Research Note

The Use of AI in Corporate Performance Management – Opportunities and Strategies

Authors
Norbert Grimm
Robert Tischler

Senior Analysts
Data & Analytics

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Preface

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Robert Tischler

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Data & Analytics

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Whether weather reports, suggestions from Netflix, YouTube and Amazon, search results on Google, the digital voice assistant, or face recognition on smartphones – artificial intelligence (AI) has long since found its way into our everyday lives, fueled by the enormous increase in computing power as well as the volume of data available.

What is artificial intelligence (AI) and machine learning (ML)?

AI, in short, describes the imitation of human cognitive processes in problem solving by computer programs. It makes use of machine learning (ML), whereby mathematical models are applied to data to detect patterns in data sets and make predictions.

What makes ML so special is the fact that it is constantly learning and improving without direct intervention by humans. The higher the volume of data and its quality, the better the results. Conversely, this also means that ML cannot deliver meaningful results without a sufficient data inventory.

Machine Learning as a Service (MLaaS) for planning and forecasting

MLaaS refers to a set of services and models offered in the cloud, with the most prominent providers being Microsoft, Amazon, Google and IBM. This makes sophisticated ML technology accessible to everyone. By using MLaaS, CPM platforms can leverage powerful ML functionality without the need to set up extensive infrastructure.

Since planning and forecasting are based on large amounts of historic data, they are ideally suited to be supported by ML and can thus be at least partially automated and accelerated decisively.

Predictive planning and forecasting

When ML is involved in planning and forecasting, it is called predictive planning and forecasting.

About this research note

This research note summarizes the current state of predictive planning and forecasting, highlights potential use cases and provides practical implementation guidance.

Predictive planning and forecasting increases productivity of the finance organization

Most companies that use it achieve measurable benefits

The BARC study *Predictive Planning and Forecasting on the Rise – Hype or Reality?* shows that today only a quarter of companies use ML and predictive models for planning and forecasting. However, about half of these companies say they are already achieving measurable benefits, and the other half say they expect to do so in the future.

The results of the study reveal a huge potential for predictive planning that many more companies can benefit from. Limited resources or other more promising investments are the most common reasons for companies not to invest in predictive planning.

The benefits of ML: better quality, less effort, new insights

The advantages of using ML in planning and forecasting are manifold. Almost two-thirds of the companies surveyed (64 percent) report that quality and accuracy has increased. The same proportion reports that the effort required has decreased by leveraging this new approach.

More than half of the companies surveyed (49 percent) create forecasts more frequently, which was not possible without the help of ML. And a similar proportion (48 percent) report that they benefit from early detection and forecasting of events, while 44 percent need less time for their forecasts and can carry them out at shorter notice – a powerful tool in economic upheaval and a way to gain advantage over the competition.

Over 32 percent of companies gain new insights through processing larger amounts of data, and 29 percent are able to relieve planners of routine tasks by using ML.

Figure 1: What benefits have you achieved by using predictive planning? (n=290)

Five steps to successfully leverage the power of machine learning in planning and forecasting

1. Target definition. The business goals and the use cases for employing ML in planning and forecasting must be precisely defined in advance. This is essential to specify business requirements, concrete goals and a framework for the next steps. The starting point could be the question of which planning steps are particularly time-consuming and labor-intensive and should therefore be automated.

If, for example, the previous year's data is used in manual steps to map seasonality across regions and product groups as part of sales planning, one goal could be to have this seasonality analyzed and predicted by ML. This would significantly reduce the manual work in the planning process and provide planners with data on which they could build and refine plans with their individual perspective and knowledge.

The defined target also determines which ML models can be used and what data is required for the model.

2. Data acquisition and preparation. Typically, this is the most time-consuming step, since the scope and quality of data are crucial for achieving optimal results. Depending on the use case, external data may be needed in addition to internal data to leverage important influencing factors for predictions.

To stay with the example of time series-based sales planning, usually it is not enough to only use data from the previous year because, depending on the forecasting method, regularity of seasonality, and other parameters, a minimum of 20 to 50 data points is required. In the case of month-based planning, this is two to four years. If the planning system only provides data from the previous year, data from earlier years must be provided for sufficient model training. If the data has to be adjusted for one-off impacts, such as those of the COVID-19 pandemic, it may be necessary to go back even further in time. And if, for example, product lines have changed in the period being analyzed, these must be harmonized to make them suitable for the ML model.

