Team 17 – Project Proposal (1176 words)

[1] Objectives

The Project is focussed on modelling the condition of rail ballast (the track bed on which sleepers lie) with the aim of better informing maintenance decisions. The project is being undertaken for Queensland Rail, a major Australian public rail network.

The project objectives include:

a. Predict maintenance required on rail ballast using a variety of factors such as track geometry in the near future (3-12 months), and
b. Provide an interactive visualisation of track condition within a geographical context.

[2] Current methods of measuring rail condition

Much of the research into the application of machine learning for the rail industry has related to rollingstock (such as locomotives) and rail.

Nakhaee et al's survey[13], summarises the use of deep learning algorithms for the detection of structural defects in rail (as opposed to ballast). Several impediments to the application of machine learning for rail maintenance were discussed:

a. Class imbalance: as the vast majority of rail is non-defective (often more than 99%), classifiers will be biased towards "non-defective" selection.
b. Availability of labelled datasets: it is time- and skill- intensive to label thousands of kilometres of rail.
c. Model explainability: rail maintenance 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. Their paper proposes minority over-sampling with noise to balance the labels. They also propose using semi-supervised techniques to counter the lack of labelled data.

Focussing on track geometry, Sharma[19] utilised Markov Decision Processes to monitor maintenance actions, but only considered major defects that violate regulation. Unlike Sharma's paper, the Project instead seeks to identify any degradation in ballast.

[3] Current Practice of Queensland Rail

Queensland Rail collect data relating to the condition of ballast through two primary sources:

1. Track Recording Car (TRC): TRC data is captured quarterly and measures rail geometry such as height of left and right rail and twist in the line. Elsewhere, fractal analysis on vertical TRC data has shown a moderate correlation with ballast fouling, indicating that TRC data is an indirect measure for ballast condition[1].
2. Ground Penetrating Radar (GPR): GPR data, collected every 3 years, is a proven technology for evaluating ballast condition[6,7,8,14]. Coupled with Machine Learning, it has been demonstrated up to 100% classification accuracy can be achieved using an SVM classifier[3,4] to detect soiling[18]. GPR data contains features such as: contamination in the ballast, ballast thickness and moisture likelihood.

Queensland Rail's network extends over 6,600 kms[17]. 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.

Current practice involves engineers conducting a manual visual inspection of the TRC readings, comparing time points to identify potential degradation, and then overlaying the GPR data to provide confirmation of potential ballast contamination (Figure 1).

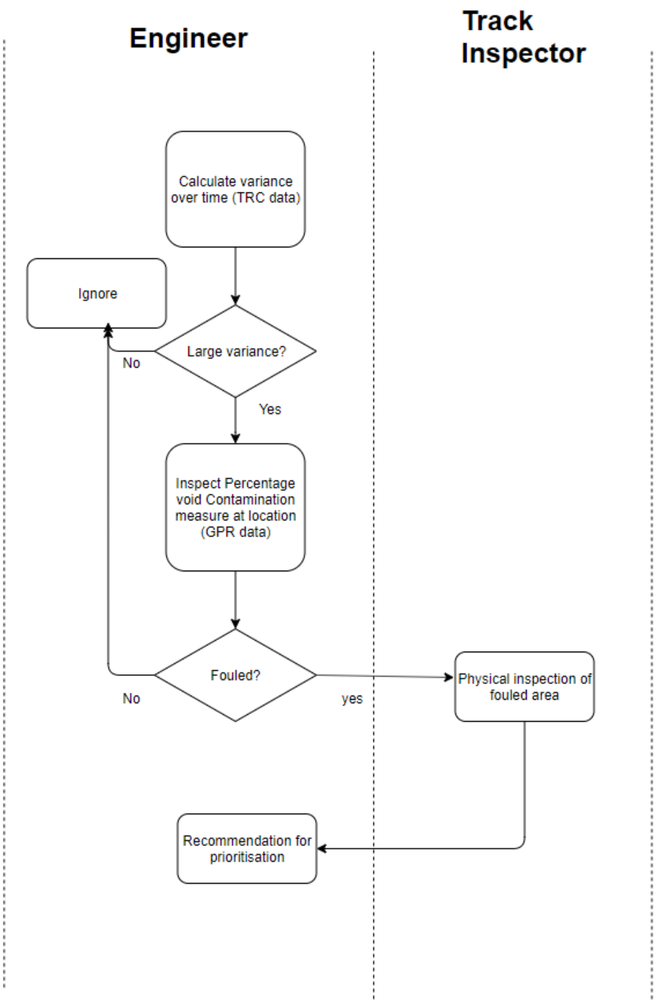

Figure 1 Flowchart of QR's maintenance decision process

The process is highly labour intensive. QR's engineers trialled a semi-automated "heatmap" within Excel but lacked visualisation of the geographical context. Additionally, the volume of data in a 10 km section of track rendered the spreadsheet unstable, and difficult to perceive heatmap data[11]. As a result, the engineers are seeking an improvement to the "heatmap" process.

