

Towards a Machine Learning Algorithm for Predicting Truck Compressor Failures Using Logged Vehicle Data



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Outline

- System Description
- Problem Statement
- Problem Approach
- Algorithm Evaluation
- Conclusions
- Review

System Description

Air compressor provides operational power for

- Brake System
- Gearbox
- Suspension
- Several other systems

System Description

Loss of compressed air immediately halts the vehicle

Resulting costs include

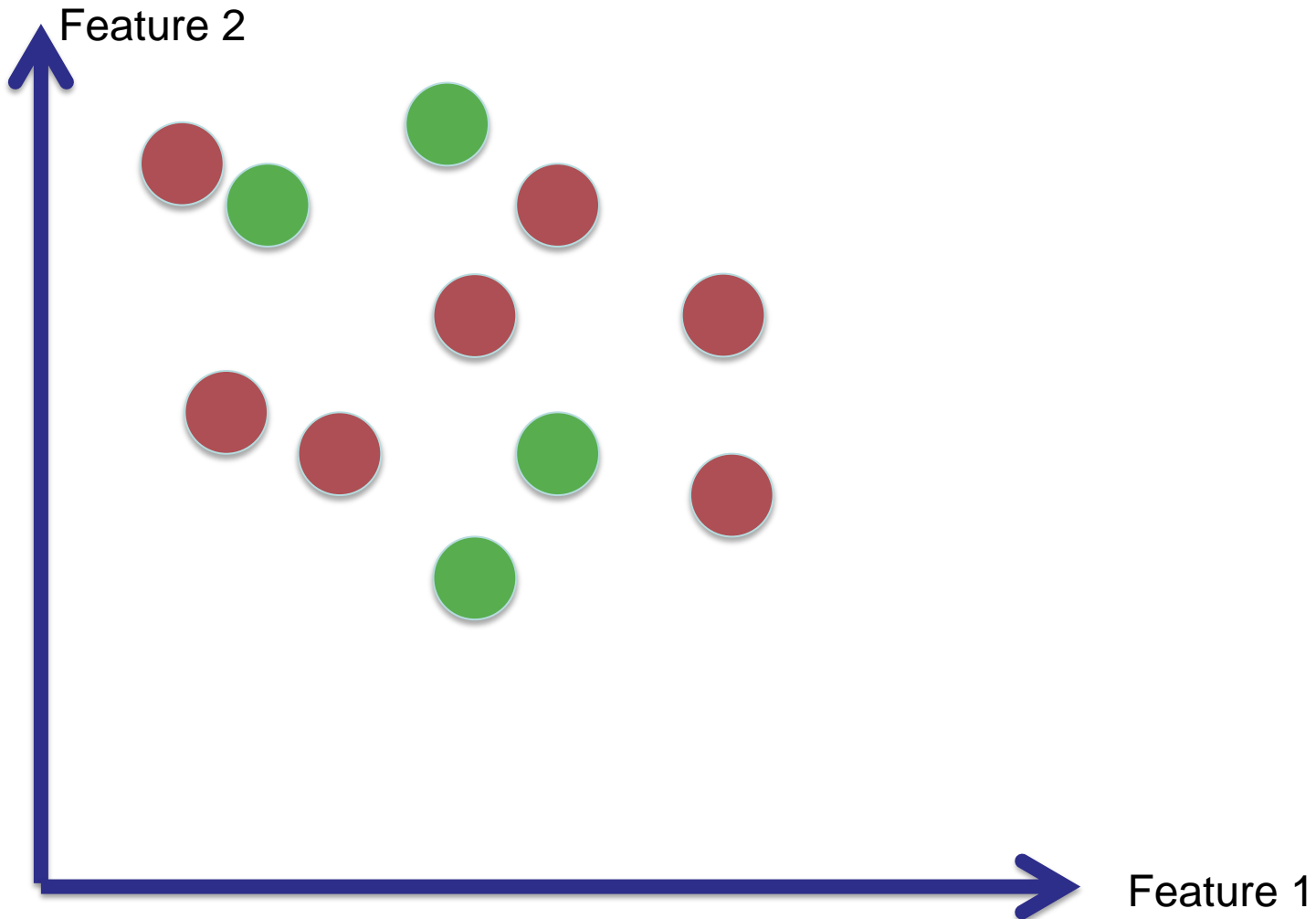
- Towing
- Disruption of garage workflow
- Repair costs
- Rent for replacement truck
- Possibly contract penalty and loss of reputation

Air compressor is a costly single point of failure!

