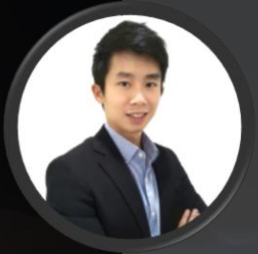
MONASH University

Tamping Effectiveness Prediction using Supervised Machine Learning Techniques

Institute of Railway Technology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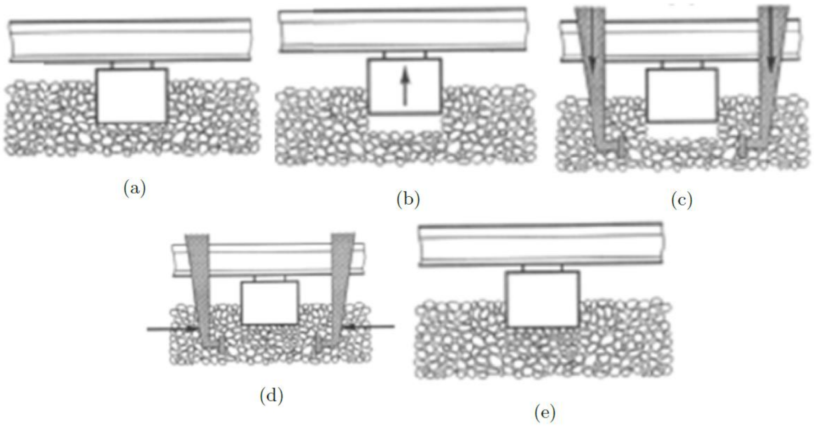
Outline

1. Tamping Maintenance
2. Motivation
3. Methodology
   - Data
   - Machine Learning techniques
4. Results
5. Conclusion & Future Work

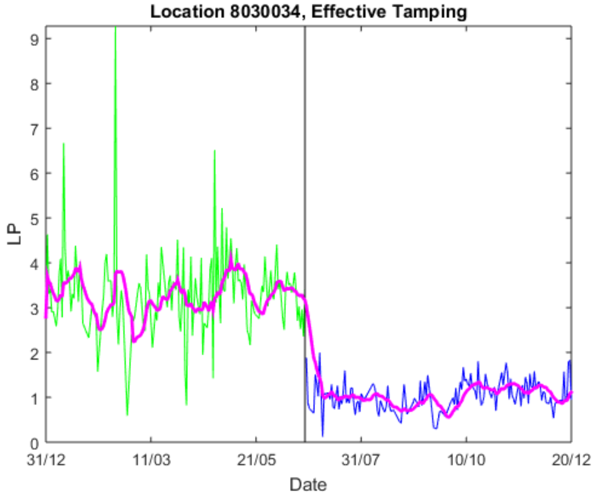
Tamping Maintenance

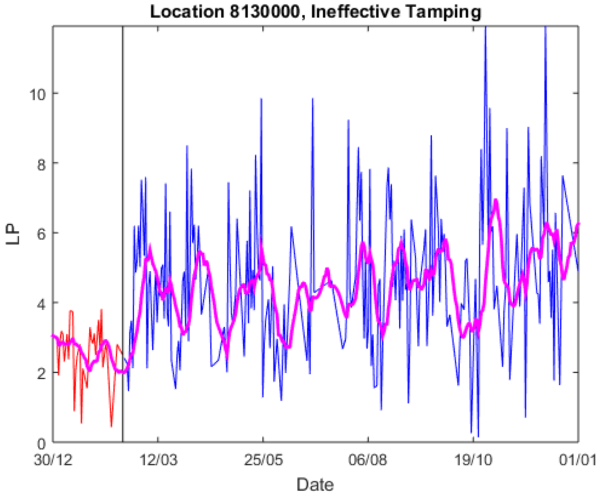
- Reset track geometry by rearranging the ballast particles



Motivation

- Historical data shows that it is not always effective
- Ineffective tamping reduces tracks' life-cycle





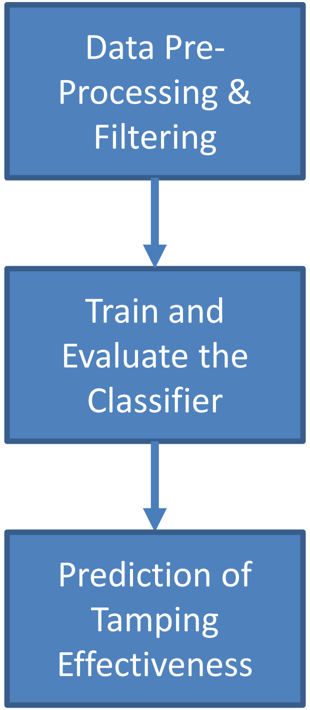
What can we do?

