Hamstring Surgery Outcome Prediction with Linear Continuous Bayesian Networks

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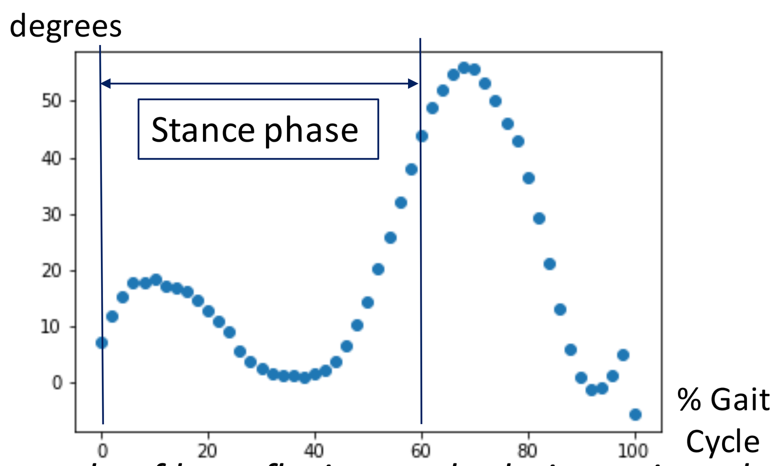
Motivation

Clinical Background

Cerebral Palsy is a neuro-motor condition that leads to a range of gait disorders, including crouch gait. Hamstring lengthening is a common procedure that can help patients with crouch gait walk in a more upright posture, but surgical outcomes vary across patients.

Children with crouch gait walk with excessive knee flexion



Example of knee flexion angle during gait cycle

Surgery outcome measure: KneeScore is an indicator of crouch severity; average knee flexion angle during stance phase of gait

Study Goals

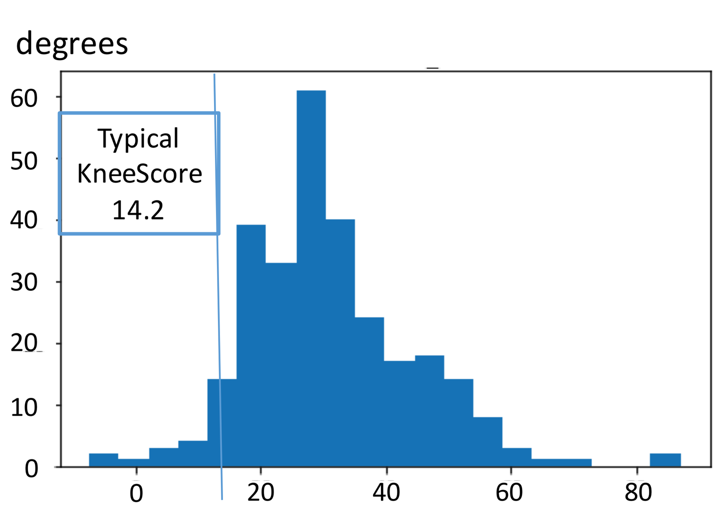
1. Predict which patients would benefit from surgery and the magnitude of expected improvement.
2. Identify key variables related to the evolution of patient post-surgical knee flexion.

Data

Our data consists of **pairs of medical visits** with surgery performed in between. we considered the left and right sides of a patient as separate training examples.

Visits include **patient information** 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 multiple surgical operations. We split them into **two groups**: one received hamstring surgery, the other not.



KneeScore distribution In Ham. surgery patients

Surgery group	# ex.
Hamstring	442
No Hamstring	1417

KneeScore ~ [10°, 40°]

We filtered out variables using a **correlation threshold with KneeScore** and a **mutual correlation threshold** between variables.

