# Failure detection in robot arms

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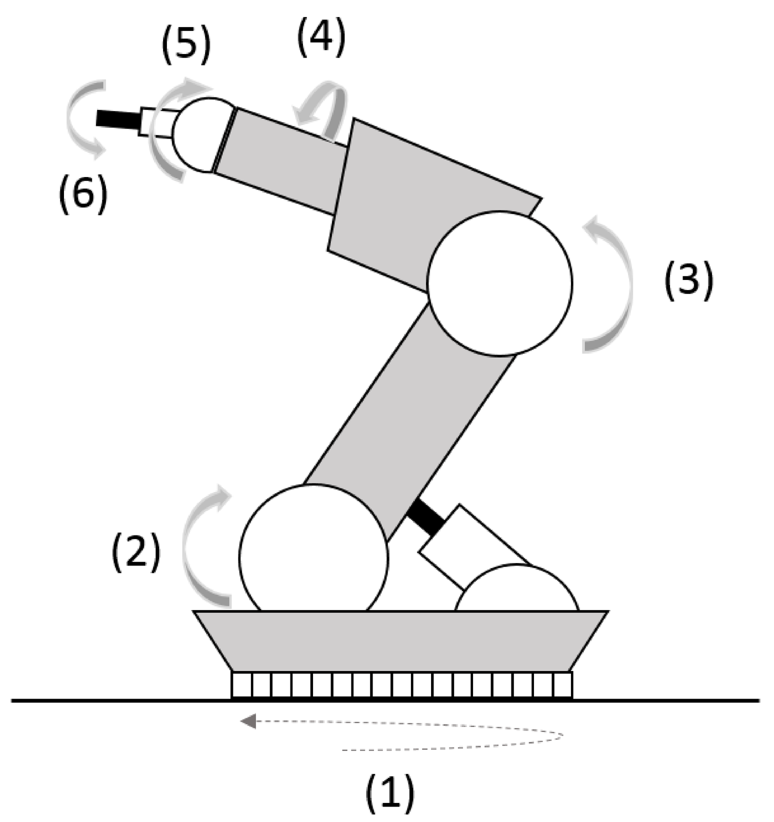
## Problem Formulation

To determine the most important factors causing failures in industrial robots and to find a model that can predict failure.




## Background

The study is based on data from more than 5000 robots in industrial use. Some properties of the data:

- For each robot data is collected from all six joints.
- For each robot approximately 250 variables are stored.
- Types of variables: Operational features and robot type.
- Operational features:
  - Joint operational features
  - Robot operational features
- Examples of joint operational features: avereage speed, average torque, moved distance
- Examples of robot operational features: production time, start time

## Classification methods

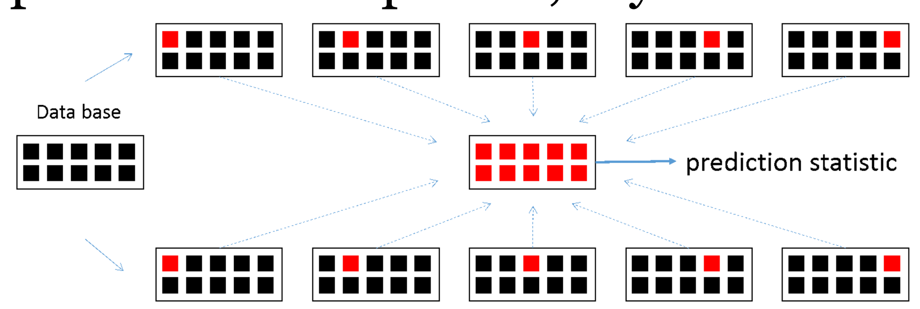
The following six methods were studied:

- Logistic regression (logistic)
- Logistic regression using elasticnet penalty (glmnet)
- Neural networks with 75 and 350 hidden nodes respectively
- Random forest
- Extreme gradient boosting (xgboost)

## Cross validation

Prediction accuracy of the proposed statistical and machine learning models were estimated using a 10-fold cross validation procedure illustrated below,

- the original database is randomly partitioned into 10 disjoint folds
- the database and the respective partitions are replicated 10 times
- for each replicate one fold is the test set and the remaining 9 folds are the training set
- resulting prediction for each fold are combined into a new database
- the entire procedure is repeated, say 10 times