- Predict Tamping Effectiveness
- A recent work calculates tamping effectiveness using ratio of average responses before and after tamping.
- Challenging problem due to many complex phenomena
- Important for 3 reasons
  1. Minimise maintenance cost and time
  2. Reduce unplanned downtime
  3. Avoid cost of failure recovery

Predict if tamping will be effective for a track location

How to do it?

1. Data pre-processing & filtering
   – Convert acquired data from Instrumented Revenue Vehicles (IRVs) into time series for each track location
2. Train a classifier
   – *k*-Nearest Neighbours
   – Classification tree
   – Naïve Bayes
3. Evaluate and cross-validate the performance of the classifier
4. Predict tamping effectiveness

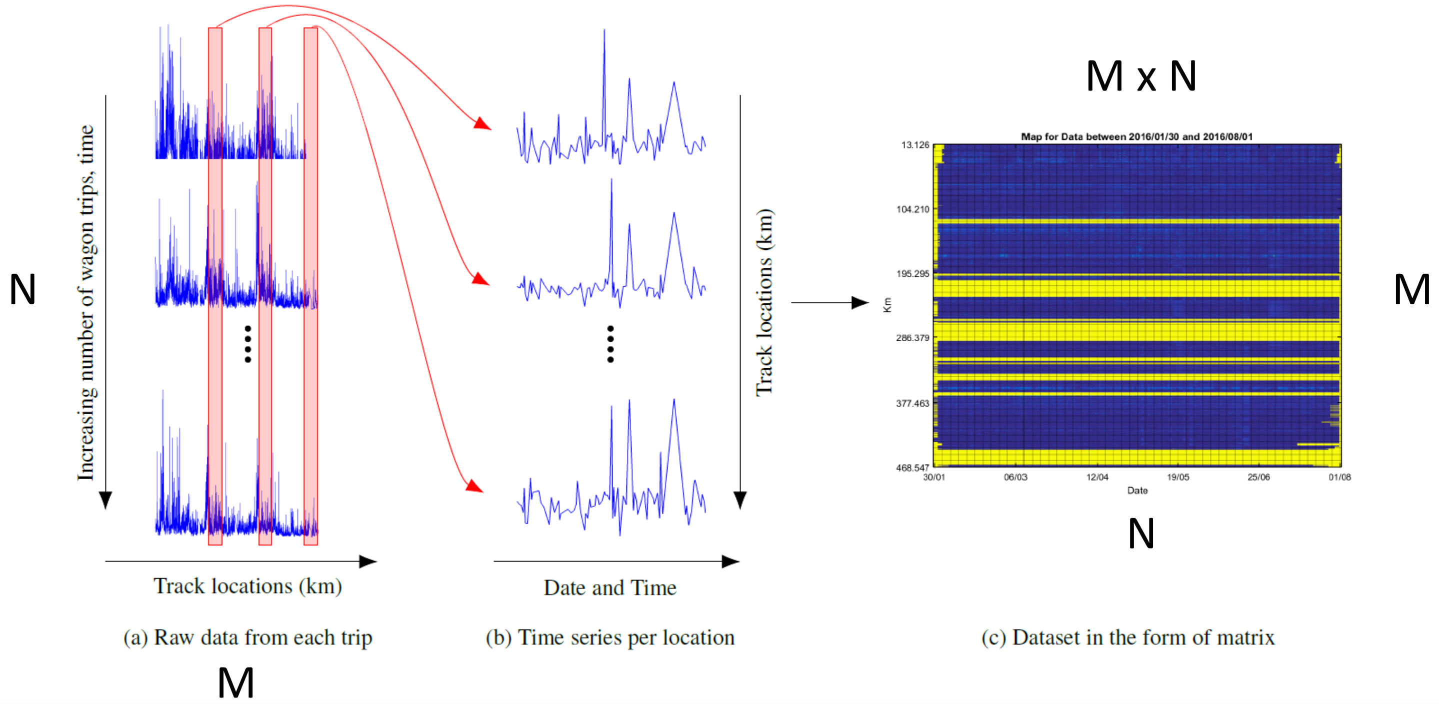


1. Data – Instrumented Revenue Vehicles (IRVs)

- Continuous monitoring system that uses measured wagon's dynamic activity to infer information about track condition
- Installed on normal revenue wagons
  - Cheap
  - Do not affect normal operations
- Measures:
  - Speed
  - Axle Load
  - Suspension
  - In Train Forces

Image taken from [UniversalMechanism]

