Machine Learning Approaches for Predicting Ground Motion Directionality Parameters

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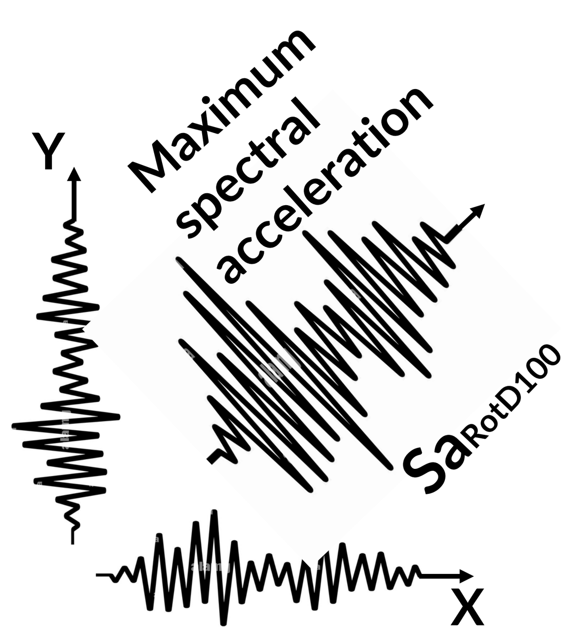
Introduction



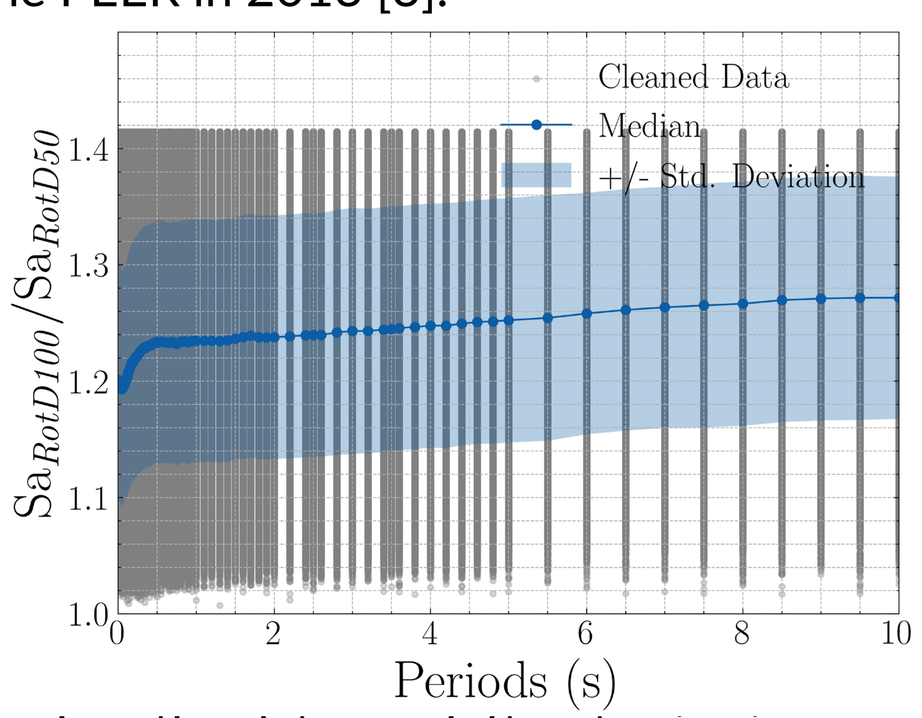
- $Sa_{RotD100}$ is the maximum spectral response acceleration in all horizontal directions [1].
- It is an earthquake intensity measure to design infrastructures.
- To predict ground motions, we use models (GMMs) that give results in

$$Sa_{RotD50} \text{ and } \sigma_{\ln(Sa_{RotD50})}$$

- To convert to *RotD100*, we need the parameters [2] $\sigma^2_{\ln(Sa_{RotD50})}$, $\sigma^2_{\ln(Sa_{RotD100})}$, $\sigma^2_{\ln(Sa_{RotD100}/Sa_{RotD50})}$, and $Sa_{RotD100}/Sa_{RotD50}$

Datasets & Feature

- We used the *NGA-West2* database released by the PEER in 2013 [3].



