CASUAL ANALYSIS

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Case Study on Machine Learning Enhancement for BI

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Abstract

Business forecast plays an important role in making the balanced financial and operational decisions. Forecasting and its impact has grown enormously in recent years as the companies are relying on data-driven strategies. In this case study we'd like to discuss the principles of ML forecasting and the benefits that forecasting gives for business purposes when used. ML forecasting generally rests in an enormous amount of information, which can be analyzed, and accurate predictions can be achieved with high performance rates. Unlike the traditional forecasting approaches, machine learning allows businesses to consider numerous driving factors and building nonlinear algos to minimize loss functions, which is a crucial ingredient in all optimization problems. Few benefits that a business can get from ML Enhancement are:

1. Acquiring insights and detecting hidden patterns that are difficult to trace with traditional approaches.
2. Reduced number of errors in forecasting.
3. Ability to infuse more data in a model.
4. Flexibility and rapid adaptability to changes.

Chapter 1: Role of AI and ML in Business Forecasting

An unprecedented rate of change is happening in the world economy. As a part of the change, the traditional methods of business forecasting are replaced with AI and ML forecasting methods. ML forecasting rests on an enormous amount of information, which can be analyzed to achieve accurate predictions and high-performance rates. Unlike the traditional methods, ML allows businesses to count in different business factors and driving key points for developing desired algorithms to reduce the loss functions and get accurate predictions.

Training of any ML forecasting model requires assessment stage, where in this stage foresees comparison of the actual and predicted results and therefore one can understand the efficiency of the forecasting model developed. Succeeding this stage would come the comparison of different forecasting models developed and finalize the one which has given minimal number of errors. With this approach, organizations can switch to ML techniques from the traditional methods and get the following benefits for their business forecast,

- Training ML models on BigData and migrating to computational cloud is now a basic standard for the industry which helps us acquire insights and detect the hidden patterns that one cannot detect with the traditional forecasting methods.
- Using ML techniques has reduced the number of errors in forecasting, McKinsey has claimed that AI-driven models can reduce the errors by 20-50%.
- ML techniques has enabled to infuse more data into the prediction models. Infusing data externally can help in getting better predictions.
- ML techniques gives flexibility and quick adaptability to changes.

All the above-mentioned points and theories are related to forecasting and not predictive modeling. Difference between these two will be discussed further in this case study.

Chapter 2: Forecasting vs. Predictive Modeling

Generally, both forecasting and predictive modeling are together applied to hulking challenges related to business planning, consumer behavior and decision-making. Yet these two techniques differ a lot.

Forecasting Modeling, is a process where the past and present data of the organization is analyzed to determine the trends, patterns etc., which helps us to estimate the probability of forthcoming events**.** Forecasting model has traceable patterns when compared to predictive models. For example, use cases for forecasting include seasonal sales of departmental store, gas sales of a petroleum company etc., all these predictions can be made using the past data of the organization.

Predictive Modeling, uses AI and the concept of data mining to assess more detailed, specific outcomes and use diversified data types. Generally, the difference between forecasting and predictive modeling is not so clear, so we'll consider an example of a product by fashion brand.

There arise two questions, one is how much quantity should the company produce for which forecasting model comes into play and which segment of the customer would be buying the product most. Here, predictive modeling comes into picture. These two models helps us to analyze the customer information database to leverage and target the proper segment of customers for the product. With this approach the organization will eventually understand which clients are most likely to use the product.

Chapter 3: Use cases of ML Forecasting

3.1 Financial Forecasting

Companies experience disruption in operations and performance without a financial projection, and C-level managers frequently make bad choices. Therefore, businesses use machine learning (ML) forecasting, which focuses on comprehending business drivers rather than dealing with menial duties. As well as assisting in the prediction of supply, demand, inventory, future revenues, expenses, and cash flow, machine learning (ML) financial forecasting also lowers the proportion of ineffective techniques in use and human errors.

