**Team 17 – Progress Report (1870 words including tables)**

**[1] Introduction - Motivation**

The Project is being undertaken for Queensland Rail (QR) to model the condition of rail ballast to better inform maintenance decisions. The Project enhances QR’s current practice by applying machine learning and visualisation.

The global benefits offered by successful innovation in track maintenance include:

1. Potential financial returns > $1 billion p.a
2. Improved safety via reduced accidents 15, 16.

**[2] Problem Definition**

Project scope includes:

1. Collation of raw data from various sources (e.g. ballast condition, location of drainage points etc).
2. Manipulation of data including alignment of disparate features (e.g. aligning maintenance work with track location), normalisation and identification of outliers.
3. Development of machine learning algorithms (refer [??]).
4. Development of visualisations (refer [??]).
5. Presentation to QR and usability testing.

**[3] Survey**

Most research in machine learning for the rail industry relates to rollingstock and rail (not ballast).

Nakhaee et al13, employ deep learning algorithms to detect structural defects in rail (not ballast). Several impediments were identified:

1. Class imbalance: as the vast majority (>99%) of rail is non-defective, classifiers are biased.
2. Availability of labelled datasets: it is time- and skill- intensive to label thousands of kilometres of rail.
3. Model explainability: algorithms typically utilise “black box” solutions, such as convolutional neural networks, which are difficult to explain to management.

Hajizadeh et al.9 addressed the first two issues proposing minority over-sampling with noise to balance the labels. They also propose using semi-supervised techniques to counter the lack of labelled data.

**[4] Intuition**

The Project will enhance current practices within QR:

* QR assesses ballast condition primarily via:
  + Track Recoding Car (TRC) data captured quarterly which measures rail geometry. Fractal analysis on vertical TRC data has shown a moderate correlation with ballast fouling, indicating that TRC data is an indirect measure for ballast condition1.
  + Ground Penetrating Radar (GPR) collected every 3 years, is a proven technology for evaluating ballast condition6,7,8,14. It has been demonstrated ~100% classification accuracy can be achieved using an SVM classifier3,4 to detect soiling18.
  + QR’s network extends over 6,600 kms17. As such, the quantity of data collected includes 10 million TRC data points split across 16 features and ~350,000 GPR data points split across 22 features.
* Much of the current analysis undertaken by QR involves manual comparison of TRC and GPR data which is highly labour and time intensive.
* The Project will introduce Machine Learning to enhance predictive power and visualisations to improve communication.

The Project will extend current methods within industry:

* Much of the current research is focused on locomotives and rail. By contrast, the Project is focussed on ballast.
* While Sharma19 focussed on track geometry and utilised Markov Decision Processes to monitor maintenance actions, he only considered major defects that violate regulations. By contrast, the Project seeks to identify any degradation in ballast.

**[5] Approach, Innovations and Plan**

**Innovations**

Key innovations include:

1. Augmenting current “heatmap” processes: collate TRC and GPR data for comparable sections of track, automate the variance calculations to visually identify degradation in geometry *(Visualisation)*.
2. Providing further insights by combining additional factors: integrate additional attributes such as the location of drainage points; train speed; and maintenance history *(Machine Learning)*.
3. Enhanced decision-making through machine learning: predicting track degradation over time contextualised to location to streamline decision-making *(Visualisation, Machine Learning)*.
4. Improving user experience with interactive visualisations: a network map for the entire state would provide users the ability to drill-down to the current status of a localised section of rail *(Visualisation)*.

**Methodology**

The following approach will be applied to achieve the desired innovations:

|  |  |  |
| --- | --- | --- |
| **Process** | **Detail** | **Status** |
| 1. Engage with QR | 1. Understand current practice 2. Identify opportunities for improvement 3. Identify information required 4. Execute non-disclosure documentation 5. Obtain raw data | Complete |
| 1. Analyse data | 1. Assess data provided and understand interrelationship between features 2. Establish schema relating to features 3. Finalise models to be developed 4. Identify and process outliers/anomalies | Complete |
| 1. Align features | 1. Develop robust procedures to align disparate features (e.g. work orders, drainage points, TRC, GPR to track meterage) | Complete |
| 1. Build models | 1. Develop various models that predict ballast condition based on features. 2. Perform cross-validation of models. 3. Consider feature reduction as appropriate 4. Assess test accuracy of models. 5. Compare and select preferred model. | In Progress |
| 1. Build visualisations | Develop visualisations:   1. “Heatmap” identifying ballast degradation 2. User input to run/vary models 3. Drilldown visualisation of ballast condition 4. Visualisation of prediction | In Progress |
| 1. Usability Assessment | 1. Presentation of Project to QR 2. Survey to assess usability of visualisations | Not Commenced |