Furthermore, extreme values (outliers) in the raw data often have to be removed for optimal results, and missing values must be replaced by interpolation. These relatively simple computational operations can also be supported by ML models in the context of predictive forecasting and planning.

3. Data modeling. When raw data is provided, it must be transformed and transferred into a form or model to which predictive planning and forecasting functions can be applied.

The example given of time series-based sales planning places relatively straightforward demands on the data to be provided and the way it needs to be shaped and modeled.

However, the scope of the data acquisition and the complexity of the data modeling become much greater if a driver-based model is used instead of time series forecasting models. This is where the time-consuming and computing-intense search for relevant drivers begins, as every potential driver and their combinations must be examined for its suitability.

For example, if the influence of weekdays on sales volume should be investigated and simulated, data must be available in a sufficient level of granularity and grouped and modeled accordingly. In many cases, data preparation and modeling are highly iterative processes, characterized by trial and error, as it is not always clear in advance how the raw data needs to be structured for the optimal model and which additional data is required.

4. Training. In this phase, the mathematical models are trained. Depending on the use case, different mathematical models are used, the most common and helpful of which are explained on page 7.

The data is split into training and test data sets. For time series forecasts, the training set is generally the earliest available data and the test set is the latest available data to simulate a forecast. A model learns certain characteristics from the training data, such as seasonality, trends and holidays. To determine accuracy, the model is then validated on known test data. To optimize accuracy, parameters can be adjusted accordingly.

To support optimization of accuracy, the mathematical model selected and its accuracy in relation to the use case may be presented. The accuracy of the selected prediction method is determined during the training phase by comparing the level of calculated data with the test data. The accuracy provides information on the extent to which the various models are suitable for the use case in question. When predicting time series, state-of-the-art tools support the automated comparison of a multitude of models and suggest the most suitable one to the user.

5. Data output and post-processing. Predicted values are ideally immediately available for analyses and comparison with historic data. In CPM, you typically want to store the results directly in your planning model. This allows you to immediately see the impact of new forecasts or changes to a budget, not only in full detail, but also with a view of the effect on profit and loss, the balance sheet and – perhaps most importantly – on cash flow.

Leading CPM platforms with ML functionality support all these steps, from data acquisition to output, in a tightly integrated and user-friendly environment.

ML delivers a box full of powerful tools for planning and forecasting

ML model	Description	Use case (example)
Time series forecasting	In time series forecasting, future results are predicted based on historical data. Seasonal patterns and trends are identified and reflected in the forecast.	Sales planning by trends and seasonal patterns.
Classification	Classification can be described as the assignment or grouping of data by predefined categories.	The scoring of customers based on multiple characteristics.
Clustering	Clustering involves grouping data sets by similarity whereby the groups – in contrast to classification – are not predetermined.	Market research and developing of marketing strategies.
Feature selection	In feature selection, data is examined to determine the extent to which it has an influence on a variable. Redundant or irrelevant data is identified to simplify the data model without losing accuracy.	Feature selection is often used in advance of driver-based forecasting to identify suitable drivers in relation to an output variable. This ML model may also be useful in data modeling and preparation.
Regressions	Regressions can be used if the relationships between target values and influencing variables are known. After the training phase, the models can be applied to use cases where no values were available for the influencing variables in the training phase.	Demand planning, e.g., where inventory values and other associated data such as weather, weekday, phase of the sales pipeline, etc. are used as driver values.
Driver-based forecasting	In driver-based forecasting, output variables are simulated based on one or multiple influencing variables. The correlation between the drivers and the target variable can be directly or indirectly and may also have a non-linear relationship: for example, in the case of curve-like progressions.	Overhead cost planning in manufacturing, where cost are mostly non-linear and influenced by multiple parameters, such as production plant, product line and shift.

Seven strategies for successful implementation of predictive planning and forecasting

Successful implementation of predictive planning and forecasting in the finance organization should be thoughtfully and thoroughly prepared and accompanied by supporting measures.

