Using a Bayesian Neural Network to Estimate Shear Wave Velocity based on Standard Penetration Test Data

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GEO 391 - Introduction to Machine Learning
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ABSTRACT

The standard penetration test provides a metric called blow count, which is commonly used to estimate shear wave velocity because it is dependent on soil relative density. In the geotechnical industry, empirical correlations are used that vary by region and local geology. A previous study by Xiao et al. (2021) developed a hierarchical Bayesian model (HBM) to estimate shear wave velocity based on blow count. In an attempt to provide a more robust method of estimating the shear wave velocity, a Bayesian neural network (BNN) approach is presented. The BNN predicts shear wave velocity with slightly less accuracy than the HBM as shown by an average R^2 value of 0.027 less. The Bayesian neural network proves to be effective when used to estimate shear wave velocity based on limited region-specific data. Although, when datasets have less than 120 data points, the BNN does not produce a significant R^2 value.

INTRODUCTION

In geotechnical engineering, the standard penetration test (SPT) is the most popular subsurface exploration test because it provides many engineering properties of soil in-situ. The test involves dropping a weight from a constant height. Each drop of the weight adds to the blow count, N. The total blow count for the hammer to progress 6 inches through the soil is recorded as the the N-value. Based on the N-value, the soil's relative density is characterized, which can provide an estimate of the shear wave velocity, V_S. Since the soil material from different geographical areas has a different chemical and physical structure, soil with the same relative density in two independent locations will likely not produce the same shear wave velocity.

Therefore, a model describing the relationship between blow count and shear wave velocity is only applicable for a singular geographic region that shares common geologic qualities.

The relationship between SPT blow count and shear wave velocity is often approximated by empirical equations in the geotechnical engineering industry. These empirical equations are often based on a simple linear regression, which provides an accurate estimate of shear wave velocity when a large dataset is presented. The linear regression requires considers the blow count and shear wave velocity to be normally distributed according to the following power-law relationship:

$$ln(V_S) = aln(N) + b$$

A previous study, by Xiao et. al (2021) produced an estimate of shear wave velocity from blow count based on hierarchical Bayesian modeling. This statistical model assigned gaussian distributions to the fitting parameters, a and b, of the power-law relationship. In addition, a model error term, ϵ, was added to account for scattering of the data points around the linear relationship. This model assumes that the N-V_S relationships from region to region are similar; therefore, the model is structured as shown in Figure 1.

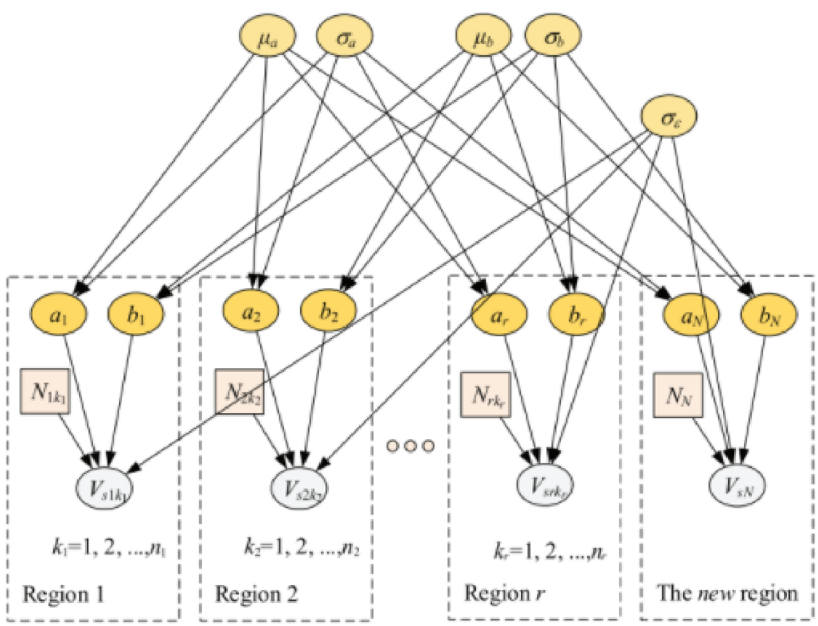

Figure 1: The HBM model is structured by accounting for intraregional and interregional variability (Xiao, 2021).