1. Data – IRVs Time Series



(a) Raw data from each trip

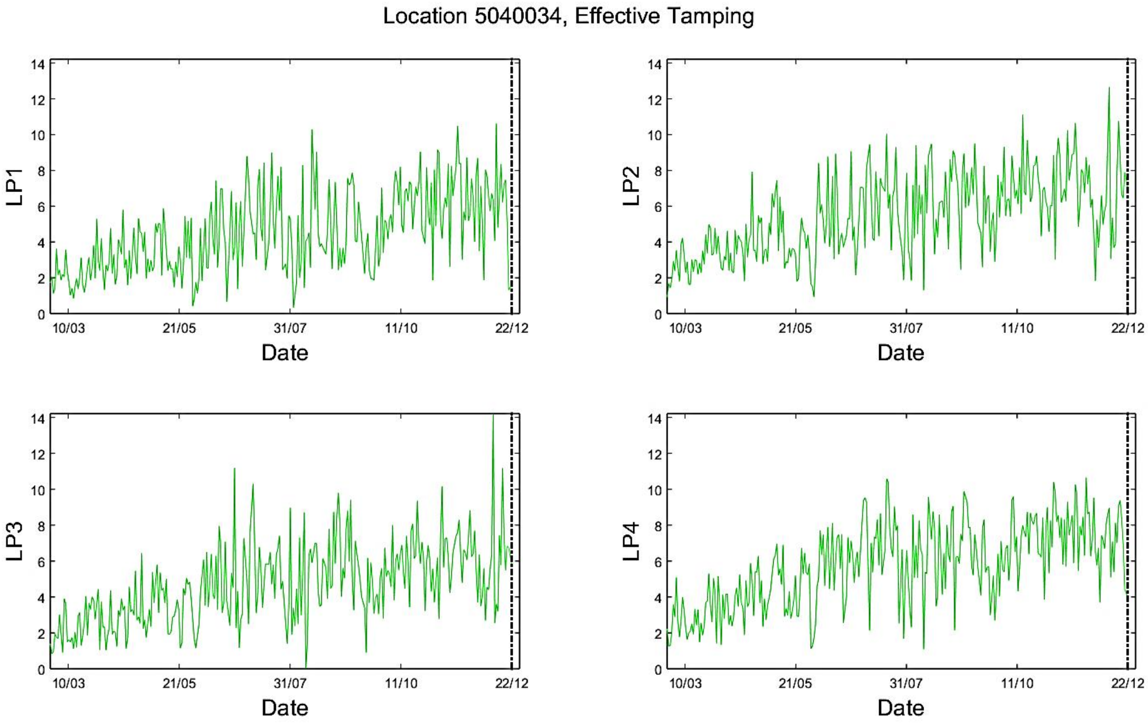
(b) Time series per location

(c) Dataset in the form of matrix

1. Data – IRVs Time Series

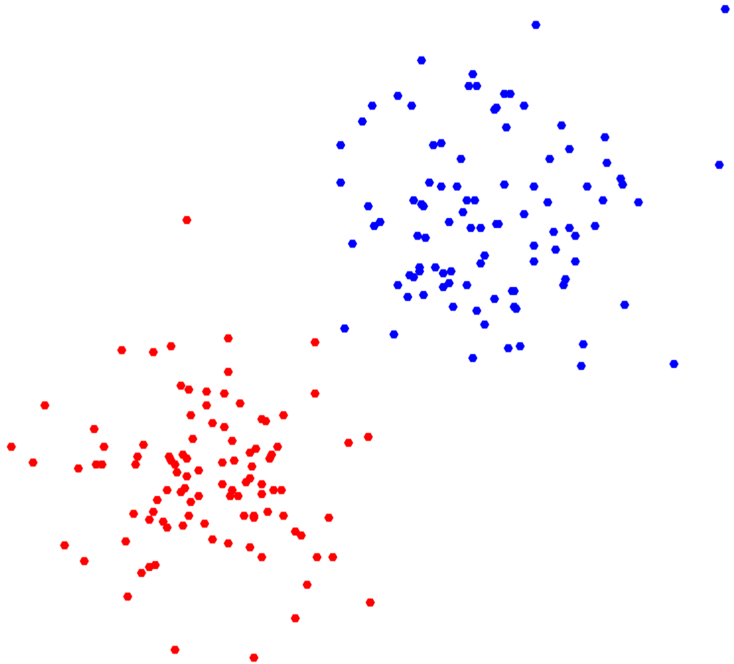
- Multivariate sensor data from IRVs collected between February to July 2016
- Multiple trips form a 4 dimensional time series for each track location
- Filters
  - Locations without tamping
  - Locations with less than 30 trips
- Pre-process
  - Linearly interpolate missing data
  - Label each location with tamping effectiveness
    - Effective and Ineffective
- Resample data to days with the average of the day

1. Data – Instrumented Revenue Vehicles Time Series



2. Train a classifier

- Supervised machine learning
  - Train a classifier using labelled data
  - Training time
    - Learn the characteristics of the data using labelled data