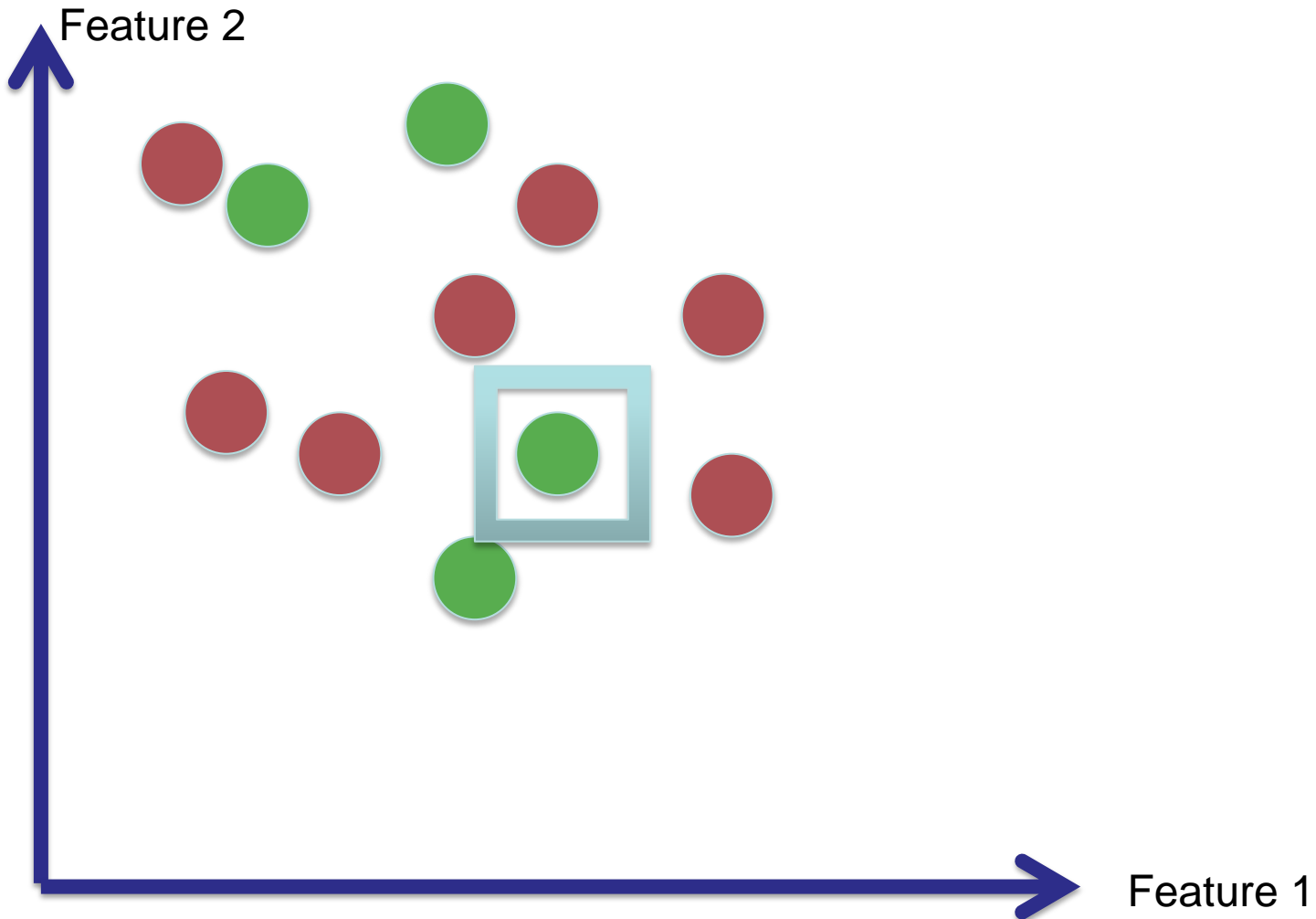
Problem Statement

- Approx. 5 per cent of Trucks have air compressors fail during lifetime (180 out of 4000 in database)
- High costs of compressor failure make prediction desirable
- Traditional approaches don't suffice
 - Previous papers used KNN, C5.0 and Random Forest