References

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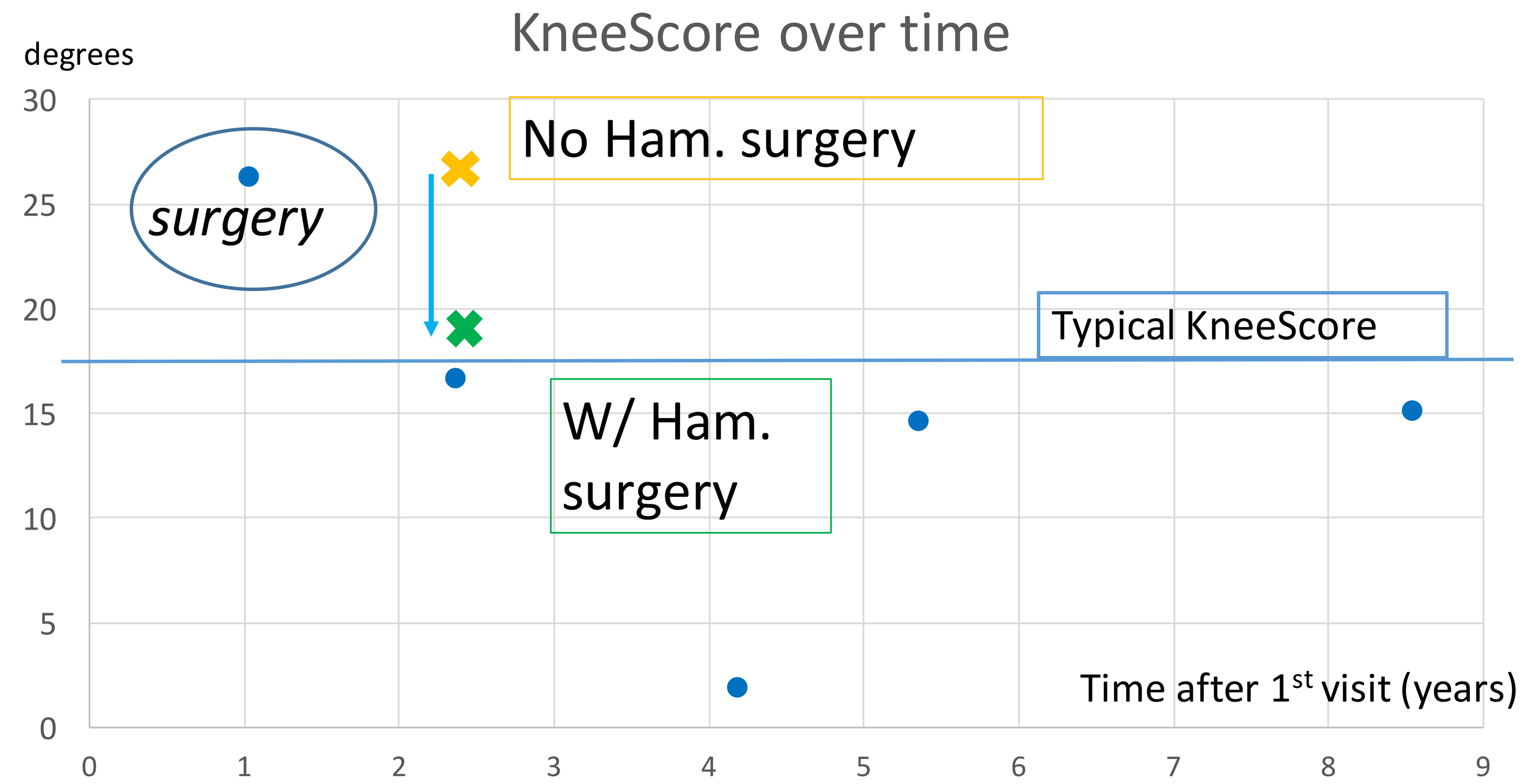
- Sesen et al., Bayesian Networks for Clinical Decision Support in Lung Cancer Care, *PLOS one*, 2013
- Bouhamed et al, A new approach for Bayesian classifier learning structure via K2 Algorithm, *Applied Artificial Intelligence*, 2012
- Hoot et al, "Using Bayesian Networks to Predict Survival of Liver Transplant Patients", *AMIA*, 2005
- Jung et al, "Bayes. network approach for modeling local failure in lung cancer", *Phys Med Biol,* 2011

Problem Setup

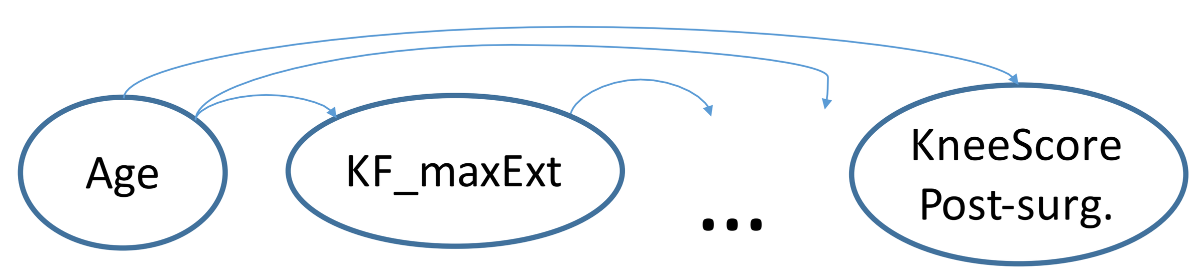
For a given patient, we predicted post-surgical KneeScore with a model trained on the 'Hamstring' population. We examined the same prediction computed by a model trained on the 'No Hamstring' population. We recommended the scenario yielding the **best improvement**



