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+ Deep Qualicision

Deep Learning Optimization—
Software tool for optimization driven learning

Software product solution for decision-making based on a multi-criteria decision engine and optimization driven machine learning

+ Connecting multi-criteria decision-making with machine learning
+ Self-adjusting optimization
+ Automated learning based on past process data and future optimization goals (KPIs)
+ Consistent decisions for complex business processes

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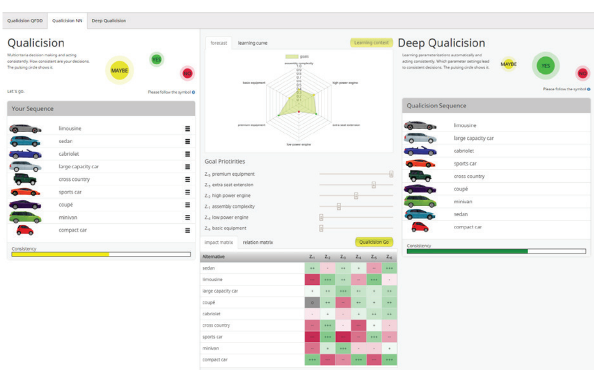
Deep Qualicision

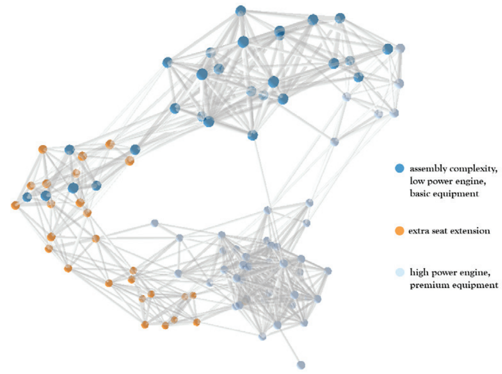
Deep Qualicision

Deep Qualicision connects the decision engine Qualicision with machine learning. This solution concept efficiently learns to adjust parameters so that decisions based on data and optimization results can be modeled.
In general, Deep Qualicision is used to determine multi-criteria preference relations efficiently on the basis of criteria specific preferences derived from process data and optimization results. Based on the multi-criteria preference relations the goal conflicts that Deep Qualicision detects from the data and the preferences are used to optimize the business processes the data come from and optimally resolves the conflicts. Deep Qualicision learns the priorities of the criteria so that consistent priorities and parameters are automatically recommended or self-adjusted.

Example: Sequencing

Deep Qualicision thus enables a deeper software-based connection between decisions and goal criteria in business processes and the process optimization. The following example of sequencing decisions, e.g. decisions in which sequence to produce cars in an imaginary factory, illustrates the principle behind Deep Qualicision: the decisions to be modelled here are about creating a sequence of car models in such a way that the sequence fulfills as many of the relevant production efficiency criteria as possible when putting it into the assembly line. These criteria are determined by the efficiency characteristic of the production line. In this example the car types the factory produces are compact car, coupé, cabriolet, sedan, limousine, minivan, large capacity car, sports car and cross country. For simplicity it is assumed that all these car models are produced on one single line of the imaginary factory. The criteria that are important for the efficiency of the line when producing the sequence are the





following car model characteristics: low assembly complexity, high power engine, low power engine, extra seat extension, premium equipment and basic equipment. The way the car models are distributed in the sequence implies the line efficiency. If a human decision maker builds the sequence (see figure below) then preferred criteria indirectly expressed by the sequence composition imply the understanding of the decision maker of what a good sequence shall look like. In this way some of the preferences imply the sequence more, some of them less. Even some of them may be (consciously or not) ignored. Usually manually generated sequences are not optimal.

Efficiency-optimized solutions are learned

The figure above shows the distribution of all goal criteria that as a result of the given example are classified in three partly conflicting clusters. It becomes clear that low assembly complexity, low power engine and basic equipment build together a production efficiency cluster whereas high engine power and premium equipment build a second cluster, and car models with a seat extension a third one. As result Deep Qualicision provides high efficiency sequences that balance the goal conflicts implied by the structure of the production line and optimizes its utilization. Balancing goal conflicts provides for much better (15% and more) results than calculations that assume linearity between the goals like, for instance, weighted sums.

Broad range of applications

Deep Qualicision covers a broad range of applications: optimization solutions based on Deep Qualicision learn their own parametrization automatically. Deep Qualicision is therefore able to handle self-adjusting optimization processes with efficient decision-making even when configurations of process input data are widely varied. Such solutions are required for example when optimizing production schedules on the basis of continuously changing order quantities and order mixes in factories and in resource planning and scheduling in general.

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