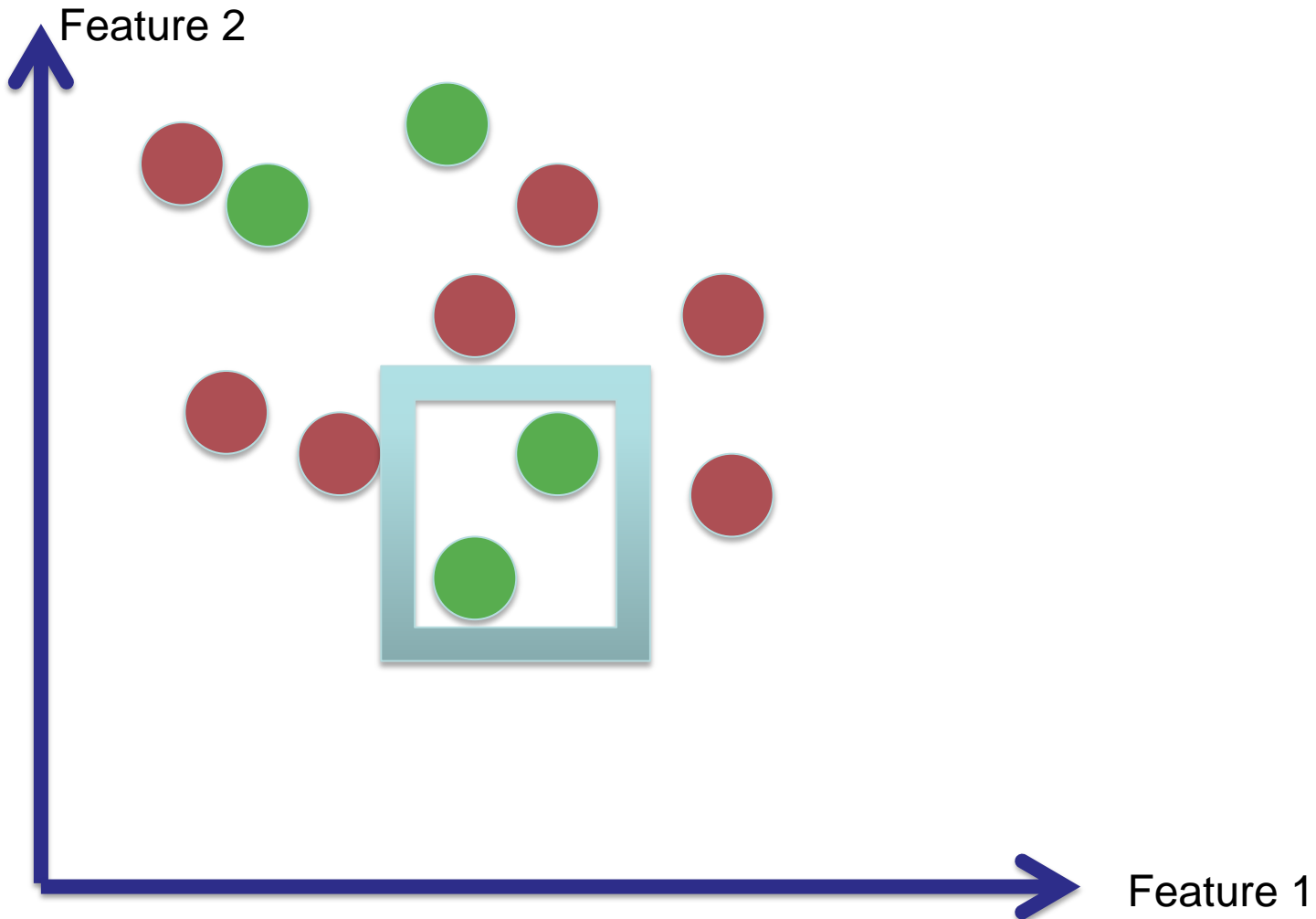
Problem Approach - Rule Induction



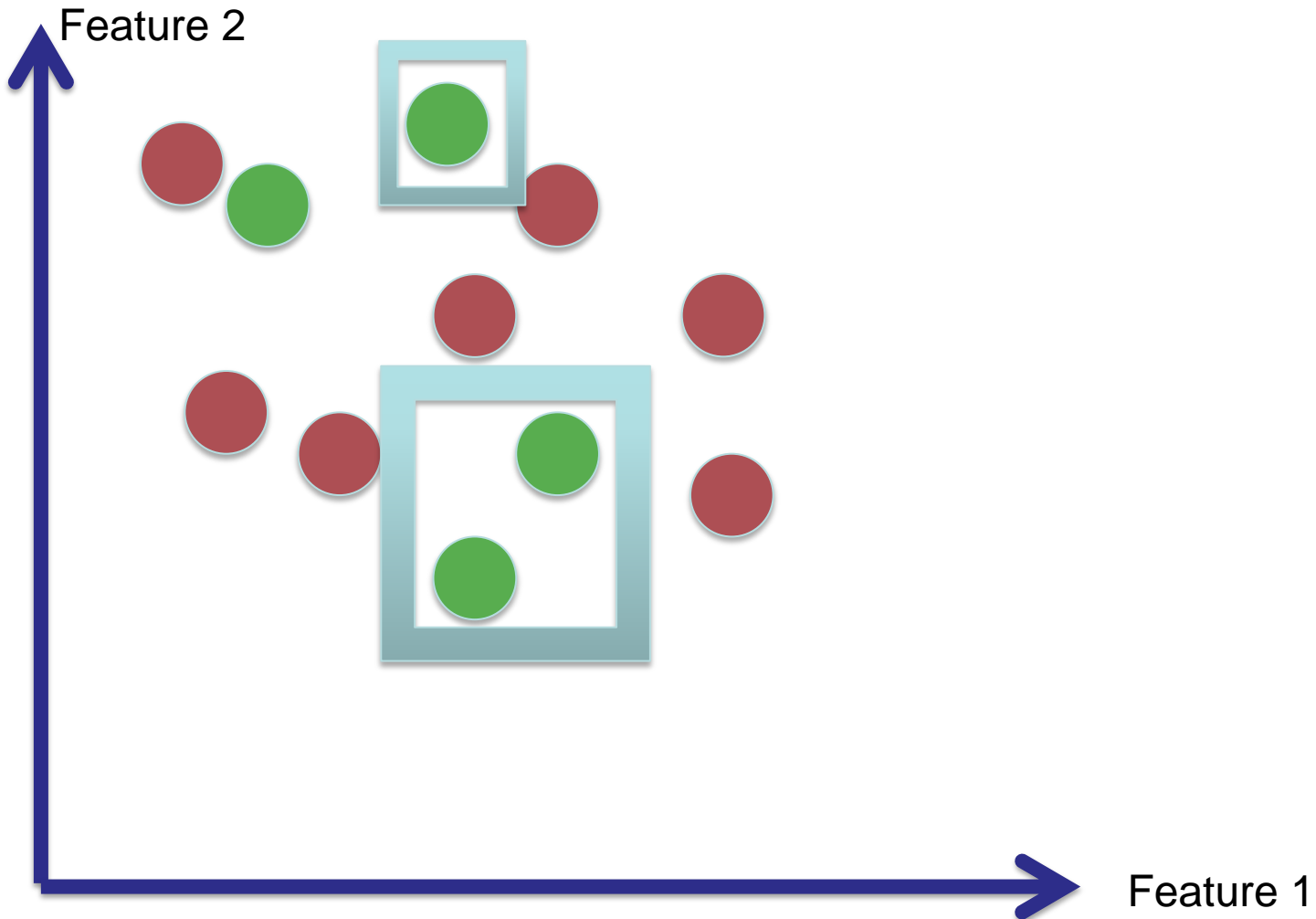
Problem Approach - Rule Induction



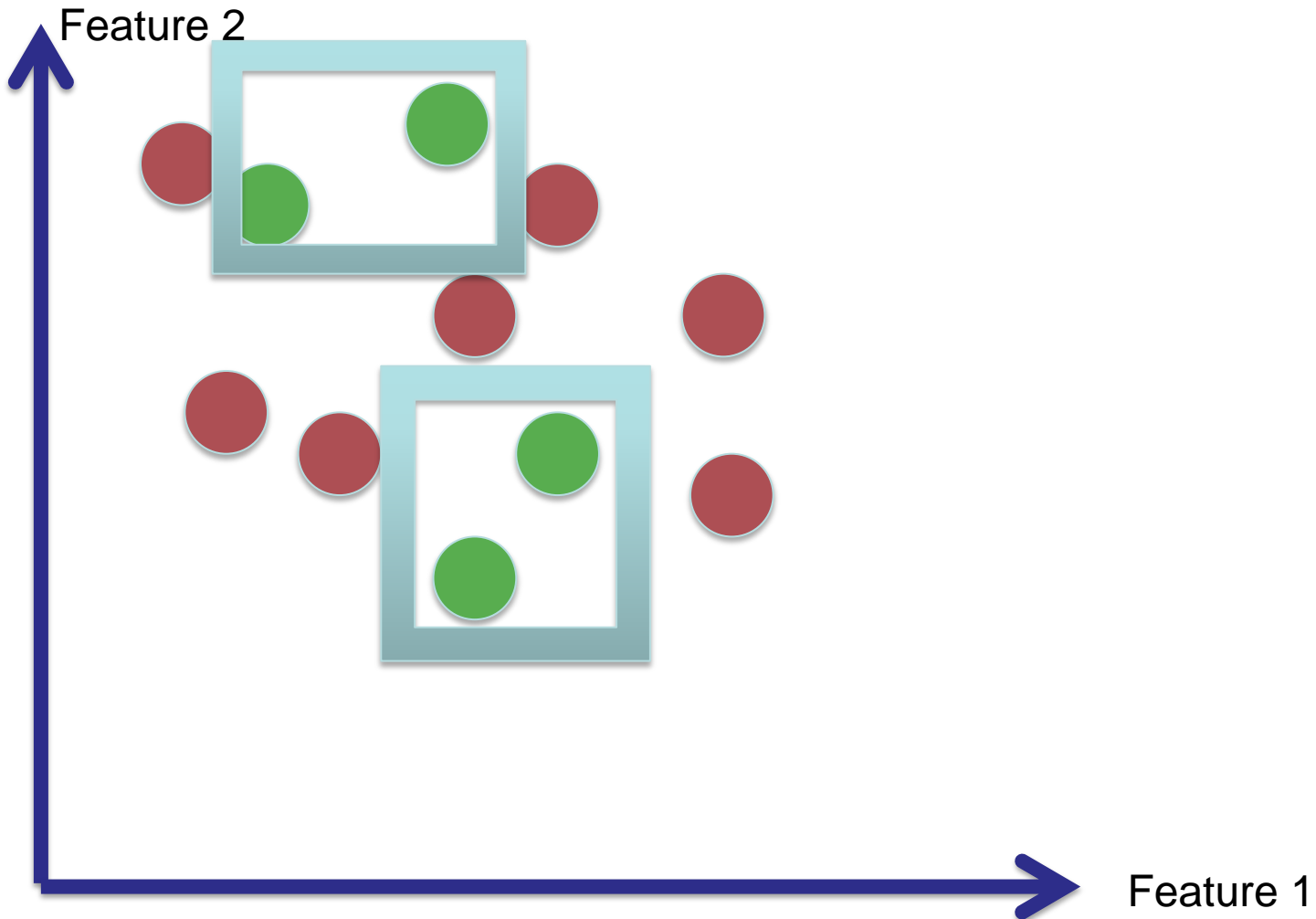
Problem Approach - Rule Induction



Problem Approach - Rule Induction



Problem Approach - Rule Induction



Problem Approach

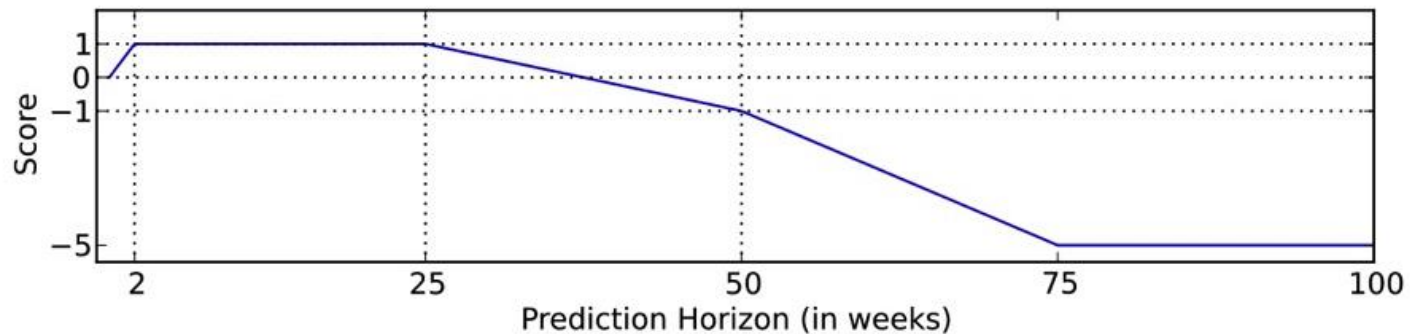
- Data
 - 3 Volvo Truck Service databases containing approximately 4000 Trucks
 - Each readout consists of hundreds of parameters
- Algorithm
 - Rule Induction with Relaxed Prediction Horizon (RRP)

Problem Approach – Novel ideas

- There is no suitable fixed prediction horizon for all vehicles
- Data sample readouts of single truck are not independent
- Cost function can be formulated as monetary cost saving function

Problem Approach – Relaxed Prediction Horizon

- There is no suitable fixed prediction horizon for all vehicles
- Preferred prediction Horizon between 2 and 25 weeks
- Penalize rules that result in too early warnings



Problem Approach – Relational Readouts

- Truck readout data exhibits relations
 - Independency assumption loses information!
- Easy solution:
 - Generate Rules based on final readout before failure
 - Generalize to match *trucks*

Problem Approach – Monetized cost function

- How much can be saved by correct classification?
- What is the cost of misclassification?