  - Testing time
    - Label a query object using the learnt characteristics from the training data
- Time series classification
  - *k*-Nearest Neighbour (*k*-NN) Classifier

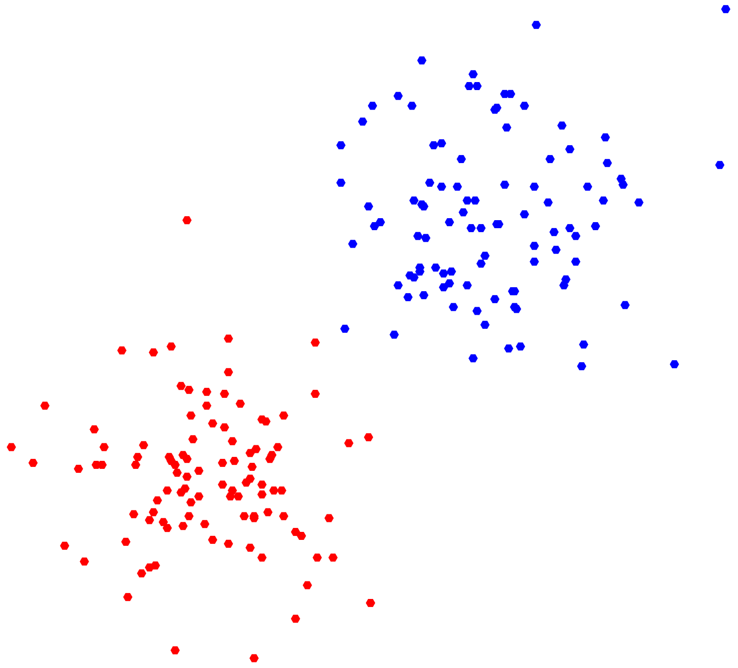


2. Train a classifier - Time series classification (TSC)

- Many algorithms that uses static features
  - Naïve Bayes
  - Classification Trees
- In most applications, features changes
- “Incorrect” to classify by observing only the static features
- *k*-NN is a better alternative

2. Train a classifier - *k*-NN Classifier

- State-of-the-art for time series classification
  - Performed the best over a wide range of time series dataset
- Outperforms others with large database size
- Search for the *k*th most similar objects (time series)
- Labels the query using the majority label of the *k*th nearest neighbours
- Uses a similarity measure