For instance, to comprehend and assess opportunities for improvement, stakeholders of the firm want to know the company's turnover and key determinants for growth during the upcoming financial period. We can create a machine learning (ML) forecasting model utilizing deep learning or regression models based on historical key business metrics for the organization and current turnover information from previous times. The essential measurements for the future will be predicted using seasonal data as well as other impacting factors. Business owners will be able to schedule the following time appropriately in this situation.

3.2 Supply Chain Forecasting

The management of supply networks, which are growing more sophisticated and multinational, can be completely transformed by ML. Companies can quickly respond to problems and threats, prevent under- and overstocking, and respond to issues and dangers with ML-based forecasting solutions. From a training dataset, machine learning algorithms for forecasting can learn relationships, which they can subsequently apply to new data. Thus, ML enhances supplier selection and segmentation, risk prediction in the supply chain, inventory management, and processes for transportation and distribution.

Let's examine a scenario where supply chain forecasting was accomplished utilizing machine learning. Each of the chain's 100 hypermarkets has an average of 50,000 SKUs and operates in a variety of locales. Automating the process of stocking warehouses is unquestionably necessary for a chain with such a large footprint. Specifically, there are two advantages:

a. There is no need to keep a lot of things that are difficult to sell in storage.
b. Timely delivery of frequently purchased items is required.

We may create an ML model to forecast the quantity of goods per SKU using historical data on the replenishment of warehouses and data illustrating the rate at which products are selling. Various time frames could be used to illustrate the prediction (e.g., daily, weekly, monthly, etc.). Managers can use this to minimize instances of product absence and organize the product storage system effectively.

3.3 Price Prediction

Price prediction algorithms establish the price at which a product must be sold to be profitable for the business, appeal to consumers, and match expectations. Product characteristics, consumer demand, and current trends should all be considered when constructing pricing projections. This strategy may be met with skepticism, but it is useful for businesses who wish to quickly adapt to a wide range of varying elements when they enter a new market or release a new product.

Business owners frequently wish to be aware of pricing fluctuations for a certain product over the course of the next few years. We can identify broad trends from the prior data and extrapolate them for the following periods after considering client data with associated pricing changes for a past period for all the current items. The beneficial effect could also be utilized by including data from external third parties, such as the inflation rate, vacations, seasonal trends, etc., that may also have an impact on prices. By combining all this data, we can create an ML forecasting model that can forecast price patterns for products.

3.4 Demand and Sales Forecasting

The entire e-commerce sector is troubled by the burdensome obstacle of fluctuating demand. To estimate consumer behavior and determine how many products to create or order, businesses, especially manufacturers, use machine learning (ML) demand forecasting. Avoiding excess inventory or stockouts is possible using ML models. Additionally, this kind of demand forecasting makes it possible to comprehend the target market and rivals.

Consider a chain of restaurants that wishes to forecast demand. Several ways will it benefit the company:

a. To know the number of dishes that will be sold in the restaurant in order to plan food stock in advance.
b. Determine the right staffing levels needed to deliver quality customer service by comprehending and defining the necessary number of employees.
c. To create a suitable and timely marketing campaign.

Analyzing historical data from earlier times will be a wonderful place to start in order to create a demand forecasting model and assist organizations in achieving their objectives. Including NLP algorithms in the model could be one method to enhance its performance. For instance, to determine the key dishes/quality of service that consumers enjoy or dislike, we can look at reviews on Google for our restaurant chain as well as the major rivals.

3.5 Fraud Detection

Between 2019 and 2021, there will be a rise in suspected digital fraud of 52.2% globally, claims a TransUnion analysis. It suggests that businesses should put more effort into creating anti-fraud strategies. By using historical data, machine learning systems can identify questionable financial transactions. They have already been used with great success in e-commerce, finance, healthcare, fintech, and other industries.