This model does not give a direct analytical solution, so Markov Chain Monte Carlo simulations are subsequently performed to provide a solution. While this solution is accurate, it is worth considering alternatives that more accurately predict the shear wave velocity, especially when there is limited region-specific data. This paper assesses the validity of a Bayesian neural network in estimating shear wave velocity.

METHODOLOGY

In order to provide a more precise method of estimating the shear wave velocity, machine learning is applied to the same problem by creating and testing a Bayesian neural network. The BNN functions similar to the HBM because it produces a result with uncertainty. There is already a lot of uncertainty in measurements recorded (epistemic uncertainty) and inconsistency between data points (aleatoric uncertainty) from the SPT test, so it makes sense that estimates of shear wave velocity are labeled with a confidence interval, unlike in practice. The BNN is different from the HBM in that it uses the blow count values themselves as inputs rather than the slope and intercept of the line that best approximates the data.

First, the data is separated by region. Then, the data is scaled to have a mean of zero and unit variance. Outliers are removed using an isolation forest. Now, the model is built. To minimize noise in the output which is attributed to aleatoric uncertainty, probabilistic layers are built into the model with dense layers. The first hidden layer is a dense layer that has ten nodes. The second layer has two nodes for the mean and variance of the Gaussian posterior probability distribution. 100 epochs is deemed sufficient to cause the model to converge. After developing and training the BNN, the results are assessed by running 10 iterations through Monte Carlo simulation. The mean and standard deviation values from this simulation are used to inform the linear regression model.

The dataset, summarized in Table 1, is a bivariate dataset used to train and test the BNN, provided by the International Society for Soil Mechanics and Geotechnical Engineering (Wang). This is the same dataset used from the HBM, which provides the actual values of shear wave velocity that can be expected in each region.

Region no.	Region (Country)	No. of data points	Soil type	N	V_s (m/s)
1	North Florida (US)	218	Cohesive soils Cohesionless soils	1–60	65.3–339.5
2	Southern San Francisco Bay (US)	38	Cohesive soils Cohesionless soils	8–81	168.9–422.4
3	Madison (US)	125	Sandy soils	1–30	101.4–235.1
4	Greece	183	Cohesive soils Cohesionless soils	3–148	116.5–1135.5
5	Caspian Sea (Iran)	117	Sandy soils	8–50	164.9–478.4
6	Yenisehir town (Turkey)	86	Sandy soils Clayey soils	6–47	148.5–372.3
7	Eskisehir (Turkey)	187	Sandy soils Silty soils Clayey soils	1–50	90.2–284.3
8	Erbaa (Turkey)	116	Sandy soils Clayey soils	4–49	70.8–453.9
9	Delhi (India)	401	Sandy soils Sandy silt/silty sand	3–50	118.2–433.2
10	Chennai (India)	144	Sandy soils Clayey soils	1–80	76.0–449.6
11	Kanpur (India)	67	Silty soils Clayey soils	10–32	199.2–310.6
12	Roorkee (India)	71	Sandy soils Clayey soils	2–18	120.2–281.0
13	Dholera (India)	191	Sandy soils Silty soils Clayey soils	2–93	94.4–512.8
14	Jakarta (Indonesia)	180	Soft to stiff soil	1–100	55.0–498.2
15	Molise (Italy)	231	Sandy soils Silty soils Clayey soils	4–92	129.3–549.3
16	Kathmandu Valley (Nepal)	78	Sandy soils Silty soils	3–42	90.3–401.2

Table 1: Summary of SPT blow count and shear wave velocity data collected across 16 regions (Xiao, 2021)

Two separate conditions of the quantity of available data are considered. The first condition considers the full amount of data available for each region. Before training, the data is split into 70% training and 30% test data. Whereas, the second condition considers a limited amount of training data (n = 5,10,20,40,80). These results are compared to the results of the HBM.

