Learning Bayesian Networks for Unfavorable Health Event Predicting in Nursing Homes

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Context

NETSoins, edited by Teranga Software, is an **electronic medical record software** used by more than 3 000 nursing homes (NH). The goal is to use information retrieved from this medical record to develop **algorithms able to predict several adverse health events** that are potentially preventable by appropriate health interventions. Here, the focus is on the occurrence of a resident's **first pressure ulcer**.

Definitions

- **Pressure Ulcer** (PU) : lesion of the skin related to prolonged compression between a bone and the support on which the patient rests. This preventable condition significantly impairs quality of life [1].
- **Bayesian Network** (BN) : probabilistic graphical model that represents a set of variables and their conditional dependencies via a directed acyclic graph [2].
- **Classifier** : machine-learning algorithm that determines the class of an input element based on a set of features.
- **BN Classifier** : to elaborate a classifier with a BN, the structure of the network has to be learned from estimates on the training base, and then the probability of belonging to a class knowing the observations of each variable on an individual is computed. It is a method that is often considered as a good compromise between accuracy and explainability.
- **Markov Blanket** (MB) : only the necessary features for the class inference. In a BN, the MB of a node contains its parents, its children and its children's other parents [2].

Methods

- Information retrieved from medical records of more than **100 000 residents** free of PU at admission in the facility
- Transformation of an **event database** into data for statistical learning, while keeping a medical meaning
- Features with potential interest were determined with **expert geriatricians** and kept in the analysis based on the **completion rate**
- Training dataset is created with the parameters of the residents and **two classes defined**: experienced the PU and control.
- Evaluation with the **F-score** : the harmonic mean of the precision and sensitivity scores and it has to be maximized.
- Three distinct datasets with **different temporalities objectives** are created: a prediction 1 month before the PU onset, 2 and 3 months before.

References

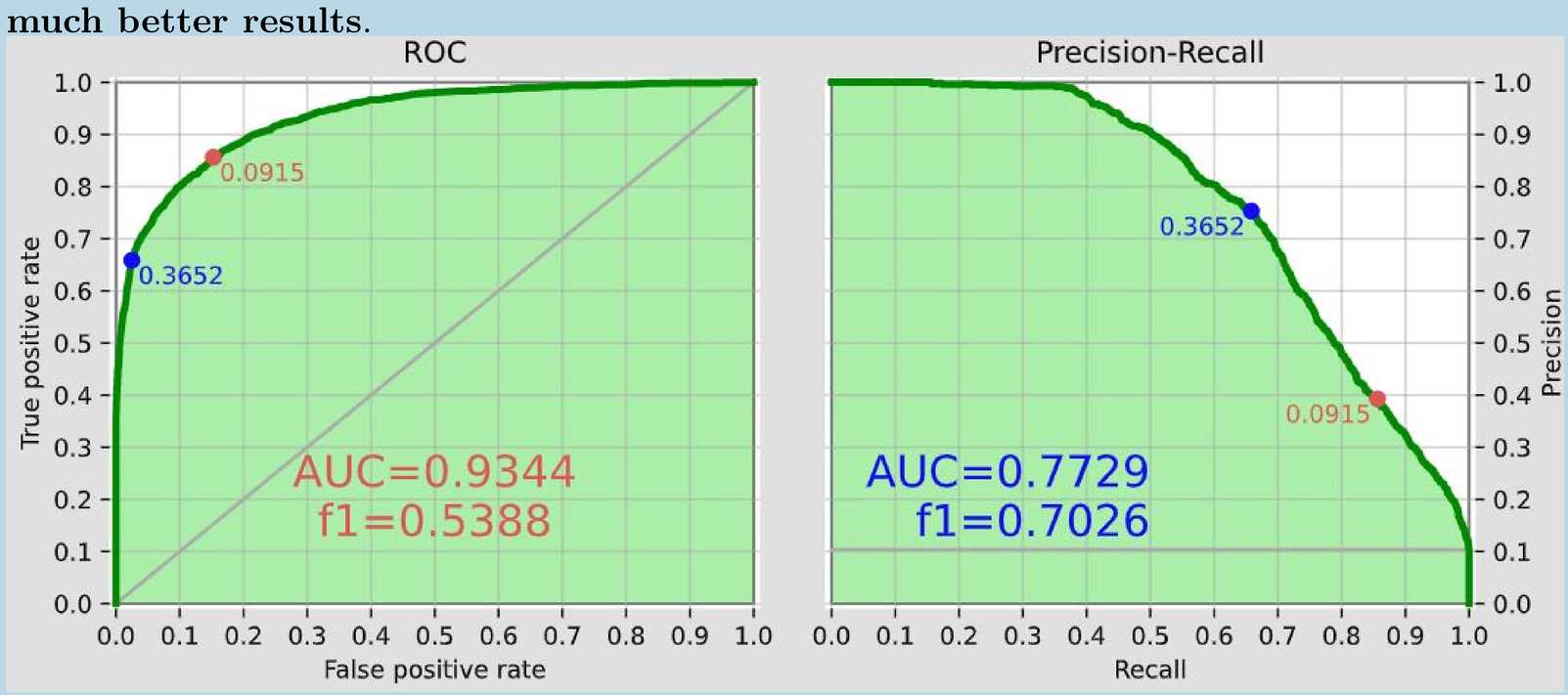
[1] J. Belmin et al: *Gériatrie : pour le Praticien*, Elsevier Health Sciences, 2016.
[2] J. Pearl *Causality: Models, Reasoning and Inference (2nd ed.)*, Cambridge University Press, 2009.
[3] G. Ducamp, C. Gonzales, et P.-H. Wuillemin *aGrUM/pyAgrum: a toolbox to build models and algorithms for Probabilistic Graphical Models in Python*, in PGM'20, vol. 138, p. 609-612.