**Algorithms to be Employed**

The features used to train the models include:

|  |  |  |
| --- | --- | --- |
| **Feature** | **Data Source** | **Expected Use** |
| Ballast fouling Percentage Void Contamination (PVC)   * Left * Centre * Right | * GPR Data (C138) * GPR Data (C195) | Correlated with ballast condition |
| Layer roughness Index (LRI)   * Left * Centre * Right | * GPR Data (C138) * GPR Data (C195) | Assess feature importance |
| Ballast Thickness Index (BTI)   * Left * Centre * Right | * GPR Data (C138) * GPR Data (C195) | Assess feature importance |
| Moisture Likelihood Index (MLI)   * Left * Centre * Right | * GPR Data (C138) * GPR Data (C195) | Assess feature importance |
| Fouling Depth Layer (FDL)   * Left * Centre * Right | * GPR Data (C138) * GPR Data (C195) | Assess feature importance |
| Ballast Volume Metric (BVM)   * Left * Centre * Right | * GPR Data (C138) * GPR Data (C195) | Assess feature importance |
| Ballast Deficit Metric (BDM)   * Left * Centre * Right | * GPR Data (C138) * GPR Data (C195) | Assess feature importance |
| Track Drainage Index (TDI)   * Left * Right | * GPR Data (C138) * GPR Data (C195) | Assess feature importance |
| Surface Mudspot Index (SMI) | * GPR Data (C138) * GPR Data (C195) | Assess feature importance |
| Top Left | * TRC Data Q1 * TRC Data Q2 * TRC Data Q3 * TRC Data Q4 * TRC Data Q5 * TRC Data Q6 * TRC Data Q7 * TRC Data Q8 | Compute standard deviation over adjacent 5m segments |
| Top Right | * TRC Data Q1 * TRC Data Q2 * TRC Data Q3 * TRC Data Q4 * TRC Data Q5 * TRC Data Q6 * TRC Data Q7 * TRC Data Q8 | Compute standard deviation over adjacent 5m segments |
| Twist 10 | * TRC Data Q1 * TRC Data Q2 * TRC Data Q3 * TRC Data Q4 * TRC Data Q5 * TRC Data Q6 * TRC Data Q7 * TRC Data Q8 | Compute standard deviation over adjacent 5m segments |
| Twist 3 | * TRC Data Q1 * TRC Data Q2 * TRC Data Q3 * TRC Data Q4 * TRC Data Q5 * TRC Data Q6 * TRC Data Q7 * TRC Data Q8 | Compute standard deviation over adjacent 5m segments |
| Versign Left | * TRC Data Q1 * TRC Data Q2 * TRC Data Q3 * TRC Data Q4 * TRC Data Q5 * TRC Data Q6 * TRC Data Q7 * TRC Data Q8 | Compute standard deviation over adjacent 5m segments |
| Versign Left | * TRC Data Q1 * TRC Data Q2 * TRC Data Q3 * TRC Data Q4 * TRC Data Q5 * TRC Data Q6 * TRC Data Q7 * TRC Data Q8 | Compute standard deviation over adjacent 5m segments |
| Drainage points | * Track Culvert and Level Crossing Data |  |
| Track speed | * Speed and Curvilinear Classification | Assess feature importance |
| Maintenance history on track segment | * Work orders (C138, C195) * QR Translation Process * QR Track Code List * LRP Details * 4th Level LRP to 3 digit TC * 5th Level LRP to 4th digit TC * Maintenance Codes | Correlated with ballast condition – must be controlled |
| Track exceptions | * Exceptions history * Notification and Activity Codes * Notification and Fault Codes | Possible predictor – possible response |
| Rainfall History | Bureau of Meteorology | Will not be used as is not sufficiently granular |

Response variables to be predicted include:

|  |  |
| --- | --- |
| **Response Variable** | **Expected Use** |
| Combined rail geometry | Prediction of combined standard deviations for Top Left, Top Right and Twist 3 |
| Track exceptions | Possible response variable (TBC) |
| Maintenance requirement | Possible response variable (TBC) |

**User Interfaces to be Developed**

JJ

**Plan of Activities**

The Project Workplan is outlined below. Variations to the original plan have been identified in red.