RESULTS

After executing the Monte Carlo simulations, the fit of the data is evaluated visually. Figure 2 shows that the BNN mean prediction fits the data well. The 95% confidence interval, as shown by the dotted red lines visually encompasses the majority of data. Therefore, an initial inspection of the model shows that it performs adequately.

In order to compare the results to the HBM analysis, the BNN mean prediction and HBM mean prediction are plotted on the same chart for each region in Figure 3. In addition, the coefficient of determination, R^2, shows how well predictions fit the actual data. It is clear that both the BNN and HBM models perform better for regions that have a significant amount of data to start with. On average, the HBM model predicts the data slightly more accurately than the BNN model with an R^2 value 0.027 greater than the BNN model. As this is a very small difference, both models are interpreted to sufficiently estimate the data. If the value of R^2 is considered to be significant when R^2 is greater than 0.6, then the BNN model and HBM model are effective for datasets with at least 120 measurements and without significant variability.

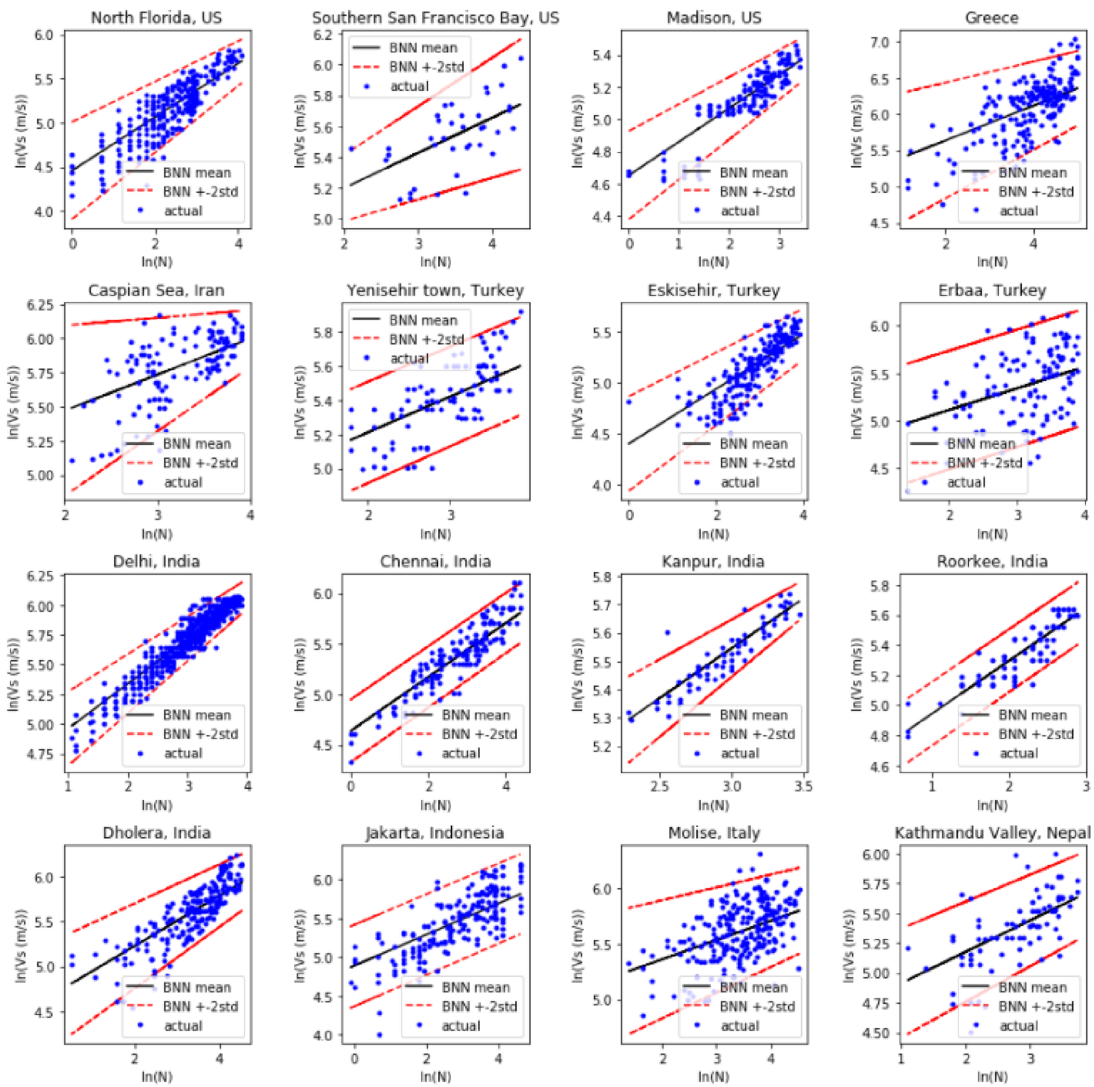

Figure 2: The BNN predictions are compared to the actual data. It is clear that the BNN 95% confidence interval encompasses most of the data and the mean prediction follows the trend of the data.