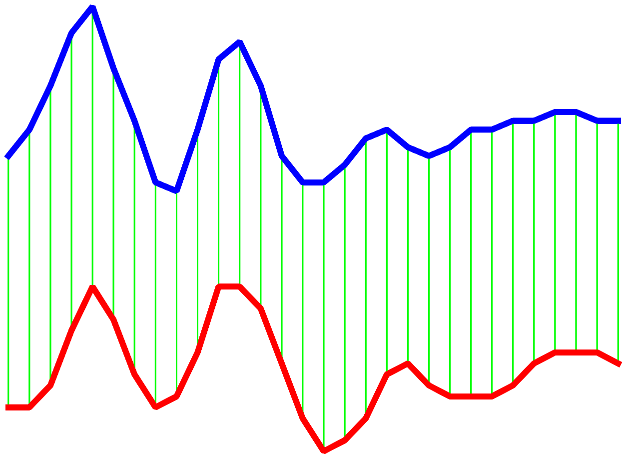


2. Train a classifier – Comparing time series (Euclidean Distance, ED)

- Calculate a distance between the two time series
- Simplest distance measure is Euclidean Distance (ED)

$$\mathrm{ED}(x, y) = \sqrt{\sum_{i=1}^{d} (x_i - y_i)^2}$$

- Euclidean distance cannot handle distortions in time axis, different length
- Time series are often shifted in time (distortions) with different length

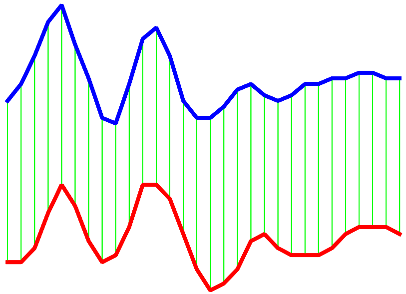


2. Train a classifier - Comparing time series (Dynamic Time Warping, DTW)

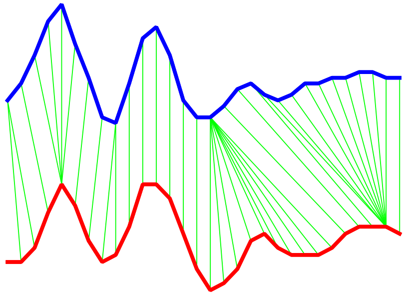
- Robust to time axis distortions and can handle different length
- Find alignment between two time series
- Given two time series *X* and *Y* of length *n* and *m*,

$$\mathrm{DTW}(X,Y) = \mathrm{ED}(x_1, y_1) + \min \begin{pmatrix} \mathrm{DTW}\big(\mathrm{Tail}(X), \mathrm{Tail}(Y)\big) \\ \mathrm{DTW}(\mathrm{Tail}(X), Y) \\ \mathrm{DTW}\big(X, \mathrm{Tail}(Y)\big) \end{pmatrix}$$

- $\mathrm{Tail}(X) = \{x_2, x_3, \ldots, x_n\}$



(a)



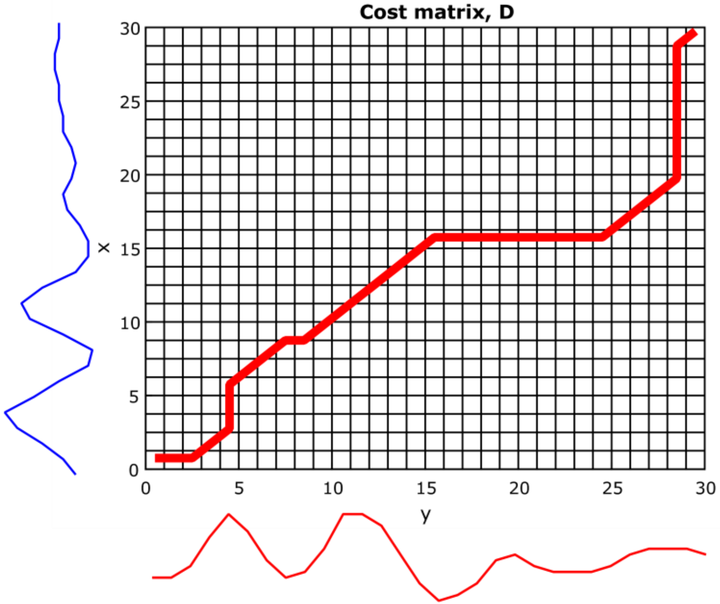
(b)

