Product report: Learning algorithm for automated calculation of KPI preferences

Learning from Decisions in Real Time

Until today, optimization of performance measurement systems in companies has been based primarily on the empirical knowledge of individual participants. In the daily planning and control of processes, this leads to the fact that interactions between individual key figures are usually evaluated based on average simplifications. With the novel learning algorithm F9118, which has been included as a new functionality in the decision tool PSIqualicision, results significantly better and to the second can be achieved, making decisions much more precise.

Some machine learning methods can automate the recognition of interactions between KPIs in business processes. The combination of historicized and current process data allows calculating very reliable decisions to the second. Based on these decisions slightly different scopes for decision-making and adequate KPI preferences can be identified in the current situation. Thus, the user systematically is provided with a better basis for his decision-making process.

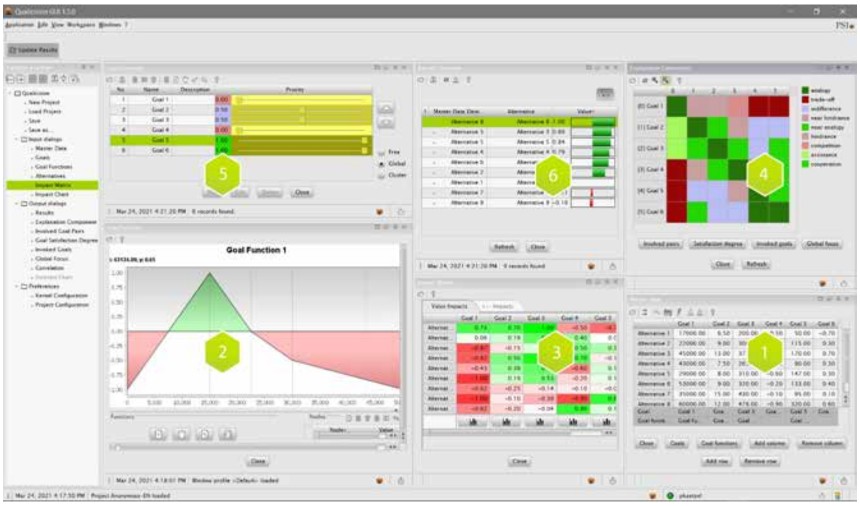

Figure 1: KPI preferences learned automatically with PSIqualicision/F9118.

Avoid mis-settings by using KPI preferences

PSIqualicision balances conflicting goals from the perspective of the current situation in real time. Balancing is controlled by automatically calculated KPI goal conflicts and KPI goal compatibilities so that different solutions are generated according to the specified KPIs. The generation of solutions follows the interactions between KPIs by moving goal-compatible KPIs in a common direction and conflicting KPIs in opposite directions, respectively. The interactions of the KPIs derived from these different solutions are summarized in point-in-time goal conflict matrices.

From this, the PSIqualicision/F9118 learning software determines meaningful constellations of KPI preferences that are neither contradictory nor unattainable in the current process situation. Non-sensible preferences are eliminated so that the risk of incorrect settings can be excluded.

The remaining constellations of KPI preferences are visualized in the form of achievable goal parameters as valid decision recommandations either via the GUI of PSIqualicision (see Figure 1) or fed to further processing (Qualicision) optimization algorithms.

Learning method can be integrated into many applications

The learning algorithm F9118 has already been used productively as a component of optimization strategies in various algorithmic previous versions. With the extension PSIqualicision/F9118, it is also available for interactive use for the first time. The connection with PSIasm (Advanced Scheduling and Monitoring) exists so that the learning procedure can be integrated into scheduling applications.

The embedding of PSIqualicision in BPM applications (Business Process Modeling) opens up another broad spectrum of application scenarios. PSIqualicision has already been linked with the BPM tool Camunda. The integration of PSIqualicision/F9118 in all software tools of the PSI platform is pending.