1. Build trust

The decision to use ML in planning and forecasting should be supported by top management and, ideally, embedded in a strategy for the digital transformation of the entire organization.

An active communication strategy is vital to deal with potential doubts, reservations and rejection among business users about the new technology, and to build trust.

Planners may have concerns about being replaced by ML algorithms. Having a strategy for how to develop and future-proof their role will help alleviate skepticism and fear. For example, if business users can spend less time planning, they can get more involved in other tasks that contribute more to the success of a business.

Business users may have doubts about this often new technology. They often lack knowledge of statistical methods and ML models and expect complete traceability of the results. To build trust in the initial phase of the implementation of predictive planning and forecasting, it is helpful to run traditional planning and predictive planning in parallel and evaluate the time taken for each approach as well as the level of detail and accuracy of the results.

2. Improve data quality

Sufficient data of good quality is the raw material for ML. Data quality can be improved by several measures. As mentioned, eliminating outliers and gaps is an effective way to create clean and valid data sets for planning and simulations.

In addition, the data model must be consistent. Uniform master data is an important prerequisite for this.

Once a suitable data model and parameters are found, data loading should be automated to continuously update ML models with consistent and clean data. This is the foundation for predictive planning and forecasting on a daily, weekly or monthly basis, without straining and wasting resources for semi-automated data ingestion.

Data often needs to be harmonized in terms of format, structure and master data, especially in driver-based ML models, where it mostly originates from different sources

In some cases, with conventional planning, figures are entered on an aggregated level and must be distributed on a more detailed level to make it suitable for ML models. In the case of demand or sales planning, this may mean that data must be distributed from product to the more granular SKU level, or to regions and sales channels, to get meaningful results with sufficient relevance.

3. Collect external data

Usually, an organization knows the factors that influence its ecosystem, such as market growth per region, gross national product per country, oil and other energy prices, exchange rates or simply climate and weather conditions. Nevertheless, the systematic collection and use of such data is often neglected, and therefore these factors may be considered based on gut feeling rather than on quantifiable evidence of their business impact.

The analysis of external data is particularly useful for the specification of driver models to detect and identify correlations and dependencies between external and internal variables. Again, as mentioned on page 5, data quality is key, and external data must also be periodically provided in a clean and consistent form.

4. Improve data integration

It is widely known that, without a sufficient amount of high-quality data, using ML in planning and forecasting is not as beneficial as it could be. Well-oiled data management is essential for a successful implementation of ML.

CPM platforms with extensive data integration functionality that can also be leveraged by business users are helpful here to ingest all the data needed to make accurate and timely predictions.

5. Invest to build internal resources in data science

Business users responsible for corporate planning usually have limited knowledge of data science. If the use of ML in planning and forecasting is to be successful, that knowledge must be acquired. This can be achieved either by training or by creating new positions for this purpose.

6. Leverage external resources for quick initial implementation

To accelerate the initial implementation of predictive planning and forecasting and benefit from best practices, the support of external know-how and resources is helpful.

7. Avoid silos – choose CPM platforms with integrated ML modules

To successfully establish predictive planning and forecasting as an integral part of the forecasting process, it is more efficient to select CPM platforms that have ML functionality than to set up parallel data storage in specific data science tools.

Cloud-based CPM platforms, in particular, can often be integrated with corresponding MLaaS web services, such as those provided by Microsoft Azure.

Ideally, the CPM platform provides intelligent user guidance and wizards that support the use of ML and enable business users to apply stochastic methods and mathematical models to the specific use case without having to rely on extensive data science expertise.

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Germany
BARC GmbH
Berliner Platz 7
D-97080 Würzburg
+49 931 880 6510

www.barc.com

Austria
BARC GmbH
Hirschstettner Straße 19
/ I / IS314
A-1220 Wien

+43 660 6366870

Switzerland
BARC Schweiz GmbH
Täfernstraße 22a
CH-5405 Baden-Dättwil

+41 56 470 94 34

Rest of the World
+44 1536 772 451

www.barc-research.com

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Jedox
Bismarckallee 11
79098 Freiburg im Breisgau
Germany
+49 761 151470
info@jedox.com
www.jedox.com