2. Train a classifier - Dynamic Time Warping (DTW)

- Dynamic Programming
- Constructs *n*×*m* cost matrix *D* and find a warping path (red) that minimises the alignment cost of the two time series

$$\mathrm{D}(i,j) = \mathrm{ED}\left(x_i, y_j\right) + \min\begin{pmatrix} \mathrm{D}(i-1, j-1) \\ \mathrm{D}(\mathrm{i}-1, j) \\ \mathrm{D}(i, j-1) \end{pmatrix}$$

$$\mathrm{DTW}(X,Y) = \mathrm{D}(n,m)$$



2. Train a classifier - Classifiers

- *k*-Nearest Neighbour (*k*-NN)
  - State of the art and widely used in many TSC applications
  - Simple and effective algorithm that does not require training
  - Labels query by finding the k^{th} most similar time series
- Classification Tree (CART)
  - Build a decision tree to classify the query based on some rules (features)
- Naïve Bayes
  - Classifies the query based on the posterior of each class observed from the features of training database

3. Evaluation and Validation

- Binary classification
- Compute performance metric for both effective and ineffective tamping
  - Accuracy, $\mathrm{A} = \frac{TP+TN}{TP+FP+TN+FN}$
  - Precision, $\mathrm{P} = \frac{TP}{TP+FP}$
  - Sensitivity, $S = \frac{TP}{TP+FN}$
  - $\mathrm{F_1}$ Score, $\mathrm{F_1} = 2 \cdot \frac{P \cdot S}{P+S}$

Actual\Predict	**Effective tamping**	**Ineffective tamping**
Effective tamping	True positive (TP)	False negative (FN)
Inffective tamping	False positive (FP)	True negative (TN)

- 10-fold cross validation
  - Split and validate the training database

4. Tamping effectiveness prediction with *k*-NN

Algorithm 1 : ε = predict_effectiveness(Q, D)

Input: Q: Query time series
Input: D: Training dataset
Output: ε: Tamping effectiveness
$knn = \emptyset$;
$knn.distance = \infty$
for *all* $C \in D$ **do**
    $d = \mathrm{DTW}(Q, C)$
    if $d < max(knn.distance)$ **then**
        remove the furthest neighbour from knn
        $knn.add(C, d)$
    end
end
return ε =mode($knn.class$)

List for K-NN

Updates the list if nearest than the furthest distance

Majority class

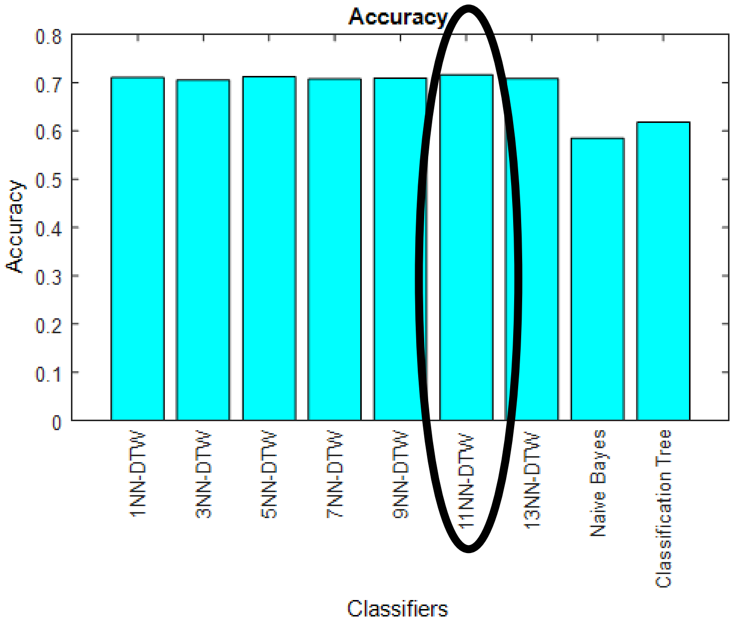
A. Classifiers comparison
B. Early prediction of tamping effectiveness

