SOLUTION SUMMARY

Machine learning forecasting and optimized workforce scheduling

Infor People Solutions

Improve schedule efficiency and coverage

Many scheduling solutions, across various industries, don't stand up to the promise of improving the coverage and efficiency of schedules. These solutions are often hampered by outdated technology. To create optimized schedules, companies should examine and understand their sales forecast data and analyze the drivers that influence their staffing requirements. Increasingly, the need to accommodate compliance laws, labor laws, and union contracts can drastically impact scheduling. Discover how you can embrace the future of scheduling with Infor® Workforce Management (WFM), powered by innovative machine learning technology.

Machine learning forecasting

Demand forecasting is the process that estimates the expected forecast of customer demand using historical data. The goal of forecasting in workforce management is to generate an optimal schedule that respects daily interval requirements, labor costs, customer satisfaction, organization and union rules, and employee preferences. In the past, this was achieved by various algorithms such as linear regression, multiple regression, and trend of historical averages (ToHA). However, with the progression of technology there is a new method called machine learning.

Machine learning technology has gained traction thanks to the increased understanding and substantial improvements made to algorithms, available computation power, and the prevalence of large data sets. The key difference between traditional programming and machine learning stems from the fact that a traditional algorithm takes input and some logic in the form of code and outputs a result. Whereas machine learning is fed an input and an output, applies logic, and then creates a new output.

Infor WFM machine learning model

The Infor WFM machine learning model uses a neural network that follows a multilayer perceptron (MLP). A multilayer perceptron is an artificial neural network with more than one layer of nodes. It has an input layer that connects to the input variables, one or more hidden layers, and an output layer that produces the output variables.

The first step in the model is to train the algorithm to find the most appropriate set of weights for each link in the network. At the end of this step, the resulting model is saved in a file for each unique store driver. The second step is the actual prediction where the saved model is used to predict the following days, one day at a time. Currently the typical length of forecasting is one week or seven days, however there is no limitation on the forecasting range.

The input layer accounts for previous days, the same days of the week for the previous weeks, the same day last year, similar stores, and similar patterns. Which means each day has more than 14 features that are used by the engine to calculate the forecast. By looking at this set of data, our algorithm can easily detect "short term" decreases or increases in forecasts and adjust accordingly.

The model also includes the following additional data points:

- Calendar, holidays, and events
- Road construction
- Marketing events
- Remodels
- External and web data
- Location and market characteristics
- Macroeconomics data
- Weather conditions

Combined, all these factors help create a machine learning algorithm that considers the past years but can also look at the near past to create the most accurate forecast possible. For example, if a location is undergoing a remodel, the algorithm can pick it up and adjust the forecast to reflect the decrease in sales and traffic.

The machine learning process

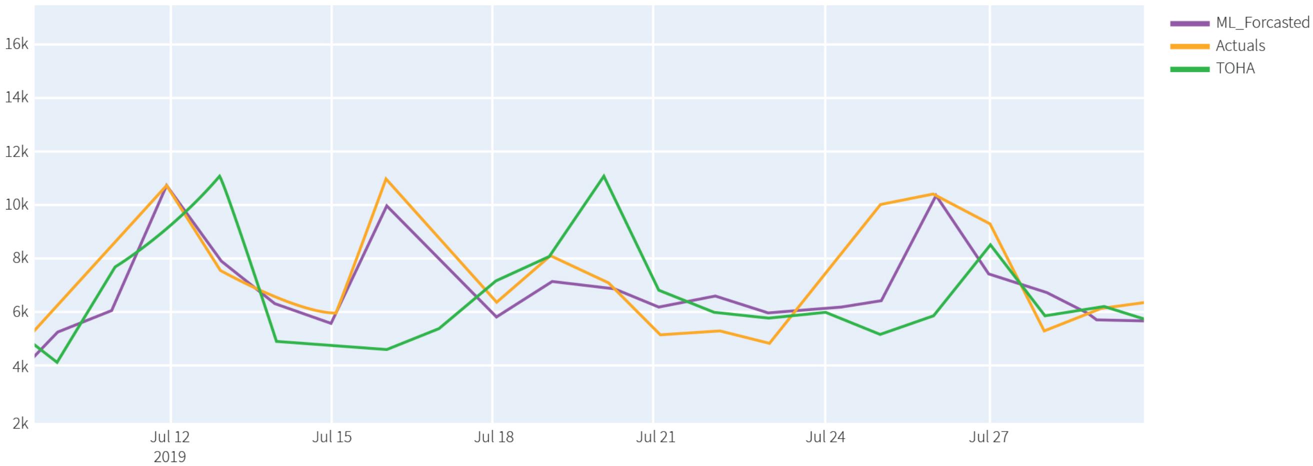
1. **Collecting data**: Gathering past data forms the foundation of future learning.
2. **Preparing the data**: Any analytical process thrives on the quality of the data used.
3. **Training a model**: This step involves choosing the appropriate algorithm and representation of the data in the form of the model.
4. **Evaluating the model**: The second part of the data is used to test for accuracy.
5. **Improving the performance**: This step involves choosing a different model altogether or introducing more variables to augment the model's efficiency.