$$C_{\text{Save}} = \text{TruePositives} \times (C_U - C_s) - \text{FalsePositives} \times C_p$$

C_{Save} Cost savings

C_U Cost of unplanned breakdown (here: 2.5 x C_s)

C_s Cost of scheduled replacement

C_p Not explained

Algorithm Evaluation – F-score

$$F = (1 + \beta^2) \frac{\text{precision} * \text{recall}}{\beta^2 * \text{precision} + \text{recall}}$$

Beta: weighting factor between precision and recall

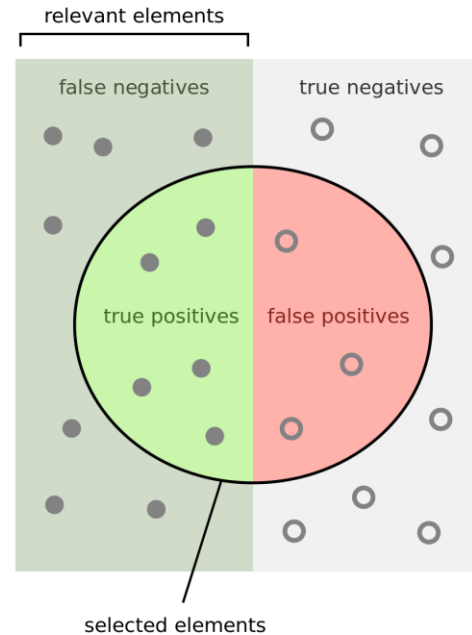
Precision: ratio of selected true positives to false positives

Recall: ratio of selected true positives to all positive

examples

Algorithm Evaluation – F-score

$$F = (1 + \beta^2) \frac{\text{precision} * \text{recall}}{\beta^2 * \text{precision} + \text{recall}}$$



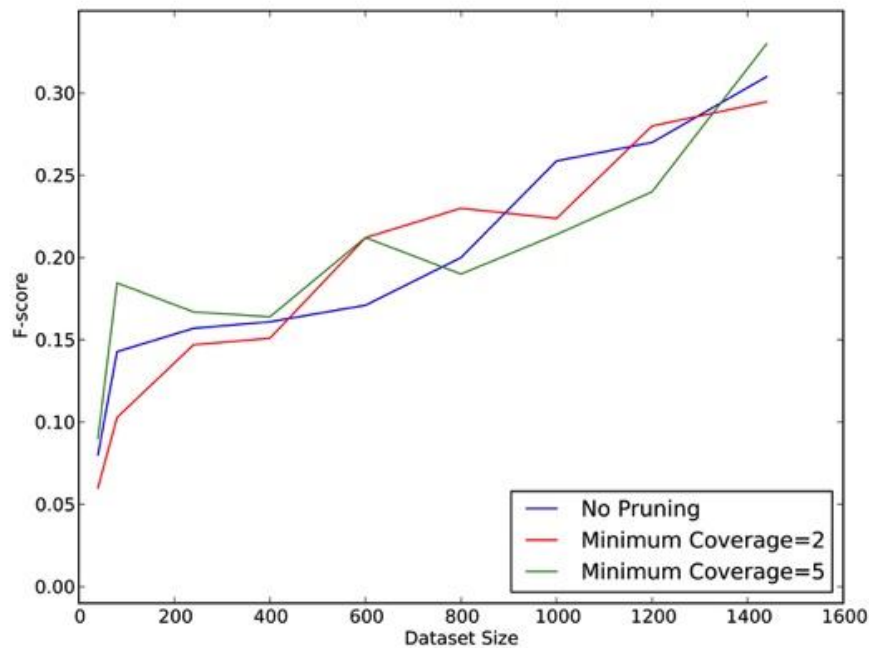
How many selected items are relevant?