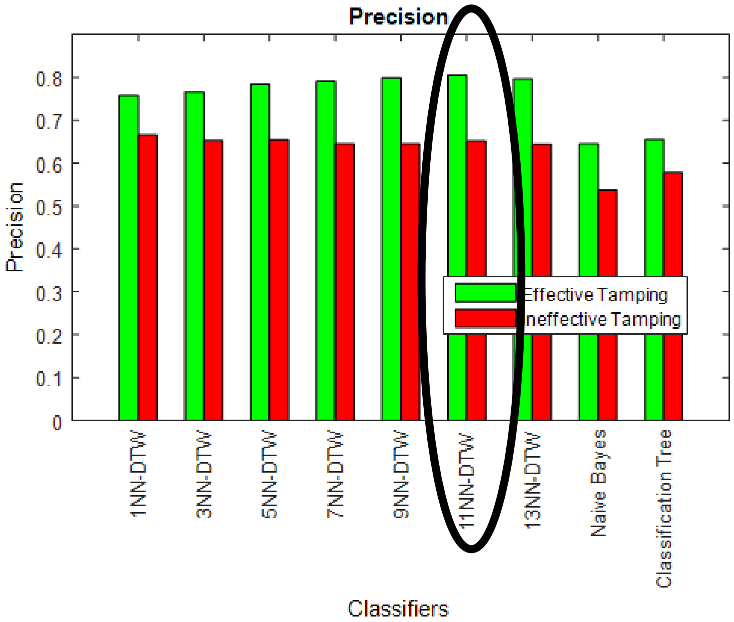
Results – Classifiers comparison

- Show that the state-of-the-art, *k*-NN works well even for multivariate time series in predicting tamping effectiveness
- Compare with Naïve Bayes and Classification Tree
  - *k* = 1,3,5,7,9,11,13 for k-NN
  - 6 statistical features, Mean, Standard Deviation, Skewness, Kurtosis, Maximum and Minimum for Naïve Bayes and Classification Tree.

Results – Classifiers comparison

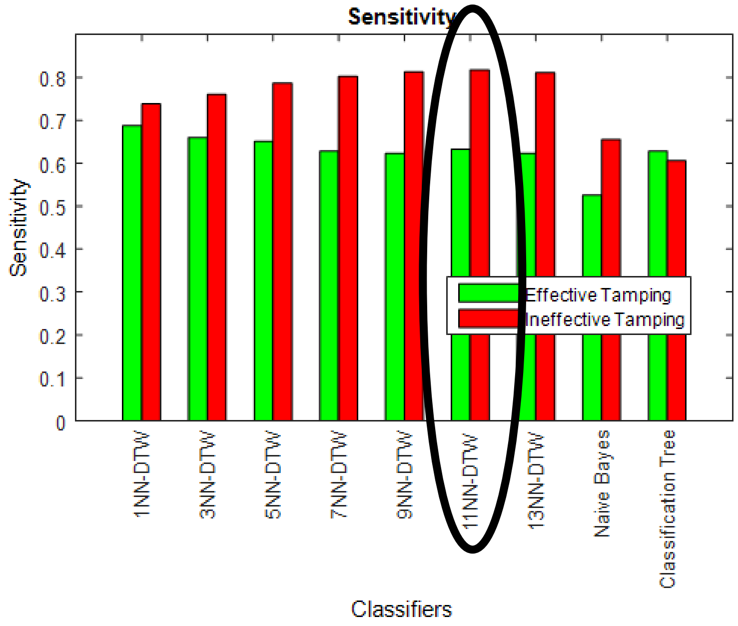
- 11-NN has highest accuracy than other two
- 11-NN has highest precision in predicting both effective and ineffective tamp than other two

