

Predicting work place accident types using data mining

Literature

Explaining and predicting workplace accidents using data-mining techniques , Rivas et al, 2010
“Prediction of Workplace Injuries” Sadeqi, Asgarian, Sibelia, 2019
Greedy Function Approximation: A Gradient Boosting Machine, Friedman, J. H. (February 1999)
R Packages: Mice, Random Forest, XGBoost, bnlearn
Netica Software

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1.Introduction

Saint Gobain is an international company specialising in construction materials. They are interested in limiting the number of accidents in the workplace by assessing the risks through **data mining**. My goal is to classify the **incident** type. The incident types are defined by Saint Gobain on a scale from TF1 to TF4.

TF1 (Lost Time Injury) : Incident leading to days missed from work.

TF2 (Minor Injury) : Incident where treatment is needed to be done in an external place.

TF3 (First Aid Injury) : Incident where treatment is done internally.

TF4 (Near Miss) : Incidents where accident or injury was avoided.

2.Data

The data consists of demographical information and incident information, coming in the form of numerical and categorical data. Focus is on the smaller dataset of 9374 incidents for TF1-3s, with 16 predictors. This is narrowed down from 119772 incidents and 30 predictors, removing the TF4 incidents because of the high amounts of missing data and the ambiguous definition of the incident type.

We solve it using **MICE** (Multiple Imputation by Chained Equations) via CART. MICE imputes the missing data multiple times based on a Gibbs Sampler procedure, which predicts the missing data using full conditionals.

Incident Type	Near Miss (TF4)	First Aid Injury (TF3)	Minor Injury (TF2)	Lost Time Injury (TF1)
Number of incidents	106061	7135	1663	584
Mean Missing Predictor Data	36.67%	20.93%	29.49%	20.21%

Fig. 1 Number of incidents by Incident type. Mean Missing Predictor Data calculated by taking an average of the missing data of each predictor.

3.Methods

Multinomial logistic regression

Assigns a probability of being classified for each class.

Choose the class with the highest probability. It uses a softmax function: (Z_i = Class i)

$$\frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}}$$

$$F_0(x) = \arg \min_{\gamma} \sum_{i=1}^n L(y_i, \gamma).$$
$$r_{im} = - \left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)} \right]_{F(x)=F_{m-1}(x)}$$
$$\gamma_m = \arg \min_{\gamma} \sum_{i=1}^n L(y_i, F_{m-1}(x_i) + \gamma h_m(x_i))$$
$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x).$$

Fig. 2 Gradient boost algorithm, where α is the learning rate, and $h_m(x)$ is a learner

XGBoost

A **gradient boosted** decision tree algorithm that is fast and has high accuracy.

