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TC304 – TC309 Student Contest on Machine Learning Extended Abstract

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Abstract: This abstract describes the use of machine learning methods to assist in predicting future soil response under loading of the Ballina test embankment. Multiple machine learning algorithms are adopted. Autoencoder is used to compress all the measurement data to maximize information value. Bayesian updating is carried out with the help of surrogate models. Python will be used to automate simulation of many trials in the finite element program Plaxis.

Keywords: Embankment, Autoencoder, Bayesian Updating, Machine Learning, Gibbs Sampler, Surrogate Model.

1. Introduction

The objective of this contest is to harness the capabilities of machine learning methods to aid the predictions of soil response under loading of an embankment. The problem geometry is established based on a full-scale trial embankment constructed during 2013, at Australia's first National Field-Testing Facility (NFTF) at Ballina, New South Wales, Australia (Kelly et al., 2018). Information on the construction sequence of the embankment is given in the contest question, which is extracted from Kelly et al. (2018).

Synthetic benchmark data has also been given for soil displacement and total pore water pressure from August 2013 to June 2014. The task of this contest is to develop an algorithm to facilitate the prediction of future displacement response (after June 2014) at the same settlement measurement locations (M0 to M3; HPG1) on June 1, 2015 and June 1, 2016 (Figure 1).

There are several innovations regarding the application of machine learning in this work. Python script is written to automate the Monte Carlo simulation of Plaxis analysis, which reduces analysis time and error. Autoencoder is used to compress all the measurement data, which maximizes the information value. Bayesian updating is used to update the soil parameters probabilistically, which can produce prediction intervals for future settlement responses. This allows assessment of the prediction uncertainty.

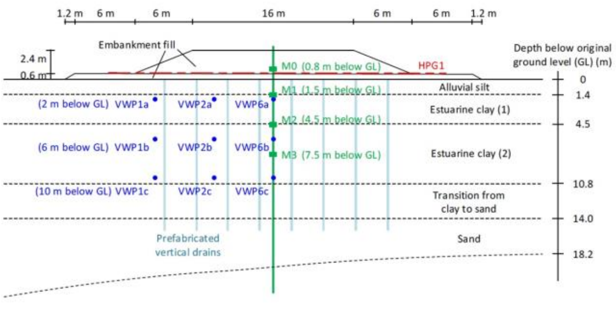

Figure 1. Cross-section of Ballina test embankment case

2. Proposed Framework

The flowchart of this project is shown in Figure 2. The first stage of the framework is to create the base geometry of the site in Plaxis and assign different possible variations to the influential soil parameters. The Soft Soil Creep Model in Plaxis is used to model the clay layers. The soil parameters that are influential to the settlement include modified compression index, creep parameter and horizontal permeability. Multiple parameter combinations are then simulated using Latin Hypercube sampling, which will offer an evenly distributed selection of combinations. Following that is to develop a script using Python to simulate multiple runs of the test embankment case in Plaxis based on the simulated soil parameters, as to produce multiple sets of soil displacement and total pore water pressure data, which is expected to reasonably envelope the synthetic benchmark data of the site, as given in the contest question. To compress the soil displacement and total pore water pressure data obtained from multiple runs of Plaxis, an autoencoder will be used. An autoencoder is a type of neural network that transforms high-dimensional data into a low-dimensional code and a similar "decoder" network to recover the data from the code (Hinton and Salakhutdinov, 2006). The structure of the autoencoder is illustrated in Figure 3. The autoencoder is implemented by Tensorflow package in Python. Next, the compressed output from the autoencoder will be used to build a surrogate model. Surrogate model can approximate the finite element or finite difference models by a quadratic function, which is much quicker to evaluate (Lo and Leung, 2019). All the steps mentioned above form the preparation stage, which are carried out before the construction commences.

