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# Geotechnical Site Characterization via Deep Neural Networks: Recovering the Shear Wave Velocity Profile of Layered Soils

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## 1. Abstract

The mechanical property of soils is a vital part of seismic hazard analysis of a site. Such properties are obtained by either in-situ (destructive) experiments such as crosshole or downhole tests, or by non-destructive tests using surface wave inversion methods. While the latter is more favorable due to the cost-efficiency, there are challenges mostly due to computational demand, non-uniqueness of inversion results, and parameters fine-tuning. In this article, we use a deep learning framework to circumvent the above-mentioned limitations to output soil mechanical properties, requiring dispersion data as input. Our trained model performs with high accuracy on the test dataset and shows satisfactory performance compared to the ensemble Kalman inversion technique.

## 2. Introduction & Objective

**GOAL:** To train a deep neural network to predict mechanical properties of a layered solid medium (shear wave velocity) using dispersion data as input (Fig. 1).

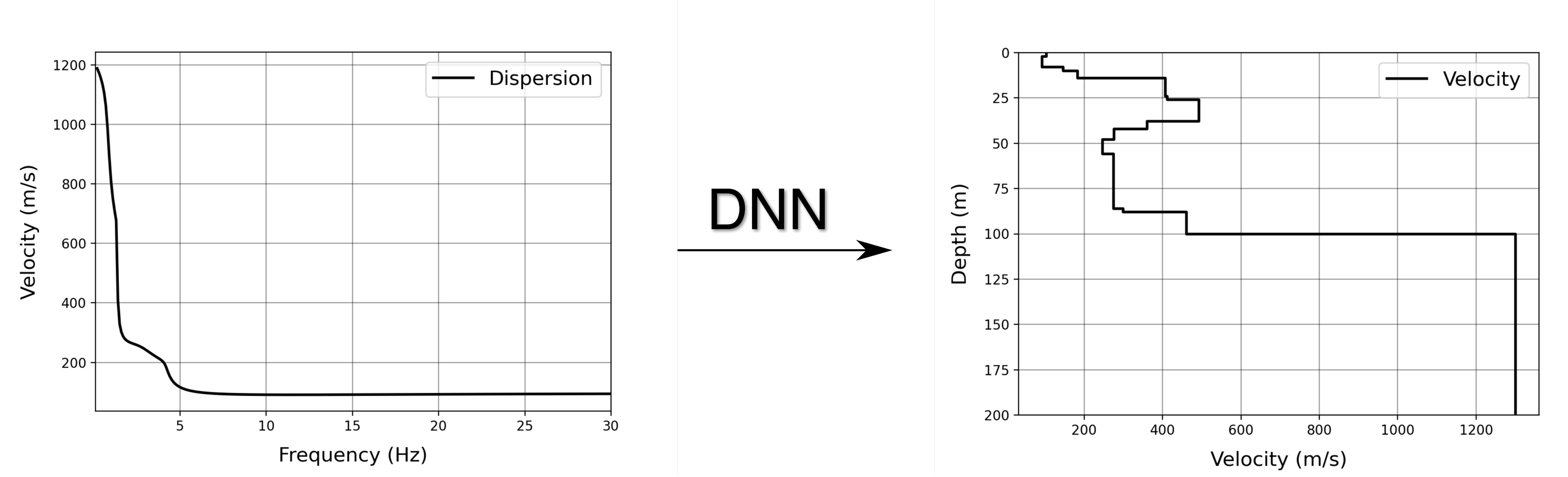


Fig. 1. The mapping between dispersion data and velocity.

**What is the input?** A dispersion curve provides the relationship between the velocity in a layered medium with frequency or wavelength.

**What is the output?** A shear wave velocity profile shows the variation of shear wave velocity in a layered medium as a function of depth.

**Why Neural Network?** Several approaches, namely Kalman inversion, stochastic grid search algorithm, fully Bayesian Markov Chain Monte Carlo (MCMC), among others, have been used to perform the inversion analysis similar to the current study. NN seems to be a powerful option tackle the problem in hand, with less challenges.

## 3. Methodology

### 3.1. Methodology

The forward model is shown in Eq. 1.

$$y = G(u) + \eta \qquad \text{Eq. 1}$$

where $y \in R^m$ is dispersion curve, $u \in R^k$ is shear wave velocity, and $\eta \in R^m$ is added noise to help with overfitting. The network tries o find a function $H = G^{-1}$ that given $y$ would output $u$.

### 3.2. Dataset

For training data, we inquire shear wave velocity profiles of California from the PySeismosoil package [1]. The numerical domain has thickness of $500\,m$, which is discretized in $2m$ elements. The package has the capability of generating randomized profiles. This profiles are later used in GEOPSY [2] to obtain the theoretical dispersion curves. Here, $y \in R^{299}$ and $u \in R^{250}$. The dataset is divided into 80/10/10 for training, validation, and testing.

### 3.3. Deep Neural Netowrk

The network has 5 hidden layers to perform regression analysis and each hidden layer consists of ResNet units [3]. ReLU activation function is added to hidden layers, and Adam optimizer, $L2$ norm as cost function, and learning rate of $lr = 10^{-4}$ are used for learning.