[4] Novelty in Approach

The Project proposes several extensions, intended to enhance QR's current methods:

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.
2. Providing further insights by combining additional factors: integrate additional attributes such as the location of culverts and embankments (which impact drainage); train load (e.g. tonnage); and maintenance history.
3. Enhanced decision-making through machine learning: predicting track degradation over time (e.g. in 3, 12, or 24 months) contextualised to location (e.g. adjacent to a current defect or feature like embankment which impacts drainage and increases degradation). This could reduce the first two decision points into a single step (Figure 1), streamlining decision-making.

   Lasisi and Attoh-Okine[12] have shown that a principal components analysis (PCA)[2,5,10] of the track recording outperforms industry-standard weighting of track recording parameters. Incorporating PCA into the Project's analysis may therefore yield a more accurate assessment of track condition than current practice.

4. Improving user experience with interactive visualisations: ideally a network map for the entire state would be developed and users given the ability to drill-down to the current status of a localised section of rail.

[5] Potential Benefits

Queensland Rail's annual maintenance and capital works expenditure on ballast and resurfacing work alone is ~$50 million p.a. Executives anticipate ~10% of this expenditure could be saved annually if maintenance activities could be predicted more reliably. Additionally, ~$30 million in capital expenditure could be avoided.

On a global scale, Peng, Kang et al.[16], identified that in a rail context, preventive maintenance costs are excessive when undertaken too early or too late. From a safety perspective, Peng[15] identified that of 1,890 train accidents in 2009, 658 were caused by track defects.

As such, the global benefits offered by successful innovation in track maintenance include:

a. Potential to harvest financial returns in excess of $1 billion p.a, and
b. Materially improved safety via reduced accidents.

[6] Assessing Success

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

a. Train/test split with K-fold cross-validation: the machine learning algorithms will be trained on data (e.g. relating to periods 2-3 years prior) and will be tested on unseen test-data (e.g. relating to recent periods). K-fold cross-validation would further assess model predictive performance by ensuring that each datum is tested on once[20]. This process will inform the Project Team as to the predictive power of the model.
b. End-user satisfaction: the usability of the interactive visualisation will be assessed via a brief survey of at least 2 end-users.

[7] Project Risks

The primary risks relate to the novelty of the Project.

In particular:

a. Data availability: will the client provide the data (including additional parameters) in a timely manner to adhere to the Project schedule?
b. Subject matter expertise: will the client provide the necessary resources to inform the Project team on areas requiring subject matter expertise?
c. Predictive power of a model: as the application of machine learning to the client's environment is novel, it is uncertain whether a model with sufficient predictive power can be developed.

While the Project Team believes each and all of the above risks have the ability to jeopardise the Project, the risks are weighed against the following mitigators:

a. The risks have been discussed with QR and support has been offered to the Project Team,
b. The Project is novel and as such of interest to the Project Team (versus a "safer" application using an established dataset), and
c. The benefits (identified in Section 5) of successful innovation in the industry are substantial.

[8] Project Cost and Timeframe

No financial outlay has been provisioned:

- Queensland Rail has offered to provide data and subject matter expertise at no cost, and
- No external consulting or contract services (such as video production) have been planned.

Team members commenced work on the Project on 1 September 2019 and the Project will be completed in accordance with the schedule required by CSE6242 i.e. 29th November 2019.

[9] Workplan, Milestones and Team-member Contribution

The Project Workplan is outlined below:

Week Ending	Core Activity	Target Milestone
6th September	• Meet with QR Executive general Manager to discuss potential scope	• Identify potential project opportunities
13th September	• Meet with QR Senior Manager Track and Civil Infrastructure to refine scope	• Refine scope • Arrange meetings with line management
20th September	• Meet with Senior Civil Engineer to review current process	• Obtain initial datasets
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
4th October	• Obtain QR feedback on proposed approach • Pursue additional information requested	• Finalise workplan and initial approach
11th October	• Finalise project proposal	• Project Proposal submitted • Proposal Presentation Slides and Video
18th October	• Finalise parameters to be used within the model	• Additional datasets obtained
25th October	• Develop model	• Initial model
1st November	• Develop model	• Objective tests of predictive power

8^{th} November	• Develop visualisation	• Submit Progress Report
15^{th} November	• Develop visualisation	• Complete visualisation
22^{nd} November	• User-testing • Refine user-interactivity model	• Obtain results of usability survey
29^{th} November	• Finalise submission • Identify limitations and potential future improvements	• Submit Poster Presentation Video • Submit Final Report

NB: items in green are mandatory deliverables

All team-members have contributed equally to the Project.

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Appendix 1: Cross Reference Heilmeier Questions

Heilmeier Questions	Section
1. What are you trying to do? Articulate your objectives using absolutely no jargon.	1
2. How is it done today; what are the limits of current practice?	2, 3
3. What's new in your approach? Why will it be successful?	4
4. Who cares?	5
5. If you're successful, what difference and impact will it make, and how do you measure them (e.g., via user studies, experiments, ground truth data, etc.)?	5, 6
6. What are the risks and payoffs?	5, 7
7. How much will it cost?	8
8. How long will it take?	8
9. What are the midterm and final "exams" to check for success? How will progress be measured?	9