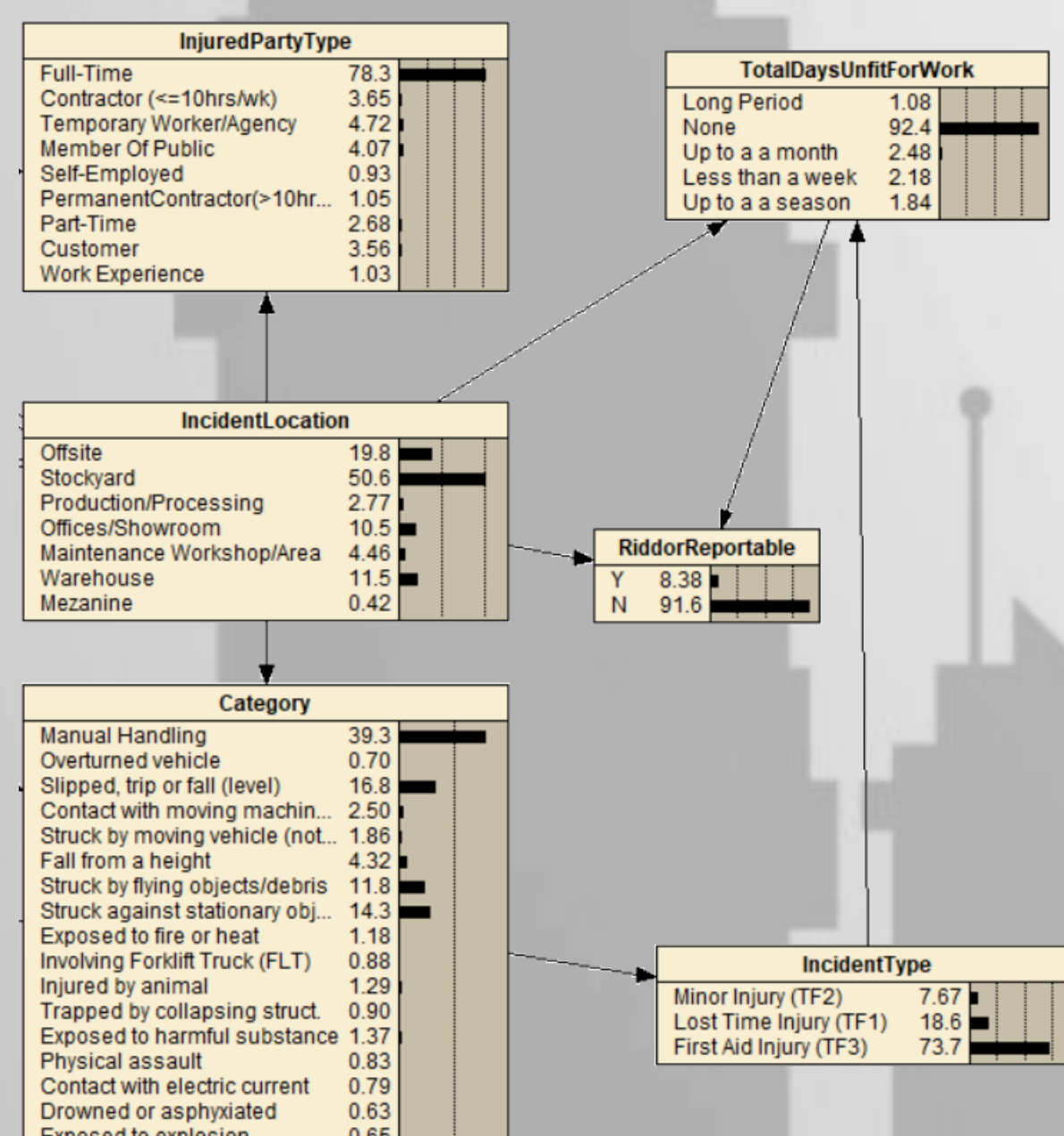
Random Forests

Ensemble algorithm which takes a collection of decision trees and uses a **majority voting** rule to decide the most likely class and classifies it accordingly.

Bayesian Networks

The directed acyclic graph represents conditional probability statements for a set of random variables. The edges represent statistical dependence between variables (nodes). The network is easy to understand provided the domain expert has verified it plausibility of the dependencies

Conditional Probability Table



4. Current Results

Method	TF3 Accuracy	TF2 Accuracy	TF1 Accuracy
Multinomial regression	High	Low	Low
Random Forest	Medium	Low	High
XGBoost	High	Low	Low-Medium
Bayesian Network	High	High	Low



Fig.4 Employee moving heavy material.
Jewsons is the largest Saint Gobain brand.