For instance, a chain cafe owner is interested in employee productivity research. One of the key objectives is to find covert trends that enable employees to cheat. Losing money could result from this and other frauds. A fraud detection model that will identify anomaly patterns and alert about them can be created using historical data. Managers can carefully examine any anomalies found in this situation and pinpoint the underlying cause of the data deviations. The management could stop such incidents from happening in the future to protect the company.

Chapter 4: ML Forecasting Algorithms

a. Regression Algorithms

Regression models using machine learning (ML) are used to forecast trends and outcomes because they can understand the relationships between the variables and the outcomes. Although training requires labeled data, the relationships between the variables can be both linear and nonlinear. Regression models may forecast the outcomes of unobserved data once the relationships between the variables are understood.

One of the most typical basic models to forecast sales, stock prices, and consumer behavior is simple and multiple linear regression. Logistic regression also works when the objective variable has just two values.

b. Deep Learning Algorithms

New deep learning algorithms are being progressively incorporated into time series forecasting. A model has a higher likelihood of being used in production if it is more adaptable and understandable. Examining a few deep learning time series forecasting models will help.

DeepAR is the initial one. Based on recurrent neural networks, it is a supervised machine learning algorithm developed by Amazon. With datasets made up of hundreds of connected time series, it has successfully demonstrated its efficacy. The method has the ability to scale, is appropriate for probabilistic forecasting, and can be used with a wide variety of inputs.

The Temporal Fusion Transformer, which comes in second (TFT). It is more adaptable than other deep learning models and can be constructed using different time series. TFT is appropriate for demand forecasting, for example, because it performs well even when trained on a short sample.

The output from one stage is converted into the input of the following step in the third method, which uses long short-term memory (LSTM) based on an artificial RNN. The LSTM's architecture is made up of memory cells and neural networks for data maintenance, and gates are used to manipulate data inside the memory. Forget, Input, and Output are the three gates present. The training process for LSTM, however, takes a lot of time and resources.

c. Tree Based Algorithms

The term "tree-based algorithms" designates supervised learning techniques. Their benefits include being accurate, long-lasting, and appropriate for mapping non-linear patterns. Here, the goal is to define homogeneous sets in the sample while accounting for the input's primary differentiator. The target variable determines how to classify tree-based algorithms. Tree-based algorithms have the advantages of being simple to understand, requiring little data preparation, and handling various sorts of variables. In this situation, the propensity for overfitting and irreconcilability with continuous variables may be considered as drawbacks.

d. Gaussian Process

Despite being less well-known than other models, Gaussian processes (GP) are strong enough to be used in the industrial sector, including for automated forecasting. Although the quantity of parameters and potential cost factor into their use in forecasting, Gaussian processes allow us to add expert opinion via kernel.

e. Auto-Regressive algorithms

Future values will be predicted using the output from the previous phase as an input by the group of auto-regression algorithms. This group's forecasting algorithms include ARIMA, SARIMA, and others. In ARIMA, forecasting is carried out through the application of moving and autoregressive averages. For instance, using data from previous periods, the ARIMA model can forecast a company's income or estimate fuel costs. SARIMA employs the same fundamental concept, but it also has a seasonal element that could influence the results.

f. Exponential Smoothing

ARIMA models can be substituted with exponential smoothing. It can be used as a forecasting model for univariate data and expanded to support data with a seasonal or systematic trend component. In this model, forecasting is a weighted sum of historical observations, but their significance (weight) is exponentially declining. Whether a single, double, or triple exponential smoothing model is used determines how accurate the prediction is. Trends and seasonality are taken into consideration by the most advanced exponential smoothing methods.

Chapter 5: Machine Learning Forecasting Applications

Whatever model is selected, the following is how ML approaches are generally adopted:

a. Set business objectives and use any available internal data.
b. By using more advanced ML models or changing the data, models' performance can be improved.
c. Determine the group of issues that need to be resolved using forecasting.
d. Look for outside information, such as market reports, trends, GDPs, product evaluations, etc.
e. The model is put into production once it produces results that are satisfactory.