## 4. Results

### 4.1. Performance

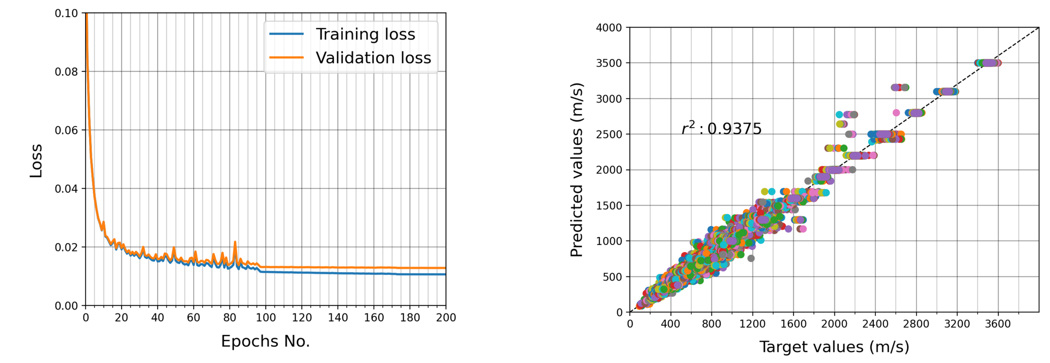


Fig. 2. Variation of loss over number of epochs (left). Comparison of predicted and target values in the test set (right).

### 4.2. Test set

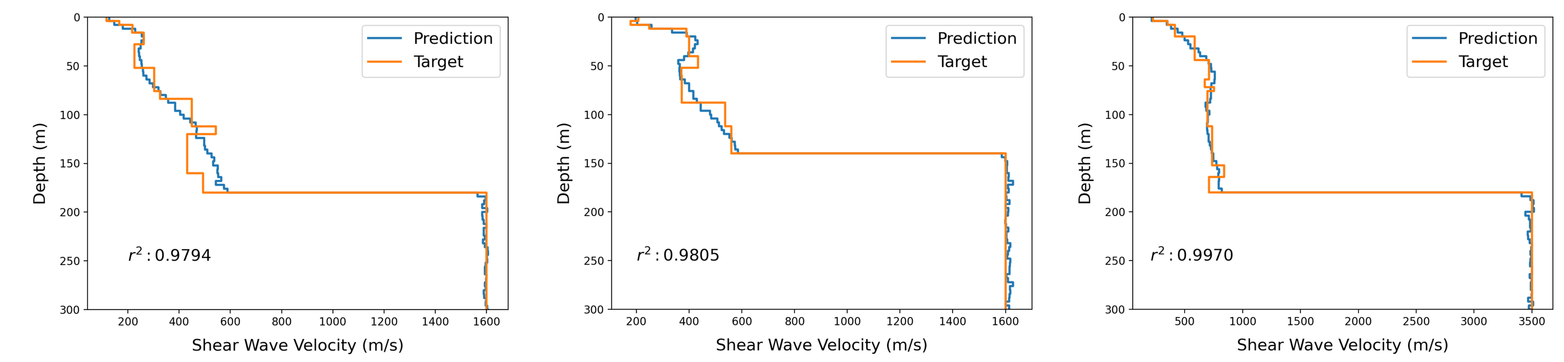


Fig. 3. Model prediction capabilities in three randomly sampled examples from test set

### 4.3. Period Prediction

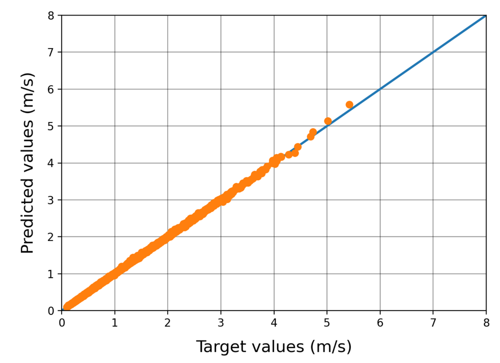


Fig. 4. Comparison between fundamental period between target profiles and predicted ones.

### 4.4. Comparison vs. Ensemble Kalman Inversion (EKI)

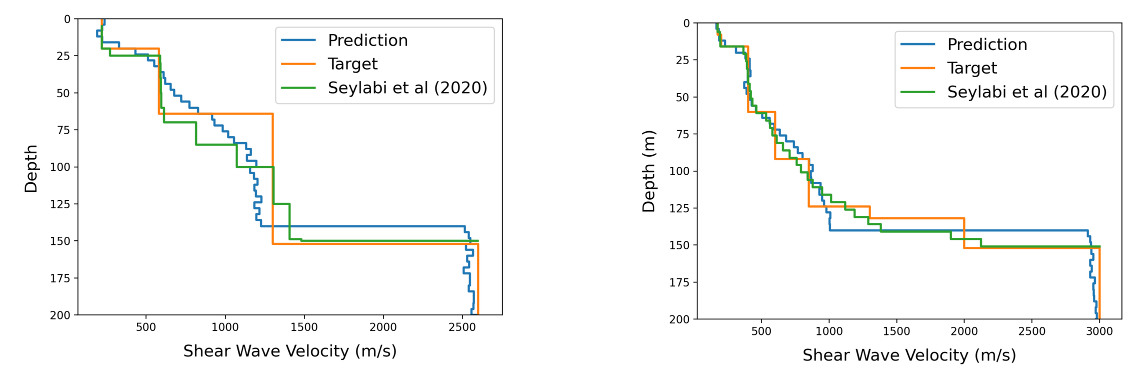


Fig. 5. Comparison versus Seylabi et al [4], where they used EKI.

## 5. Conclusion

- DNN converges fast and shows high accuracy on the test dataset. This shows the capability of the trained model against overfitting.
- The comparison with EkI shows that DNN is capable of performing at the same level as an advanced statistical method without challenges regarding hyper-parameter tuning and non-uniqueness of results.

## 6. Future work

- Including higher modes of Rayleigh wave into the training set.
- Making the model more generalized by generating new training data to incorporate the effect of other influential parameters.
- Extending the model higher dimensions by solving wave equation in 2D.

## References

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