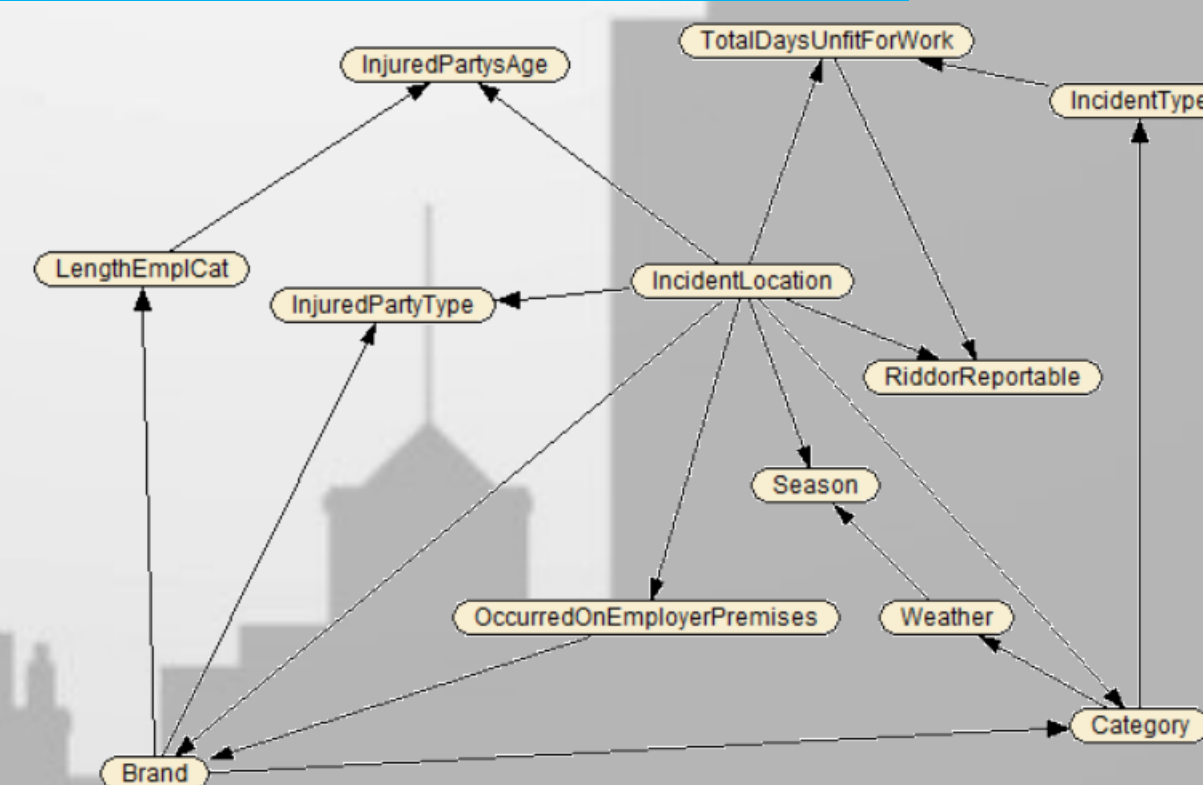


Fig.5 Data-driven Bayesian network

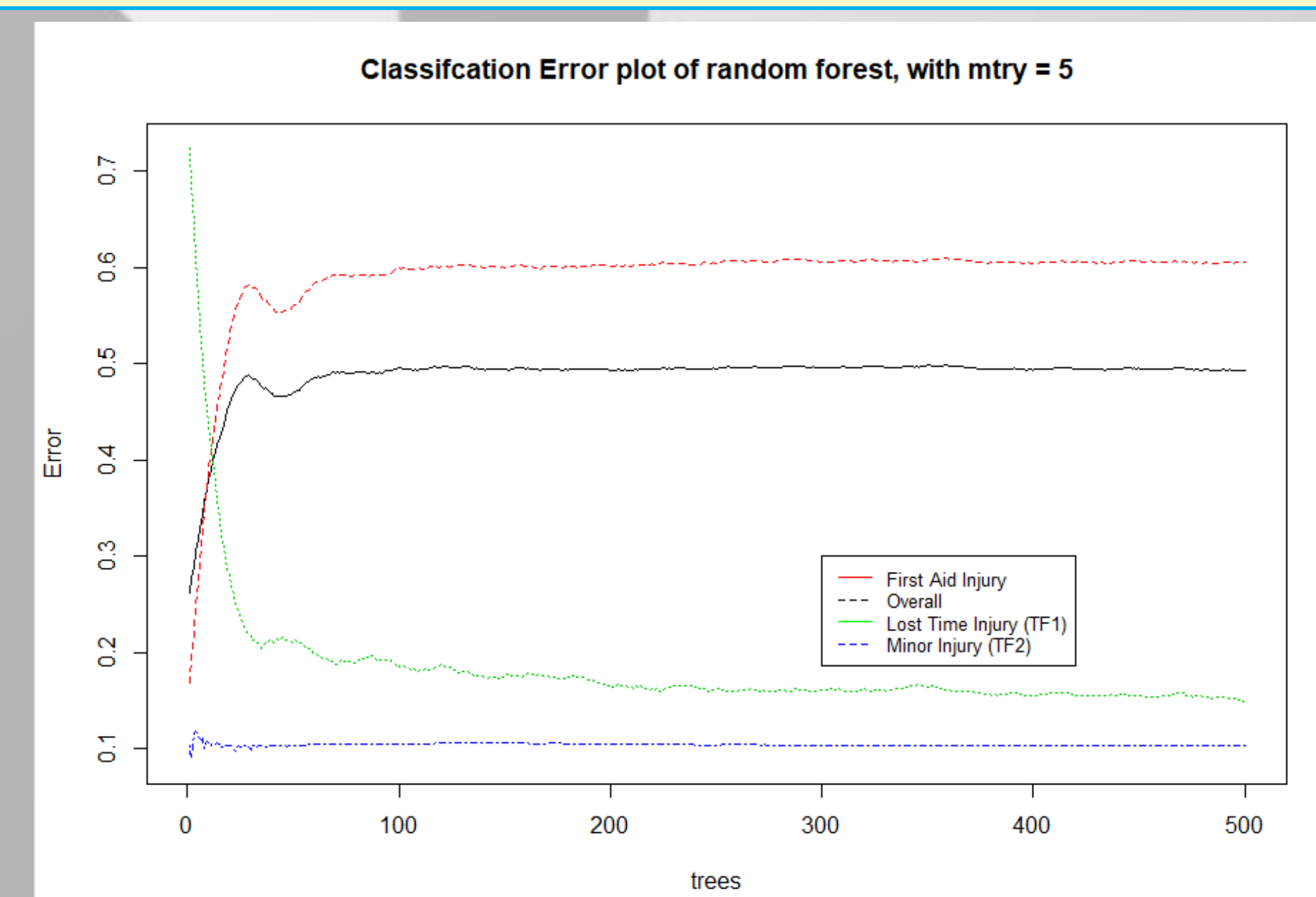


Fig. 6 Classification Error Plot, mtry is the number of variables randomly sampled at each split.

Fig.3 Selected subsection of a Bayesian network created by a Data-driven Bayesian network.