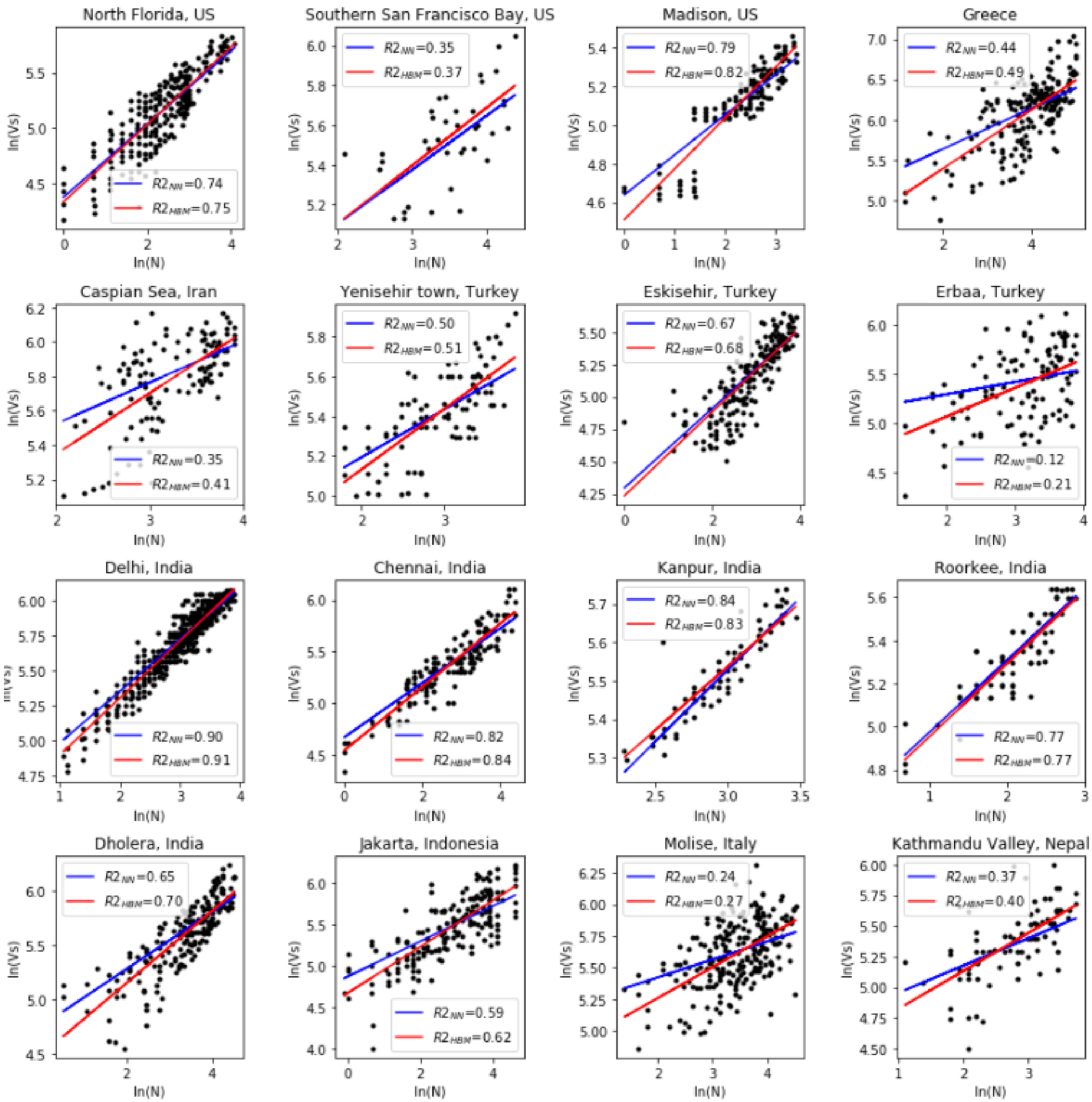

Figure 3: The BNN predictions are compared to the HBM predictions. R^2 is shown for each region.

In order to assess the BNN's ability to estimate the shear wave velocity with limited SPT data, the North Florida, US dataset was evaluated. A random sample of 5, 10, 20, 40, and 80 