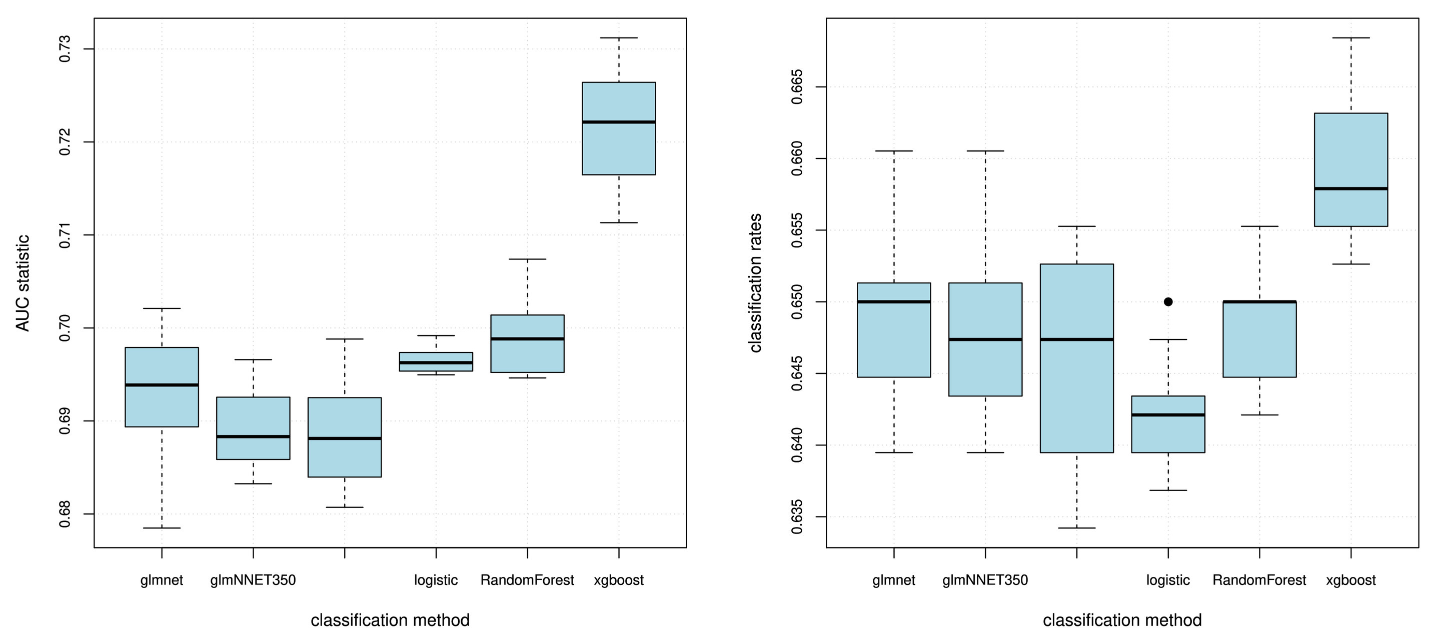



## Results

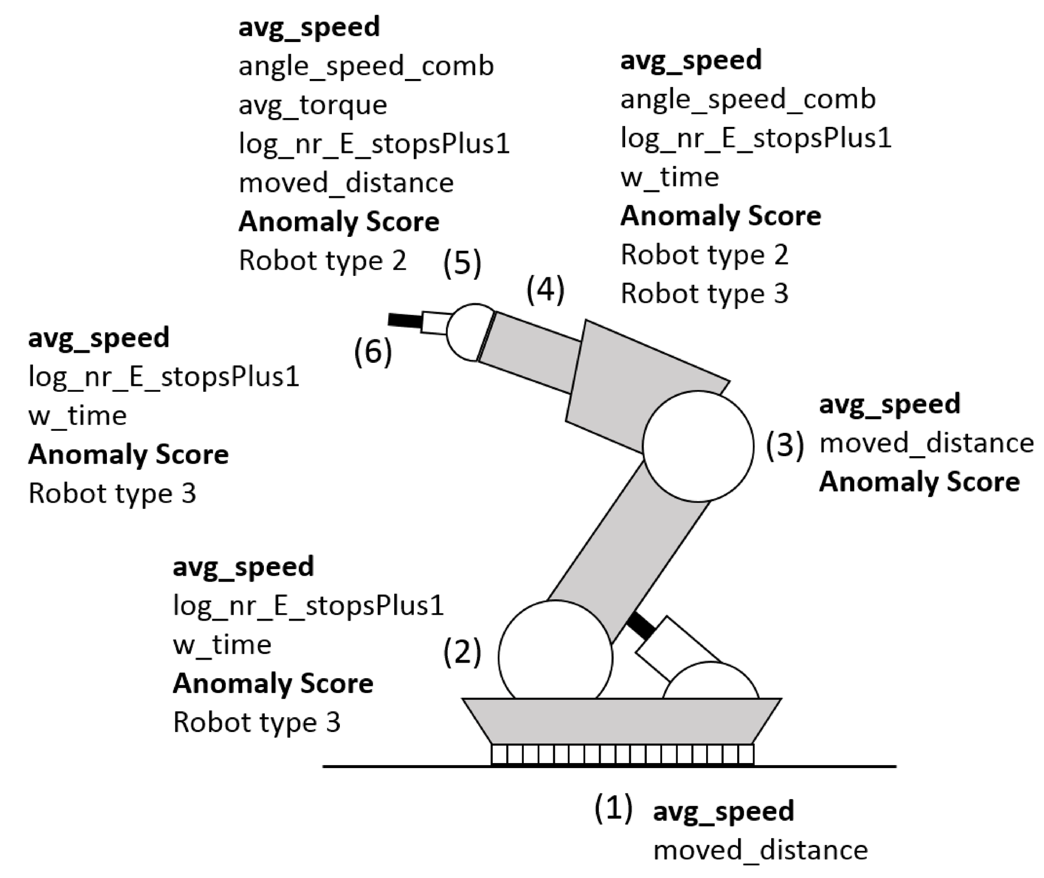
AUC, classification rates and computing time evaluated using 10 runs of the selected classification methods for failure detection in joint 4. Best results and minimum standard deviations are indicated as bold type.

| | AUC | | Classification rates | | Computing time (min) | |
|---|---|---|---|---|---|---|
| method | mean | sd | mean | sd | mean | sd |
| glmnet | 0.6929 | 0.0074 | 0.6486 | 0.0064 | 32.2128 | 4.8953 |
| glmNNET350 | 0.6891 | 0.0047 | 0.6481 | 0.0067 | 103.4436 | 184.2138 |
| glmNNET75 | 0.6888 | 0.0062 | 0.6459 | 0.0076 | 13.1653 | 2.2524 |
| logistic | 0.6965 | **0.0013** | 0.6421 | **0.0039** | **0.0138** | **0.0012** |
| Random Forest | 0.6990 | 0.0043 | 0.6486 | 0.0040 | 65.9301 | 14.4743 |
| xgboost | **0.7216** | 0.0067 | **0.6593** | 0.0056 | 0.1468 | 0.0071 |

AUC (Area Under the Curve) statistic (left) and classification rates (right) for failure detection in joint 4 using the selected classification methods and 10 runs.




Statistically significant predictors using the Logistic model.




Best classification models for failure detection in joint 2 to 6. Observed proportion of failures are indicated in parenthesis.

| Joint | AUC | Classification rates | Computing time |
|---|---|---|---|
| 2 (1.1%) | glmnet, logistic, xgboost | glmnet, logistic, xgboost | logistic, xgboost |
| 3 (1.6%) | glmnet, logistic, Random Forest | glmnet, logistic, Random Forest | logistic, xgboost |
| 4 (6.3%) | xgboost, Random Forest, glmnet | xgboost, Random Forest, glmnet | logistic, xgboost |
| 5 (2.4%) | glmNNET350, xgboost, glmNNET75 | xgboost, Random Forest, glmNNET350 | logistic, xgboost |
| 6 (5.7%) | xgboost, Random Forest, glmnet | xgboost, Random Forest | logistic, xgboost |

In general, there is no single method that achieved the best AUC or classification rate performance for all joints. For larger proportion of failures the black box models performed better. For lower proportion of failures the regularized logistic (glmnet) and the logistic models performed better. The logistic and xgboost were the fastest methods in all joints. This is because these method are compiled into lower level language whereas the remaining method use high level programming language. The methods were evaluated using i7 core intel and the R language.

## Conclusions

- No single method that gives best results in all cases.
- Indications about the critical factors for each joint.
- The portion of failures appears to play a role.

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