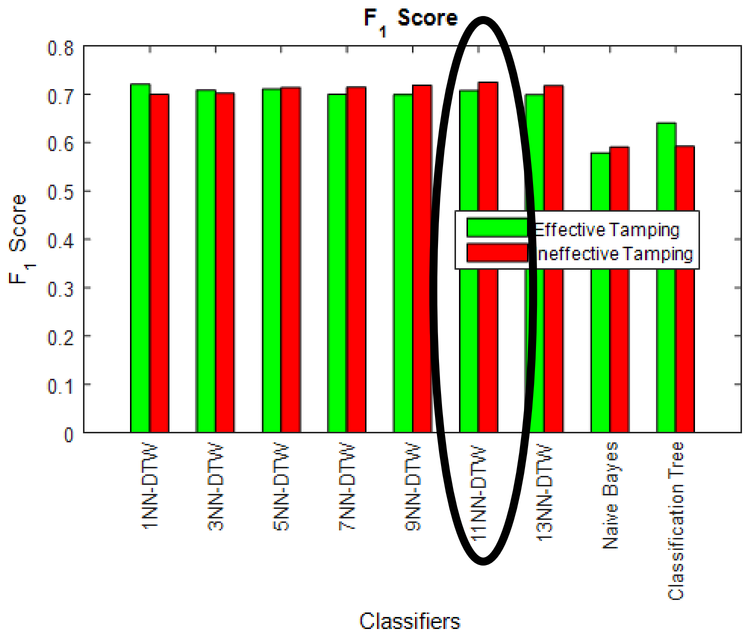




Results – Classifiers comparison

- 11-NN has higher Sensitivity in predicting both effective and ineffective tamp than other two
- 11-NN has higher F_1 Score in predicting both effective and ineffective tamp than other two



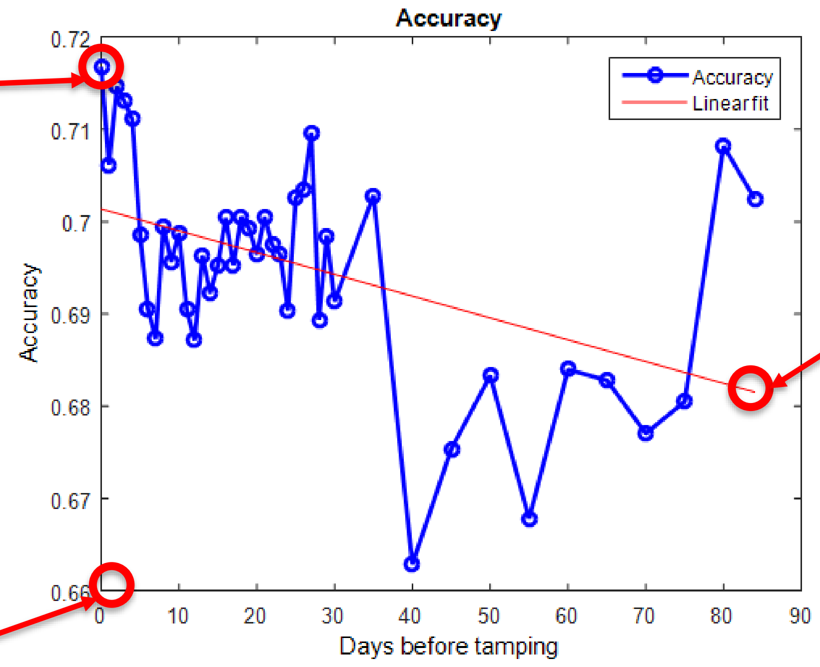


Results – Early Prediction of Tamping Effectiveness

- Predict tamping effectiveness as early as possible, typically 12 weeks
- The earlier we know about the effectiveness, the better the maintenance can be planned.
- Procedure
    1. Truncate the existing time series by the number of days before tamping
    2. Predict the tamping effectiveness of the query location with 11-NN-DTW
    3. Repeat with days ranging from 0 to 84 days (12 weeks)

Results – Early Prediction of Tamping Effectiveness

72%



66%

68%, Predicting tamping effectiveness 12 weeks (84 days) ahead

Conclusion

- Present a tamping effectiveness prediction system using *k*-NN-DTW.
- Showed that 11-NN-DTW gives good prediction.
- The system is able to give good prediction 12 weeks before tamping.
- Significance
  - Improve efficiency of railway track maintenance
  - Can be used with other maintenance procedures
- Future work
  - Optimise with more data
  - Predicting an actual response

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