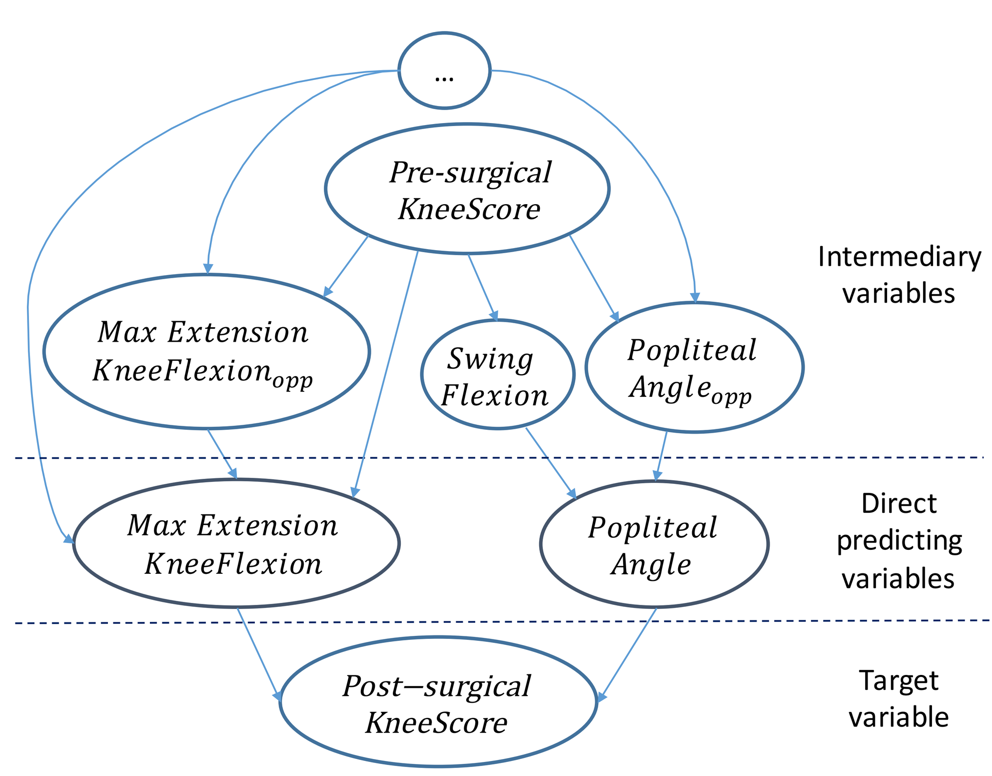
Linear Continuous Bayesian Network

We trained a **Linear Continuous Bayesian Network** on each patient group. Variables are modeled as **Gaussians** and tied by **linear relationships**.

We adopted a knowledge discovery approach by learning network structure and parameters through the **K2 algorithm**. Starting from an **initial node ordering**, K2 looks for a structure that optimizes a **regularized likelihood** score. Number of parents per node is bounded.



The best performing initialization followed the **order of correlation** to the post-surgical KneeScore. We also tested random and Minimum Weight Spanning Tree initializations. Selected thresholds yield 37 variables; selected parents bound is 6.



Partial network structure of the 'Hamstring' model. The opposite side equivalent of a variable is denoted by the suffix 'opp'.

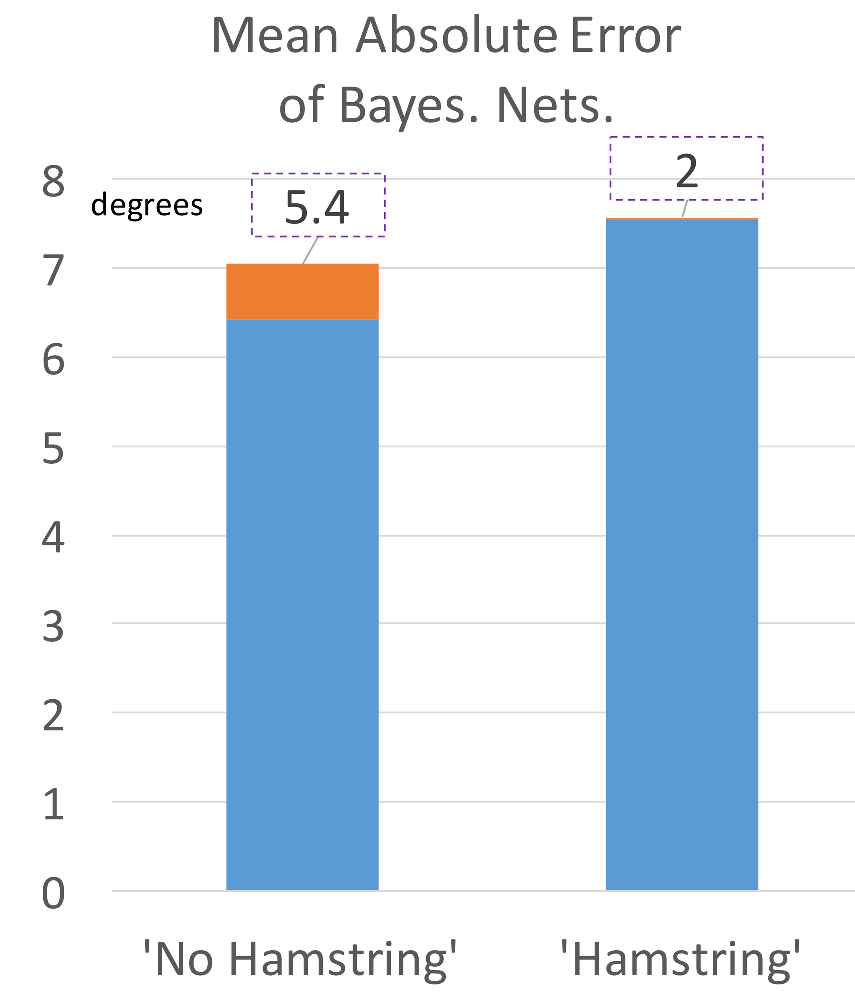
Structure learning selected a small number of direct predicting variables: **2** for the 'Hamstring' model and **5.4** for the 'No hamstring' model, averaged on CV.

