Cerebral Palsy is a neuromotor condition that leads to a wide range of walking disorders. Musculoskeletal surgery, including a hamstrings lengthening procedure, is a common treatment. Given the variability in improvement of walking following a hamstrings lengthening, it would be useful to predict which patients would benefit from the surgery, and the expected amount of improvement. To achieve this, we built a decision support system based on a Linear Continuous Bayesian Network. One variable used to quantify the success of a hamstrings lengthening is the patient’s mean knee flexion during the stance phase of the gait cycle (KneeScore). A reduction (improvement) in KneeScore indicates the patient walks in a more upright posture following the surgery. We built a Bayesian Network to predict the value of KneeScore after hamstrings lengthening surgery, by training the model on a set of retrospective patient data from a large clinical center. We evaluated the model’s ability to identify good candidates for surgery. We compared model performance to a Random Forest model and outcomes achieved using current standard of care.

Our dataset consists of pairs of medical visits (pre-treatment, post-treatment). Each visit provides patient characteristics such as age, clinical measurements such as strength assessment, and kinematic data in the form of 11 joint angles time series obtained during a gait cycle. All patients received a single event multi-level surgery, a common treatment consisting of multiple surgical operations including at least one major and one minor orthopedic operation. There are 442 visit pairs where a hamstrings surgery was part of the intervention and 1417 visit pairs without hamstrings surgery, which were used as controls.

We performed regression with a Linear Continuous Bayesian Network, where all variables were modeled as Gaussians, to predict the post-treatment KneeScore. We trained separate models for the hamstrings surgery and control groups. The inputs to the model are the variables gathered at the pre-surgical visit. We learn the structure and parameters of the network directly from the data, through our implementation of the K2 algorithm. We obtain a Mean Absolute Error (MAE) of about 7°, 6.5% better than the MAE for Random Forests. For reference, KneeScore values fall in the interval [10°, 40°]. The dimensionality reduction (the network models use 2-5 variables) as well as the structure of the network makes the Bayesian Network easier for physicians to interpret (compared to the Random Forest model) and will allow us the study of relationships between intermediary variables.

To evaluate the clinical relevance of the model, we tested its ability to predict whether hamstrings surgery would be a success. An observed intervention is defined as ‘successful’ if the post-surgery KneeScore gets closer to the KneeScore value for typically developing children. Using this criterion, 70.5% of hamstrings surgeries performed were successful, which means the precision of doctors’ decisions is 70.5%. For all patients in the dataset, we used the regression models to predict post-hamstrings surgery KneeScore and KneeScore in the control scenario. The potential intervention is predicted to be ‘successful’ if the KneeScore improvement predicted after hamstrings surgery is greater than the KneeScore improvement predicted in the control scenario. This recommendation system obtains 76.3% precision and 85% recall on the hamstring surgery patient group. Its precision is 5.8% higher than that of the clinical team planning the surgeries. Thus our system could help prevent physicians from operating on patients who would not benefit from hamstrings surgery.