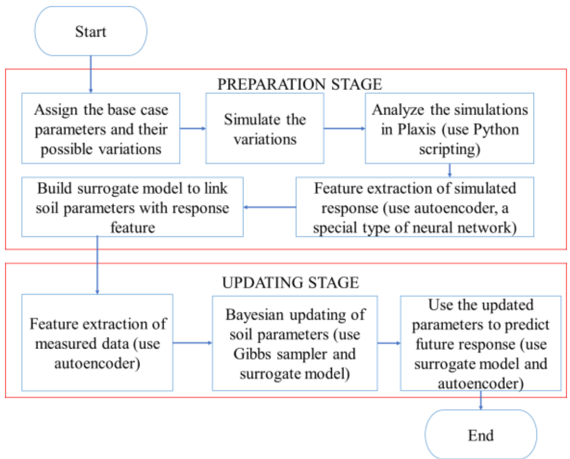

Figure 2. Flowchart of project

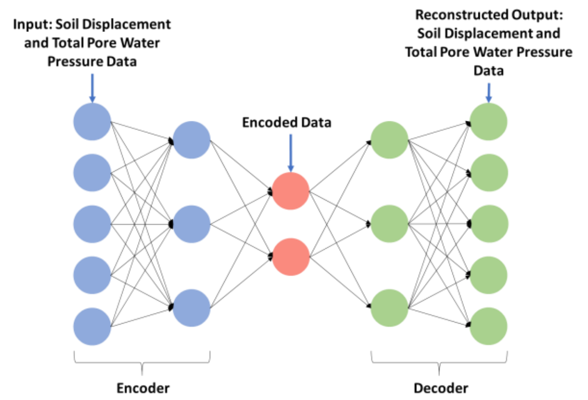

Figure 3. Autoencoder neural network

In the updating stage, the encoder portion in the trained autoencoder will be used to compress the actual measurement data. Utilising both the Gibbs sampler and surrogate model, the soil parameters can be updated by Bayesian updating based on the compressed measurement data. Gibbs sampler is an algorithm which aims to generate samples from the distribution of the updated soil parameters based on the settlement and total pore water measurement (Geman and Geman, 1984). Gibbs sampler will be implemented using the rjags package in R software. Lastly, the updated soil parameters are used to predict future settlement responses from the surrogate model. The predictions from surrogate model are decompressed using the decoder portion of the autoencoder.

3. Current Progress of Project

3.1 Simulation of trial embankment in Plaxis

Based on the geometry of the Ballina test embankment site given in the contest question, a soil model is created in Plaxis (Figure 4) for the analysis of soil displacement response and pore water response. The soil models used in Plaxis are the Soft Soil Creep Model (SSCM) for estuarine clay and transition zone, Soft Soil Model (SSM) for alluvial clayey sandy silt and Hardening Soil Model for the sand layer. SSCM accounts for stress dependent stiffness of soil within the framework of hardening plasticity as well as time dependent creep. SSM is similar to SSCM, but without the creep effect. The influential soil parameters for SSCM that control compressibility are modified compression index (λ^*), creep parameter (μ^*) and horizontal permeability (k_h). The wick drains modelled in Plaxis are 3.2m apart from one another. The construction sequence of the embankment project for the input in Plaxis follows that of Jostad et al. (2018). In the Plaxis analysis, updated mesh and water pressures option is selected. This is to account for that the excess weight of the embankment is gradually reduced as the fill material settles below the ground water table. This allows for a more realistic analysis of the settlement.

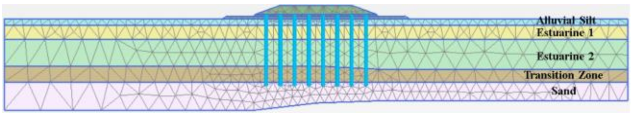

Figure 4. Plaxis model of embankment case

3.2 Python Automation of Embankment Case

The current Python script that has been developed can perform multiple runs of Plaxis analysis by assigning different soil parameters in each run, and automatically save the soil displacement (M0 to M3; HPG1) and total pore water pressure (VWP6a to VWP6c) (Figure 1) of each run in excel format. The range of soil parameters used in the simulation is shown in Table 1, which is based on the reported range of compression index (C_c), creep index (C_α) and k_h in Kelly et al. (2018). All parameters are uniformly distributed.

Table 1. Range of soil parameters

Parameter	Minimum	Maximum
λ^* Alluvial Silt	0.03	0.1
λ^* Est(1)	0.08	0.36
λ^* Est(2)	0.075	0.38
λ^* Trans	0.02	0.1
μ^* Est(1)	0.00217	0.011
μ^* Est(2)	0.002	0.013
$\log_{10}k_h$ Est(1)	-4.46	-1.88
$\log_{10}k_h$ Est(2)	-4.46	-1.88

300 combinations of soil parameters are then selected using Latin hypercube sampling. The soil displacement and total pore water pressure results based on these 300 combinations are then compared with the synthetic benchmark data given in the contest question, which are shown in Figures 5-7. The benchmark settlement and pore water pressure are all enveloped within the simulation results, which justifies the assigned range of soil parameters.