|  |  |  |  |
| --- | --- | --- | --- |
| **Week Ending** | **Core Activity** | **Target Milestone** | **Status** |
| 6th September | * Meet with QR Executive general Manager to discuss potential scope | * Identify potential project opportunities | * Complete |
| 13th September | * Meet with QR Senior Manager Track and Civil Infrastructure to refine scope | * Refine scope * Arrange meetings with line management | * Complete |
| 20th September | * Meet with Senior Civil Engineer to review current process | * Obtain initial datasets | * Complete |
| 27th September | * Attempt to automate a sample of “heatmap” * Present status to Executive General Manager * Identify opportunities for machine learning * Identify additional parameters required | * Initial heatmaps * Communication of “next steps” to QR team and request for additional information | * Complete |
| 4th October | * Obtain QR feedback on proposed approach * Pursue additional information requested | * Finalise workplan and initial approach | * Complete |
| 11th October | * Finalise project proposal | * Project Proposal submitted * Proposal Presentation Slides and Video | * Complete |
| 18th October | * Finalise parameters to be used within the model | * Additional datasets obtained | * Complete |
| 25th October | * Develop model | * Initial model | * WIP |
| 1st November | * Develop model | * Objective tests of predictive power | * WIP |
| 15th November | * Develop visualisation | * Submit Progress Report | * Complete |
| 15th November | * Develop visualisation | * Complete visualisation | * WIP |
| 22nd November | * User-testing * Refine user-interactivity model | * Obtain results of usability survey | * Scheduled |
| 29th November | * Finalise submission * Identify limitations and potential future improvements | * Submit Poster Presentation Video * Submit Final Report | * Scheduled |

*NB: items in green are mandatory deliverables*

The Gannt Chart is presented below.



**[6] Testbed Description**

Key questions to be addressed during testing include:

|  |  |
| --- | --- |
| **Key Questions** | **Considerations** |
| Most meaningful response variables | Which variables best serve as the independent variables e.g.:   * Track geometry measures * Maintenance requirement * Track exceptions |
| Validity of features | * Which features explain variance in the response? * Are predictors highly correlated? * Should feature reduction be performed (e.g. Ridge Regression, Elastic Net or Lasso) * Should dimensionality reduction be performed (e.g. PCA) |
| Predictive power of the models | * What is the training/cross-validation error of the models? * What is the test error of the models? * Are any of the models overfit? * What is the variance in the models to changing inputs (data, random seeds etc)? |
| Preferred model(s) | * Which model is preferred wrt predictive power? * Which model is preferred wrt communicability (e.g. to management) * Which model(s) will be selected for final implementation? |
| Usability of visualisations | * Do the visualisations reflect the objective of the models? * Are the visualisations meaningful to end-users wrt decision making? * Are the visualisations usable and “attractive” to users? |
| Future improvements | * What additional improvements could be made in the future? * Is there academic/commercial value in the Project that should be explored? |

**[7] Experiments and Observations**

**Experiments and Assessing Success**

The key questions to be addressed in the experiments are outlined in Section 6, Testbed Description.

The following algorithms will be applied to train models to predict the response variables using the features described above:

|  |  |
| --- | --- |
| **Machine Learning Algorithm** | **Objective** |
| 1. Support Vector Machine (various kernels) | Classification of ballast as defective/non-defective |
| 1. Logistic Regression | Classification of ballast as defective/non-defective |
| 1. Linear Regression (possible transformation of features) | Assess importance of features  Provide real-valued prediction |
| 1. Decision Tree | Identify a model with expressive ability |
| 1. Random Forest | Develop model with high predictive power |
|  |  |
| Possible algorithms that will be considered | |
| 1. LASSO/Ridge Regression | Assess importance of feature selection |
| 1. Principal Component Analysis | Potential feature reduction |
| 1. Artificial Neural Network | Develop model with high predictive power |

The following are planned to objectively measure the success of the Project:

1. Train/test split with K-fold cross-validation: the machine learning algorithms will be trained on data (e.g. 70-80% of samples) and tested on unseen test-data. K-fold cross-validation will assess predictive performance by ensuring that each datum is tested on once20.
2. End-user satisfaction: the usability of the interactive visualisation will be assessed via a brief survey of at least 2 end-users.

**Observations**

To be developed

**[8] Conclusion**

To be developed

**[9] Distribution of Team Member Effort**

All team members have contributed similar amount of effort.

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