Auto Assignment Engine

Scheduling managers can apply the flexible Auto Assignment Engine to the concept of auto assignment groups. Auto assignment groups are a direct evolution from Infor WFM LFSO (labor staffing and schedule optimization) staff groups. They offer additional configurations points such as:

- Filters
- Shift orders
- Employee orders
- Enhanced scheduling rules
- Shift rules
- Break rules
- Weekend definitions

Actuals versus trend of historical averages (ToHA) versus machine learning forecasted



The above chart shows real world data that illustrates the accuracy of the current machine learning algorithm. The Infor WFM machine learning algorithm (blue line) follows the actuals (orange line) within a close range, whereas the ToHA (green line) deviates considerably. This means that the machine learning forecast is much closer to the actual demand at the store compared to ToHA, which then flows into the schedule as staffing requirements to be filled by the Auto Assignment Engine.

All these parameters are now contained in one area to streamline configurations and changes. Building on Infor's years of experience in scheduling, there is a large library of scheduling rules with additional configuration parameters within the rule itself, which helps to increase flexibility. For example, the minimum hours per time period ensures the employees in the auto assignment group are scheduled a minimum number of hours based on a user defined time period. Within this rule it's possible to refine behavior by exercising the following parameters:

- Hard or soft constraint, allowing the rule to be broken
- Weight of the rule against other rules in the auto assignment group
- Respect for employee specific values
- Time period that can be configured for an amount of days or to reflect the schedule's length
- The number of hours to be worked

The filters allow users to configure what employees will be included in the auto assignment group.

There are four filters provided as standard:

- Employee job
- Employee team
- Employee flag
- Employee age

Each filter has additional parameters that allow you to further control the granularity of which employees are included in the group. The "age" filter allows the user to create auto assignment groups for employees within a specific age range, while the "team" filter allows you to specify what team of employees would be scheduled by the auto assignment group.

The combination of various rules, filters, and orders gives the scheduler the required tools to build schedules that meet today's demands as well as future demands. Additionally, Infor collaborates with our clients to continuously evolve the library of rules and filters to support evolving needs.

Sample list of available rules:

- Honor availability
- Honor position
- Minimum/maximum hours per shift
- Minimum/maximum weekend shifts per time period
- Minimum/maximum scheduled days per time period
- Minimum hours between shifts
- Schedule to budget
- Maximum schedule budget
- Minimum/maximum type X occurrences in block

Auto Assignment Engine and machine learning forecasting

While the Auto Assignment Engine can be used on its own without machine learning forecasting, its true potential is unlocked when paired with Infor's machine learning forecast model. The machine learning forecast can create realistic staffing requirements using past and recent data, while the Auto Assignment Engine creates shifts that are auto assigned to employees. Combined they're a very powerful schedule optimization product with sensational flexibility and accuracy.

The future of machine learning is Infor WFM

As technology evolves, so will the Infor WFM machine learning platform. Infor is committed to working with our clients and partners to identify improvements to the machine learning engine. The machine learning engine will undergo a continued evolution to constantly improve forecast accuracy and to be applied across the WFM application. For example, one application could be using machine learning to understand employee work preferences by analyzing past schedules and identifying common trends. Infor is also working on introducing new algorithms to the engine like recurrent neural networks (RNN) and convolutional neural networks (CNN). Infor is also analyzing productivity and utilization, as well as leveraging new programming languages to help better visualize the forecast and deliver a best in class scheduling solution.

LEARN MORE

Follow us:

641 Avenue of the Americas, New York, NY 10011

INF-2496693-en-US-0521-1