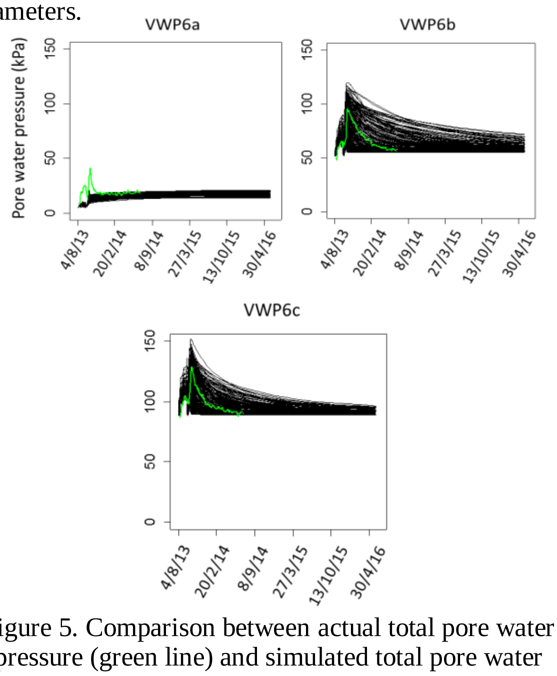

Figure 5. Comparison between actual total pore water pressure (green line) and simulated total pore water pressure (black lines)

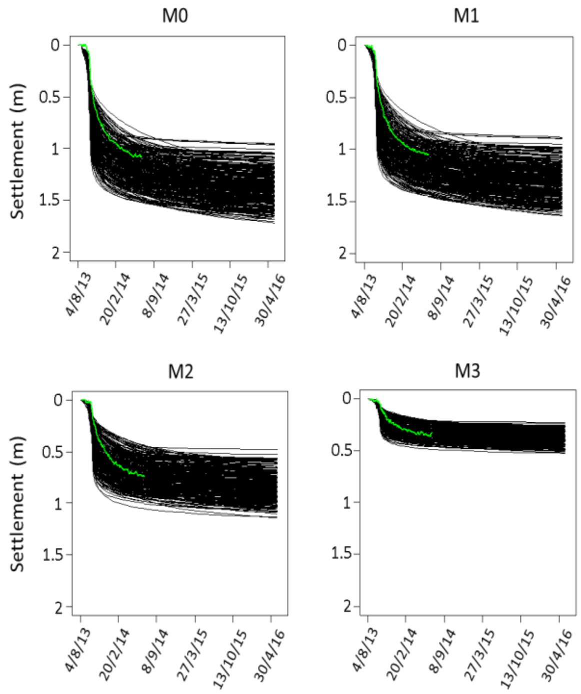

Figure 6. Comparison between actual extensometer settlement data (green line) and simulated settlement (black lines)

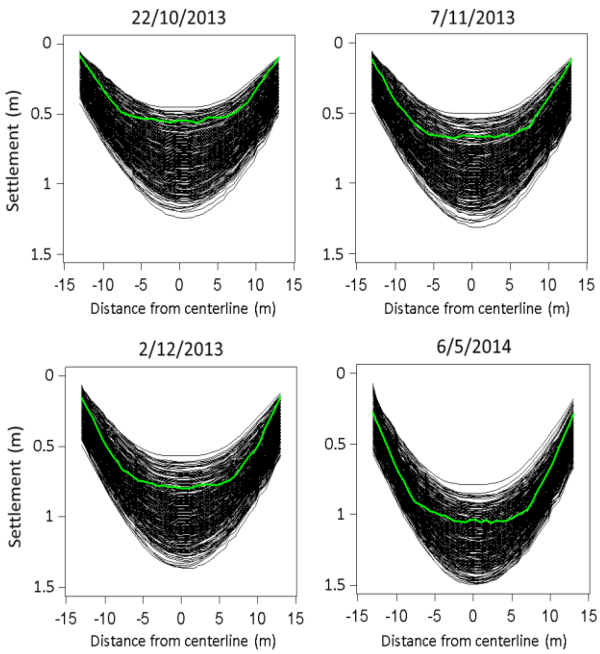

Figure 7. Comparison between actual settlement across embankment cross-section (green line) and simulated settlement (black lines)

4. Conclusion and Future Works

As the research has not yet concluded, the next stage of this research is to carry out the remaining steps, which include autoencoder, surrogate model and Bayesian updating. Table 2 shows the details of the remaining timeline.

Table 2. Details of the remaining timeline

31st Aug to 3rd Sep	Analyse simulations in Plaxis
4th Sep	Submission of extended abstract
5th Sep to 13th Sep	Build surrogate model to link soil parameters with response feature
14th Sep to 16th Sep	Feature extraction of measured data by autoencoder
17th Sep to 20th Sep	Bayesian updating of soil parameters
21st Sep to 3rd Oct	Use updated parameters to predict future response and prepare research findings
4th to 7th Oct	Presentation on research findings

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