data points, n, were selected from the dataset to train and test the model. Figure 3 shows the quality of the data predictions for each quantity of data. Figure 4 shows the same analysis performed by the HBM model.

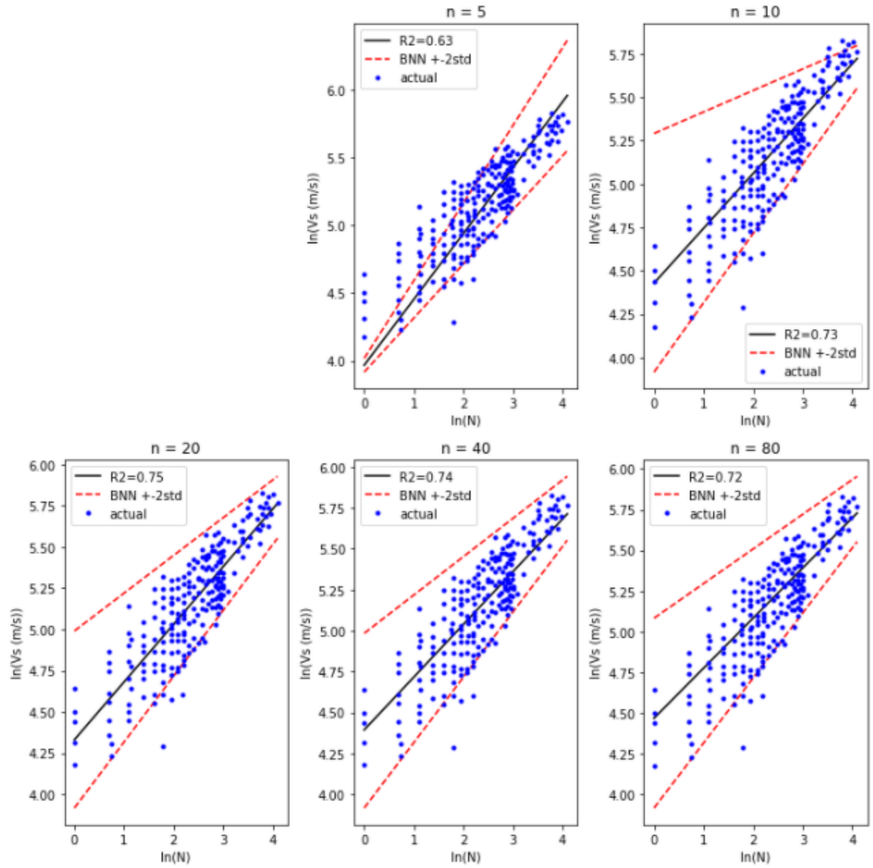

Figure 3: The BNN predictions are shown with limited training data.

