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Harnessing Data Analytics for Customer Insights

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Customer insight is all about understanding your customer better, and it focuses on what is not working. It is critical for any carrier to understand the key events causing a sub-optimal customer experience.

Data plays a key role in identifying issues and events and resolving them in a timely manner to improve the customer experience. Given the complexity of a carrier's network, it's crucial to understand the key data types and how to harness them together to have a more reliable and accurate 360-degree customer view.

The key aspect of harnessing data analytics for customer insights begins with collecting and correlating different network data as perceived by end users. Network transactional data, available as a continuous data stream, is something of key interest here. As a typical carrier network is composed of multiple vendors, multiple domains and multiple technologies, it's vital that carriers adopt a vendor-agnostic unified information model to correlate such data. One example is the correlation of a multi-vendor radio access (RAN) and core network to capture the journey of a customer from start to end, providing near real-time data and stats related to accessibility, retainability, and quality of service (QoS). Network data can be further enriched with other data types, such as customer relationship management (CRM) and device data, to have a more comprehensive view of the customer and perceived service quality.

Analytics itself could be seen as descriptive, predictive, and prescriptive. Each has its own constructs, scope, and value to offer. Descriptive analytics is drawn from historical data by identifying different trends and patterns. A good example is different available business intelligence (BI) insights to understand customer churn rate and lifetime value. Predictive analytics also leverages historical data, but as opposed to providing statistical analysis, it uses machine learning (ML) algorithms to provide future customer insights, trends, and behavior. The historical data that is being used to train such ML algorithms, and the rate at which a given ML algorithm is trained with new historical data sets, define the accuracy and effectiveness of predictive analytics. Potential churners and high-value customers are examples of predictive analytics. Identification of patterns, trends, and anomalies is not enough; providing actionable recommendations is equally important. Predictive analytics generates actionable recommendations and the next best action based on patterns and trends detected among customer queries. A list of improvements ranked by the highest positive impact on churn reduction is an example of prescriptive analytics.

Adopting an optimal architecture between edge and central data processing is critical for the effectiveness of data analytics and the timely generation of customer insight. It is not one versus the other but a balanced combination that drives optimal results. For example, optimal results can be driven by having effective curation and correlation at the edge, closer to the data collection layer, while centralizing historical data storage, enrichment, and other post-processing tasks such as ML algorithm training. cca

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