Both models selected a '**Popliteal Angle**' variable and the '**Knee Flexion at maximum extension in the gait cycle**'.

Several variables were related to their opposite side equivalent in the graph.

The **central position of pre-surgical KneeScore** in the network suggests this variable is a good fit to quantify patient health status.

How Well Does the Model Predict Outcomes?



Mean Abs. Error ~ 7°

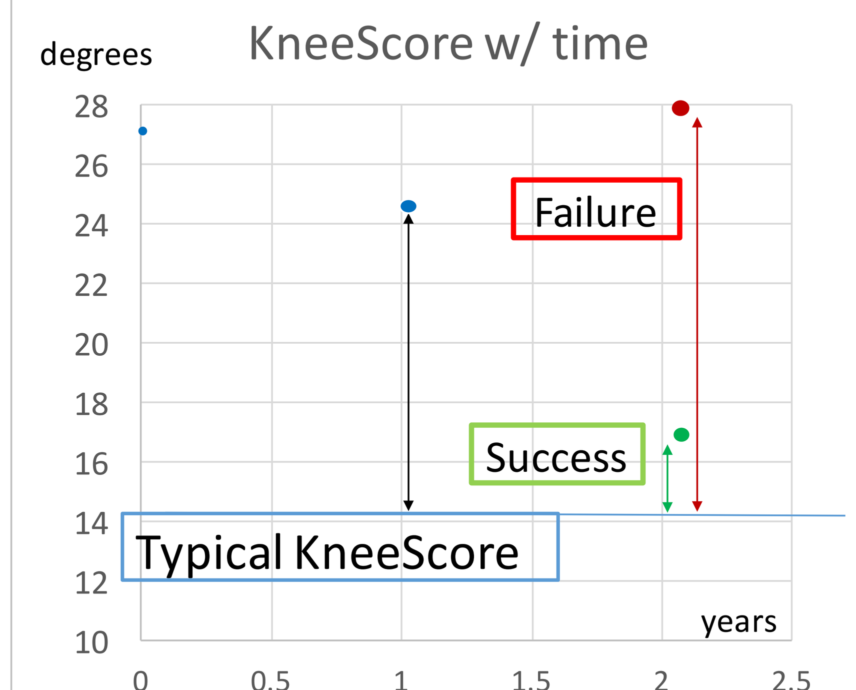
Bayes. Nets. MAE are 6.5% better than Random Forest MAE.

Bayes. Nets. use less than 6 variables to predict KneeScore.

Can We Improve Surgical Decision-Making?

We used the models to **predict hamstring surgery success** on patients who received Hamstring lengthening. Operation is defined successful if it **reduces the gap** to the KneeScore for typically-developing children.

We compared our recommendations with the **decisions of the clinical team**. Test patients all received surgery, so the clinical team forecasted a success for all of them.



70.5% success Ham. lengthening

	Doctor	System
Accuracy	70.5%	70.5%
Precision	**70.5%**	**78.8%**
Recall	N/A	79.6%

Detects patients not suited for Ham. lengthening

We assumed all patients who needed a Hamstring lengthening received it. System's recommendations agree with 79% of the decisions of the clinical team.

Conclusion and Next Steps

Our results suggest that our model could help the clinical team ***confirm*** their operation plans and reduce the incidence of patients who will show no improvement after surgery.

Next steps include leveraging the learned Bayesian network structure to introduce **latent variables** representing patient state over time or subpopulation, and investigating a setup with **multiple surgery outcome variables**.