Results

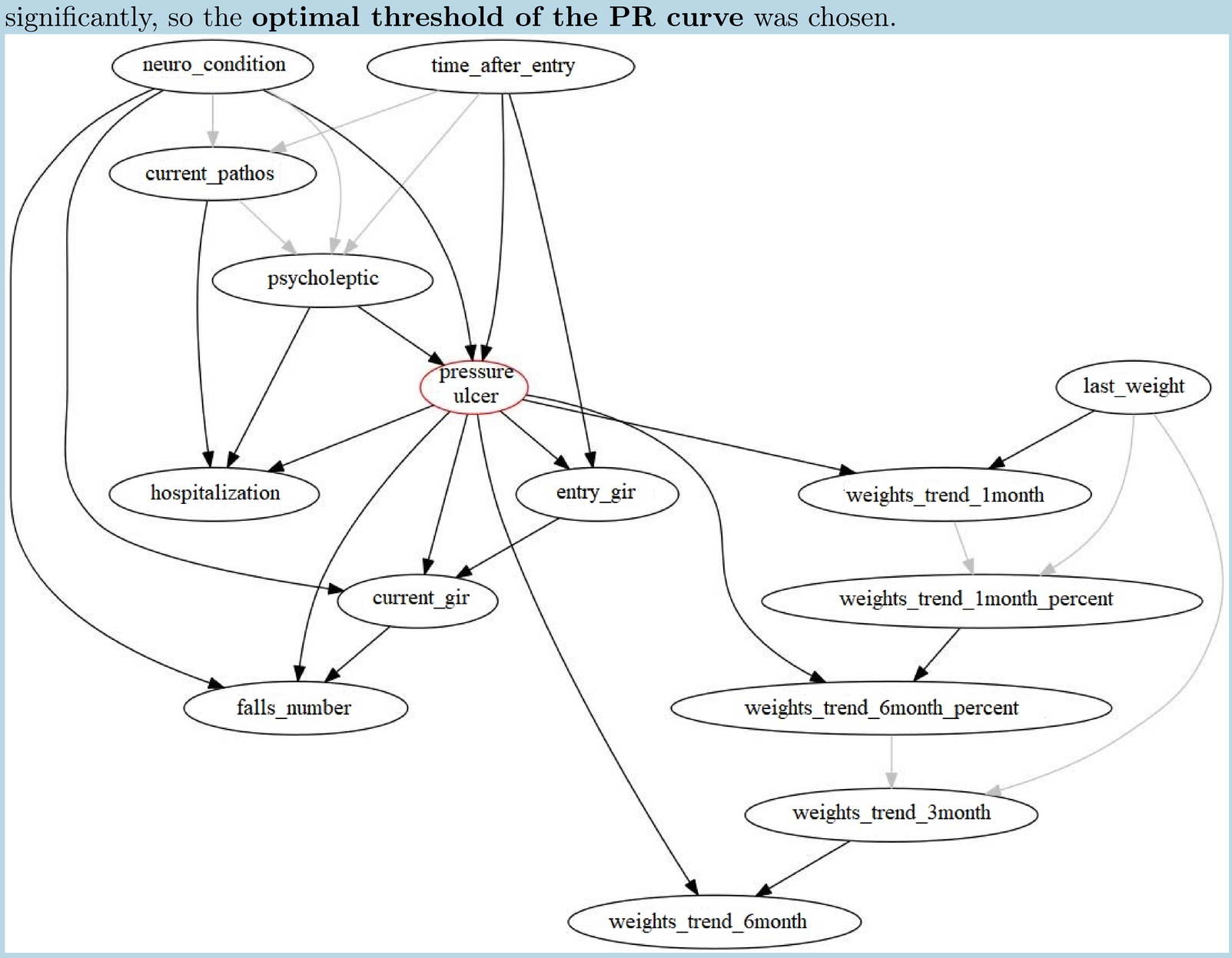
F-Score	1-month	2-month	3-month
BN Classifier	0,70	0,69	0,67
Random Forest	0,72	0,69	0,70
AdaBoost	0,69	0,67	0,69
Logistic Regression	0,32	0,36	0,42

F-Score	1-month
Braden	0,32
Norton	0,29

The F-Scores of the BN Classifiers, implemented with `pyAGrum` [3], have been compared with other classifiers of `scikit-learn` and their **predictive power was similar** to that produces by Random forest and AdaBoost. The F-scores of the Norton and Braden scales, clinical tools to identify the residents at risk to develop PU currently used in NH, were also calculated and **our method has much better results**.



The ROC and PR curves of the "one-month-before" BN Classifier have also been plotted. To know to which class our individual will be assigned, the probability threshold can be selected between this two curves. By using the optimal threshold of the ROC curve (in red), the F-Score decreases significantly, so the **optimal threshold of the PR curve** was chosen.



It is the Markov Blanket for the "one-month-before" BN Classifier. The MB was studied and the **explanations provided by the model** satisfied the expert. Indeed, **links with known risk factors** can be observed: the lack of mobility which is expressed by the GIR (a variable reflecting dependency), the weight of diseases with neuro-psychiatric affections and hospitalizations, or even undernutrition visible with the weight variations.

Conclusion

→ An **efficient** and **relevant** classifier based on BN in a predictive medical context was created.
→ Many improvements possible such as the **exploitation of the time series**.
→ An intent to put into practice the approach with **alerts in NETSoins** to encourage the implementation of preventive interventions for the targeted events.
→ It would also be calculated automatically, which is a significant **time saving for the caregiver**.