$$\text{Precision} = \frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

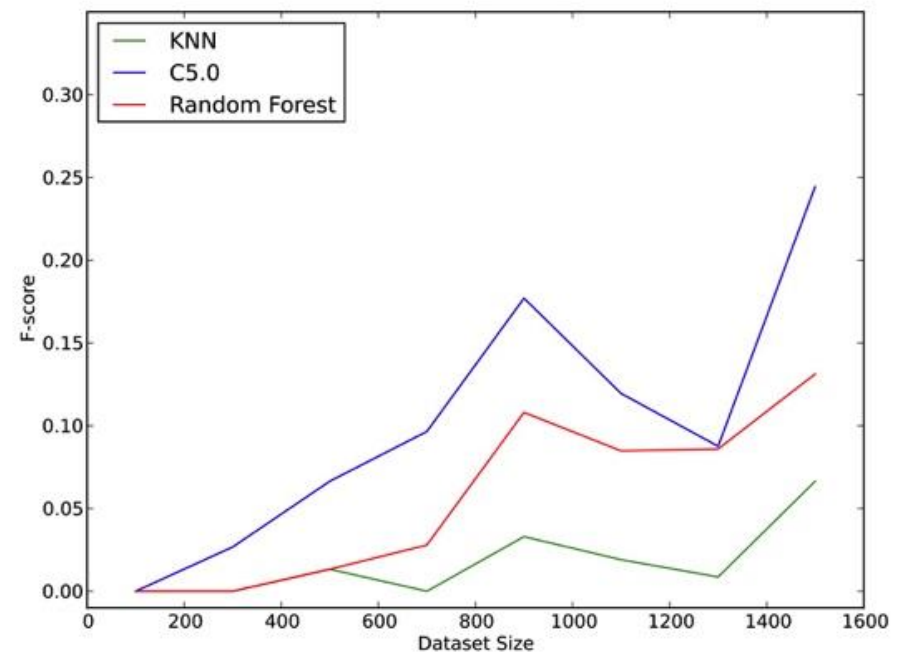
How many relevant items are selected?

$$\text{Recall} = \frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$$

Algorithm Evaluation – F-score over dataset size



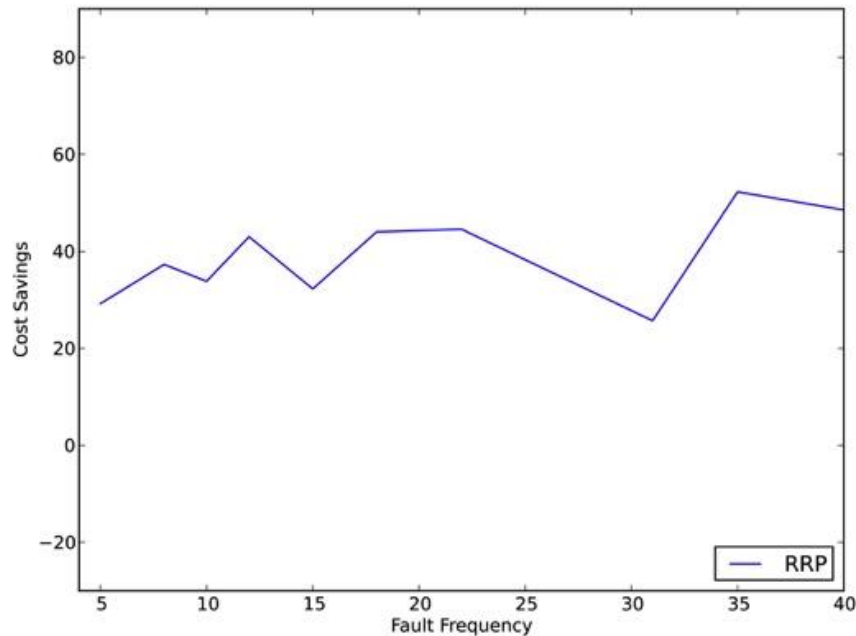
(a)



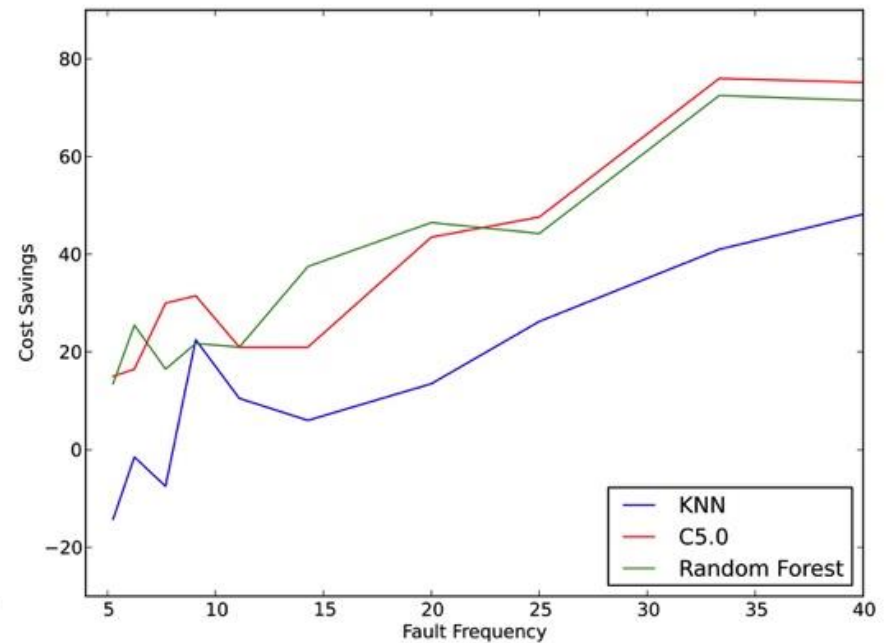
(b)