- To clear the data, we left out seismic records with no *RotDnn*, outliers, and *Sa* values for periods beyond the lowest usable frequency.
- $Sa_{RotD100}/Sa_{RotD50}$ is independent of the earthquake magnitude, source-to-site distance, and soil Vs30 [4].
- We assume the only feature is *the period of vibration*.

Methods and Experiments

For all models:

- Hyperparameter selection with grid search
- Cross-validation to train data
- MSE as the objective function → $\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$
- R^2 as the performance metric

XGBoost Regresor:

$$L^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t)$$

- Regularized gradient boosting tree
- 432 hyperparameter combination

Supported Vector Machine SVM:

- Balancing Margin and Complexity using the RBF kernel
- 290 hyperparameter combination

$$\min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\xi_i$$

Random Forest RF:

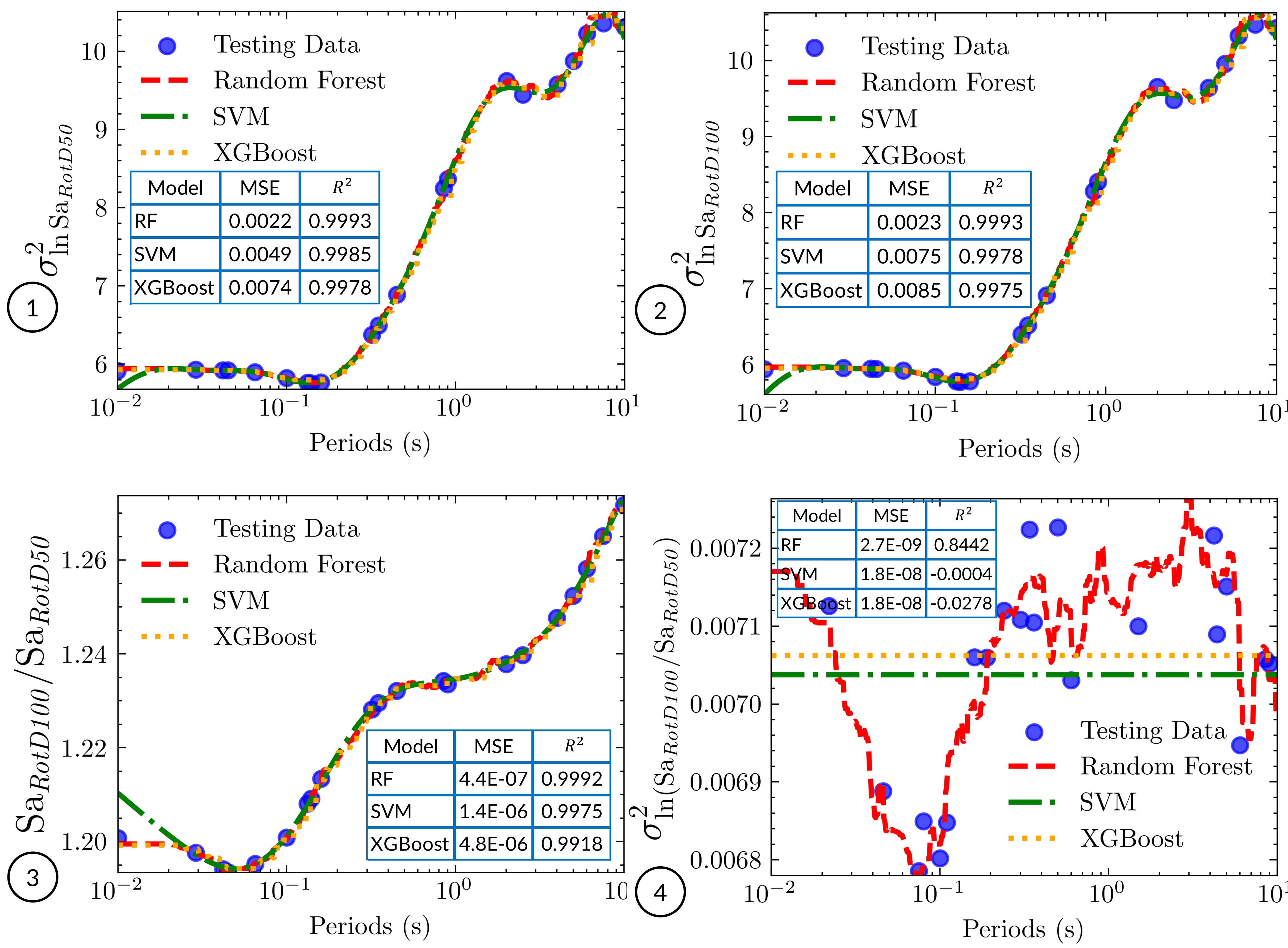
- Hierarchical structure to capture nonlinear patterns
- 1440 hyperparameter combination