Figure 1 shows the main steps of the learning algorithm. In step 1, the current point-in-time data of the business process is retrieved from the surrounding systems and loaded into a data table. Each row of the data table represents a possible decision alternative in the current situation.

The columns of the table represent data values that map a raw measurement of the alternatives for a KPI. For example, the decision alternatives may be possible production start times for an order. One column of the data table can then stand for the forecast delivery date (KPI: delivery reliability), for example, and another for the forecast earnings (KPI: contribution margin) of the order.

Organized data becomes micro labels

Once the data is organized in the table as described above, in step 2 the data is qualitatively micro-labeled by the goal functions qualifying the KPIs. In step 3 it is then stored as micro labels in a so-called impact matrix. This scales the raw data from step 1 and standardizes their evaluation on a scale from -1 to +1. The closer the evaluation is to the value +1, the better the related KPI is fulfilled in the current situation. The closer the evaluation is to the value -1 the less satisfactorily the KPI is currently performing.

If, for example, the delivery date of an order is to be evaluated as a date, then meeting the deadline precisely is given the value +1 as a KPI. The further the delivery date is exceeded, the more the value of the KPI micro label moves in the direction of -1. In step 4, the Qualitative Labeling is condensed further from the KPI micro labels by aggregating the current goal conflicts and goal compatibilities between the KPIs in a goal relation matrix.

Adjustments via preference slider

Step 5 of the F9118 learning algorithm is the decisive one. Now, the consistent preferences are learned and visualized via specially designed preference sliders. Whenever the user readjusts the individual preference sliders, the other sliders automatically adjust according to the learned correlations either increasing or decreasing them, so that the shifts best match the setting of the preferences (see Figure 2, box).

Result calculation by decision ranking

The related decisions resulting from this as step 6 are calculated and visualized as a result in the form of a decision ranking. In this process, the user (or an optimization algorithm) has the certainty that the preferences set and thus also the decisions calculated are selected in such a way that they correspond as best as possible to the empirical values (described via the micro labels of step 2) of the current business process situation. In this way, the learning and decision-making process takes place exclusively within the scope of what is currently feasible with the best possible certainty.

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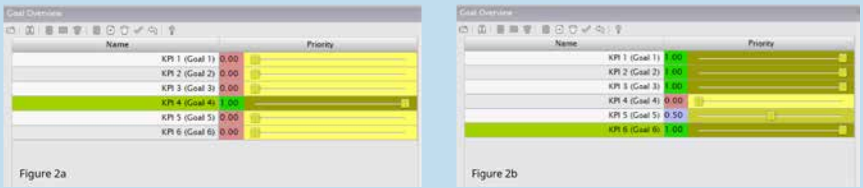

Figure 2: Learned preference settings and scope for decision-making with F9118.

Learned KPI compatibilities and KPI goal conflicts result from the goal conflict analysis. The learning algorithm F9118 learns from this, which preferences on the set of KPIs harmonize or mutually exclude each other and how. If, for example, the user (or an optimization algorithm) sets the preference to KPI 4 (Figure 2a) by moving the slider for this to the right, the preferences of the other sliders are automatically set to low (here to the value 0) according to the learned relations because in this case the remaining KPIs are obviously in conflict with KPI 4. If, on the other hand, KPI 3 is assigned a high preference (Figure 2b), the conflicting KPI 4 automatically sets itself to a low value (0 in this case) due to the relations learned by F9118. However, KPIs 1, 2, and 6, which are compatible to KPI 3, increase in terms of preference, and related sliders automatically move toward high (here 1). In this example, KPI 5 is neutral to KPI 3 and to the other KPIs. It remains in a neutral position (here 0.5) and can be further readjusted manually or algorithmically, if necessary, because it has a corresponding scope for decision-making. If the data ratios in raw data of business process change, the F9118 learning algorithm automatically adjusts to the new ratios because it continuously monitors the raw data and relearns in the event of changes.