Figure 2. Impact of dataset size on $F_{0.5}$ -score, comparing (a) the RRP algorithm against (b) results obtained by three popular methods, as described in an earlier work

Algorithm Evaluation – Maintenance cost savings over fault frequency



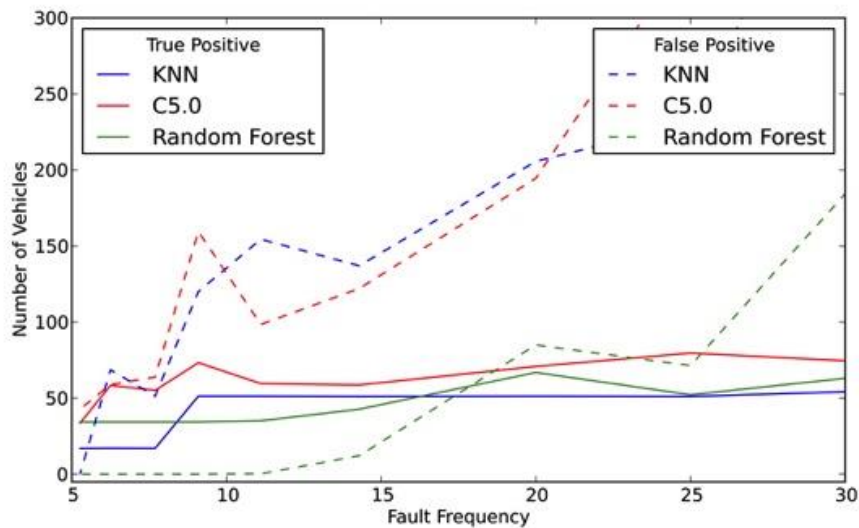
(a)



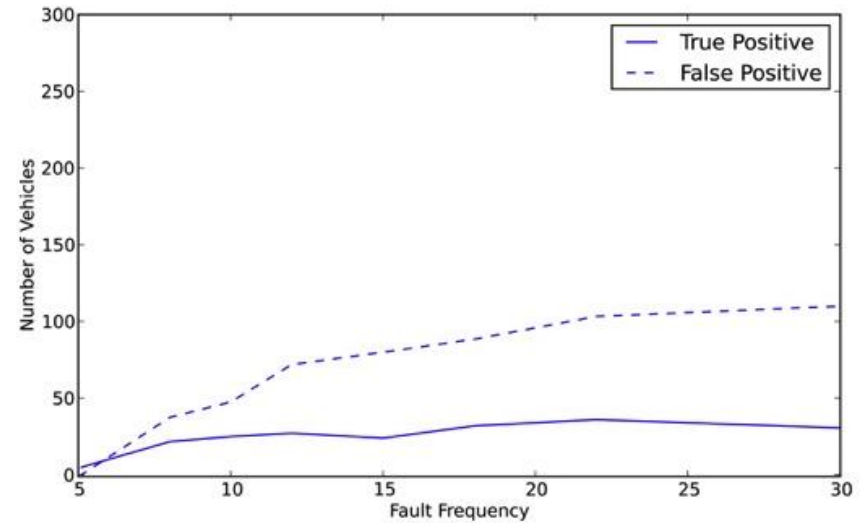
(b)

Figure 4. Maintenance cost savings, for different fault frequencies.

Algorithm Evaluation – Classification errors over fault frequency



(a)



(b)

Figure 5. True Positives and True Negatives, trained on data with varying fault frequency and tested on data with 5% of faulty trucks

Conclusions

Key properties of new approach:

- Conservative classifier
 - Less mistakes on healthy trucks
 - Issues fewer warnings overall
- Relaxed Prediction Horizon

Conclusions – Future work

- Analysis of further components
- Automatic parameter selection
- Adaption to wear and tear parts
- „Time to Repair“ prediction

- Cost function lacks parts of information
- It is not exactly clear which data is used and if/how it is preprocessed
- Minor inconsistencies in text
- It is not exactly clear how the independency assumption is circumvented
- Authors acknowledge this paper is intermediate step
- Overall this paper provides good insight to a novel adaptation of well-known algorithm



Thanks for your attention!

Picture sources:

Precision and recall graphic:

<https://upload.wikimedia.org/wikipedia/commons/2/26/Precisionrecall.svg>, created by Walber