$$\hat{y} = \frac{1}{B}\sum_{b=1}^{B}\hat{y}_b(x)$$

Results

Dataset	Number of Observations
Total Dataset (100%)	105
Training Dataset (80%)	84
Testing Dataset (20%)	21

- The trained models and the testing data for each target variable are shown:



Discussion and Future Work

- Except for $\sigma^2_{\ln(Sa_{RotD100}/Sa_{RotD50})}$, all machine learning models demonstrated strong performance, with low MSE and high R^2 scores.
- The results indicate a high correlation between the period of vibration and the target variables.
- We consider that low variance and tightly clustered values of $\sigma^2_{\ln(Sa_{RotD100}/Sa_{RotD50})}$ led to straight-line predictions from both SVM and XGBoost. Some methods were explored to resolve this issue, but none proved effective. The authors suggest assigning a constant value to this parameter for all periods.
- Random Forest performs slightly better, likely due to testing more hyperparameter combinations with lower computational effort.
- The predicted directionality parameters can be utilized to update those currently used in modern GMMs to estimate $Sa_{RotD100}$ and its variance.

Future Work

- The NGA-West2 database has not been comprehensively utilized to estimate directionality parameters. For consistent comparison, applying regression models previously utilized in similar studies alongside this database would be necessary.

References

[1] Boore, D. M., "Orientation-Independent, Nongeometric-Mean Measures of Seismic Intensity from Two Horizontal Components of Motion," Bulletin of the Seismological Society of America, Vol. 100, No. 4, 2010, pp. 1830–1835. https://doi.org/10.1785/0120090400

[2] Beyer, K., and Bommer, J. J., "Relationships between Median Values and Aleatory Variabilities for Different Definitions of the Horizontal Component of Motion," Bulletin of the Seismological Society of America, Vol. 96, No. 4, 2006, pp. 1512–1522. https://doi.org/10.1785/0120050210

[3] Ancheta, T. D., Darragh, R. B., Stewart, J. P., Seyhan, E., Silva, W. J., et al., "PEER NGA-West2 Database," Tech. rep., Pacific Earthquake Engineering Research Center, May 2013.

[4] Shahi, S. K., and Baker, J. W., "NGA-West2 Models for Ground-Motion Directionality," Tech. rep., Pacific Earthquake Engineering Research Center, University of California, Berkeley, May 2013.

[5] Buitinck, L., Louppe, G., Blondel, M., Pedregosa, F., Mueller, A., Grisel, O., Niculae, V., Prettenhofer, P., Gramfort, A., Grobler, J., Layton, R., VanderPlas, J., Joly, A., Holt, B., and Varoquaux, G., "API design for machine learning software: experiences from the scikit-learn project," ECML PKDD Workshop: Languages for Data Mining and Machine Learning, 2013, pp. 108–122.

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