reduction in time to get approvals, profit and revenue visibility etc. should be clearly articulated to the sales force.

  It is very important to give the sales person visibility into the entire recommendation process while suggesting a price i.e. the pricing tier along with similar bid prices in the past and their outcomes, price ratio vs. the probability of win as well as the profitability at various price points to illustrate the rationale behind the decision. A well-designed dashboard depicting the recommended price vs. deal outcome of similar deals in the past will boost end user confidence.

- **Business ownership:** The pricing models should be owned and maintained by business. It is a solution built for business and the role of IT should be to support it by providing the right technology infrastructure. Business ownership helps in the following two ways :

    - Business ownership is required to find the right champions of the model across the organization and effectively drive the change management to build user adoption.

    - Business ownership will also ensure putting in place the necessary processes to assimilate the feedback from the field sales force, effective performance reviews of the model post production and re-training of the model.

Process

- **Set up clear discounting policy:** Bad discounting practices either result in leaving money on the table or the loss of a deal. A well-structured discounting policy with clear attribution of the discount to various parameters saves the time for the sales force and reduces one-of-a-kind discounts.

- **Streamline the pricing approval process:** Getting the necessary approvals consumes significant amount of the sales person's time. With the pricing solutions in place and the revenue and profit projections along with the win probability becoming much more visible, it is an opportunity for the organization to reduce the levels of approvals they need if the price quoted is in line with the recommendations and organizational policy.

Technology

If you are starting your ML-enabled pricing journey, creating the pricing analytics platform is the first and the most important step. The pricing analytics platform will have the following four components.

- Data Processing Layer
- Pricing Analytics Workbench
- Model Integration and Orchestration
- Technical Infrastructure

1. **Data Processing Layer:** The data processing layer should have the capabilities to extract data from various transactional systems, enterprise data warehouse as well as external sources, perform the necessary data quality checks and store it in a format where it can be consumed by data scientists and business users. The key data topics required for pricing analytics are:

    - Customers and their demographic data : This contains the master data about customers, their nature of business

    - CRM data covering sales lifecycle: Organizations which have already invested in a CRM will find it easy to get this data which starts from leads, opportunity to quote to order booking

    - Cost and financials data: This information is critical to profit simulation

    - Competitors & market information: This is the most difficult to capture. Part of it may be unstructured and may come from online sources like trade journals

2. **Pricing Analytics Workbench:** Pricing Analytics workbench enables data scientists to train and test predictive models. Pricing analytics work bench sits on the top of data processing layer to access production data. In addition, it will have the ML tools like Python/R for Model Building.

3. **Model Orchestration and Performance Monitoring:** Pricing models need to be integrated to transactional systems e.g. CRM which were used by the field sales force. Integration with transactional systems is key to drive user adoption as the sales force won't have to log into a separate application to get the pricing guidance from the models. It should also enable bi-directional data flow i.e. convey the pricing guidance generated by the model and capture the feedback from the field back to the pricing analytics platform. Such integration also enables quick experimentation and testing different hypothesis which are required for building the right model. The pricing models should be monitored in order to keep the recommendations relevant. One key component of such measurement is to track a set of accuracy measures over time baselined to the accuracy measures obtained from the test/validation data during model creation. It is also essential to monitor the changes to the input variables and the data distribution as they impact the final outcome. Monitoring of accuracy measures and the distribution of the features provide the necessary input for model re-training. Last but not the least, the business impact of the model in terms of revenue and margin uplift should be measured and shared with the stakeholders periodically to build confidence, drive user adoption and secure additional investments.

4. **Infrastructure Layer:** There are two primary choices here i.e. on premise vs. on cloud. A cloud based pricing analytics platform will require less up-front capex. Most of the cloud providers like AWS, AZURE or GCP provide efficient data processing and machine learning capabilities which will also expedite the operationalization of pricing analytics platform. Less upfront cost and a quicker turnaround time will help to build a stronger business case for investment in the pricing analytics platform. However, the final decision on the infrastructure layer should be based on the organizational policies towards cloud adoption.

About the author

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