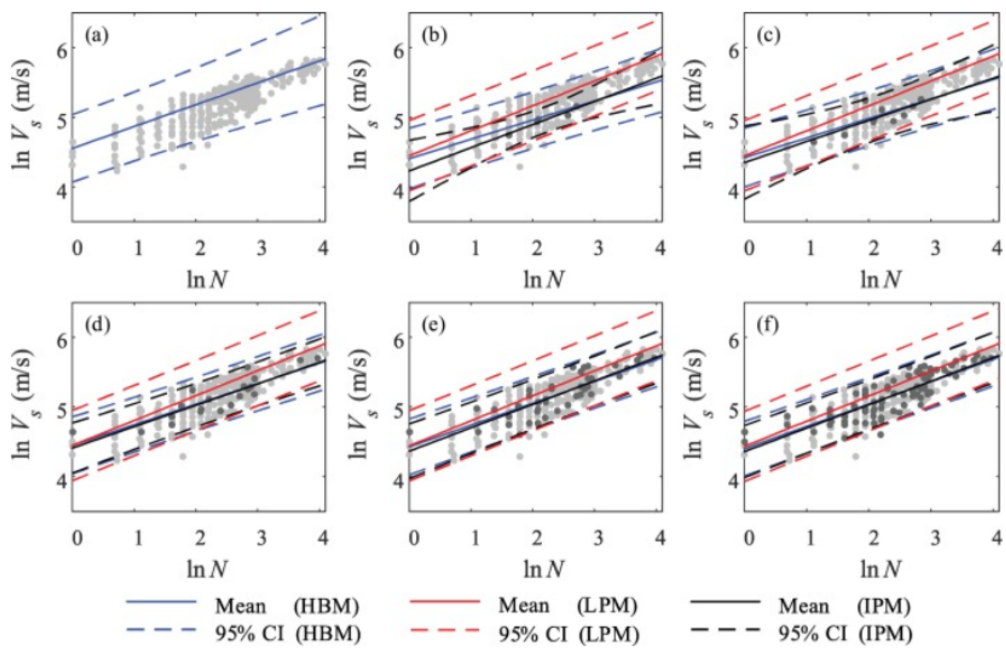

Figure 4: The HBM predictions are shown with limited training data where b) through f) represent n = 5 - 80. LPM and IPM represent alternative methods of analysis used in this previous study. (Xiao, 2021)

CONCLUSION

The BNN prediction of shear wave velocity provides an estimate of data as shown by significant R^2 values. Further, 95% confidence interval accurately encompasses the vast majority of data. When compared to the HBM results, the BNN predictions are slightly less accurate, which is proven by the BNN R^2 value that is on average 0.027 less than the HBM R^2 value. When the data is adjusted such that only 5, 10, 20, 40, and 80 data points are used to predict the shear wave velocity, the R^2 value produced with only 5 data points is still significant, meaning the BNN does a good job characterizing a region without much region-specific data. The BNN 95% confidence interval varies widely for the 5 and 10 data point sets; whereas, the HBM model provides a confidence interval that contains most of the data.

In order to provide a better representation of the shear wave velocities, a greater number of data points would be preferred for some of the regions. For example, the BNN Southern San Francisco Bay, US model produces an R^2 value of 0.35. Datasets with more than 120 data points prior to training consistently estimated shear wave velocity with a significant R^2 value (greater than 0.6). Comparing the BNN to the HBM, the largest downfall of the BNN is that it cannot predict the shear wave velocity of a region without region-specific data. Whereas, the HBM does not require region-specific data to make a prediction. For further comparison, the HBM predictions of limited region-specific data shear wave velocity would provide R^2 values to compare, but they are not publicly available. Without comparing qualitatively, it appears visually, that the BNN has a better mean prediction fit on the actual North Florida, US data.

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