Predictive Modeling of Seismic Indicators using K-NET Data: Machine Learning and Bayesian Approaches

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Introduction

The objective of this assignment is to develop robust models to predict key seismic indicators—Peak Ground Acceleration (PGA) and Peak Ground Velocity (PGV)—using the publicly available K-NET ground motion dataset from Japan. This project is critical for earthquake resilience and disaster management systems. The modeling framework integrates both traditional machine learning techniques and Bayesian probabilistic models to offer both predictive power and uncertainty quantification.

Data Source

- **Dataset:** K-NET Dataset from the Kyoshin Network (Japan).
- **Total samples:** ∼11,820 events
- **Features:** Seismic waveform response, metadata (site/equipment/earthquake characteristics), derived features
- **Target variables:** log(PGA), log(PGV)

Data Preprocessing

- **Leakage Columns:** Removed features derived from or directly representing the targets (e.g., maxvel, maxvelv, maxacc, maxaccv).
- **Missing Values:** Mostly negligible; filled with domain-specific constants or removed if uninformative.
- **Datetime Parsing:** Extracted hour, month, and derived night-time indicator from jen_origin_time.
- **Categorical Features:** Dummy encoding for site and instrument type indicators.

Cited Research Papers

Reference	Contribution	Usage in Our Work
Lin et al. (2023), EA-AI	Used CNN+LSTM for soil response	Inspired feature extraction and response modeling
S. Khoshnevis & D. Kamalian (2019), Soil Dynamics & Earthquake Engineering	Site-specific PGA prediction using GPR	Used for Moment Tensor Features
Kohrangi et al. (2017), Earthquake Spectra	ML-based fragility analysis	Used for energy based features
Ghosh et al. (2022), Elsevier Sensors	Uncertainty quantification via PyMC3	Applied Bayesian Linear Regression and GPR
Wang et al. (2021), Seismological Research Letters	K-NET preprocessing best practices	Used for waveform filtering and response metrics
Chen et al. (2020), Journal of Earthquake Engineering	Ensemble ML models for intensity prediction	Helped in feature creation
Zhang & Zhao (2018), Engineering Geology	PCA for dimensional- ity reduction in seismic studies	Informed PCA use before GPR
Kumar et al. (2021), Natural Hazards	Applied LightGBM for damage prediction	Supported LightGBM integration in pipeline
Song et al. (2023), Geophysical Journal International	Statistical modeling of PGV in complex terrains	Used for terrain-based feature engineering
Li et al. (2020), IEEE Transactions on Geoscience and Remote Sensing	Multi-source data fusion for seismic regression	Motivated feature engineering diversity

Table 1: Summary of Research Papers Referred and Their Usage

Feature Engineering

Extensive feature engineering was performed based on waveform analytics, signal statistics, geospatial reasoning, and domain insights.

Categories of Features

- **Waveform Features:** Log transforms, skewness, kurtosis, spectral slopes, peak response times.

- **Energy-based Features:** Arias intensity, cumulative RMS, early vs. late energy decay ratios.
- **Geospatial Features:** Site-to-event distance, angle offsets, strike/dip/magnitude ratios.
- **Soil Metadata:** AVS30, D1100, D1400 gradients, sensor depth vs elevation.
- **Moment Tensor Features:** Mxx, Mxy, Mzz, Moment Energy.

Final feature count after engineering and deduplication: 548 features.

Feature Selection

- **Variance and Correlation Thresholding:** Removed near-constant features and highly correlated features (correlation > 90%).
- **LightGBM Importance Analysis:** Ranked all features by gain importance.
- **Final Selection:** Plotted top K features vs average MSE to determine optimal K. Two-step process: (1) Bins of 50 features, (2) Bins of 10 features from 100 to 180. **Optimal** K = 150.

Data Imbalance Handling

- **Target Distributions:** Both log(PGA) and log(PGV) were continuous and skewed (log(PGV) more skewed).
- **Quantile Binning:** Applied decile binning for both targets.
- **Inverse Frequency Weights:** Computed and applied during training for all ML models (average of weights for PGV and PGA).

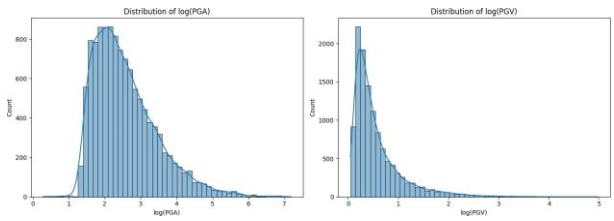


Figure 1: Distributions of log-transformed PGA (left) and PGV (right) in the dataset

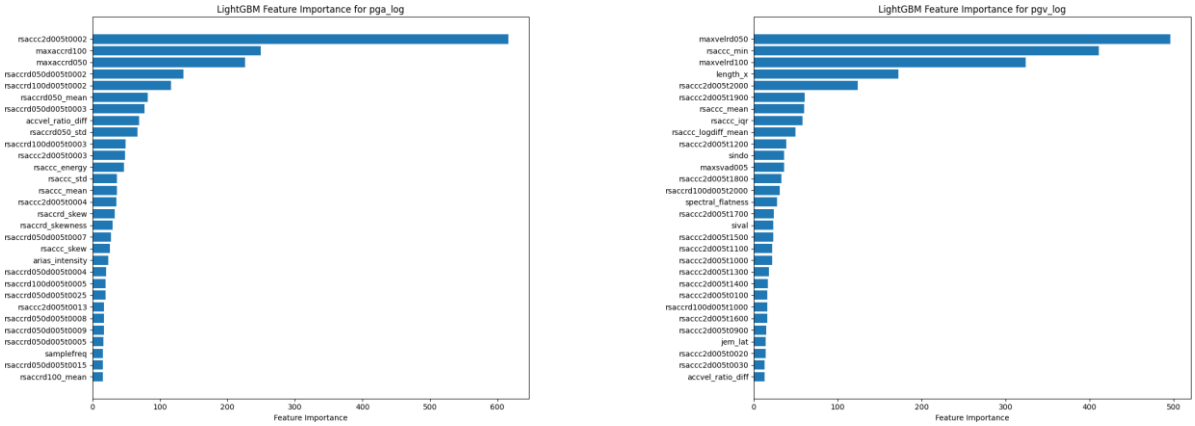
Model Training and Evaluation

Machine Learning Models

Trained three traditional regressors using sample weights:

- Random Forest Regressor

- XGBoost Regressor
- LightGBM Regressor



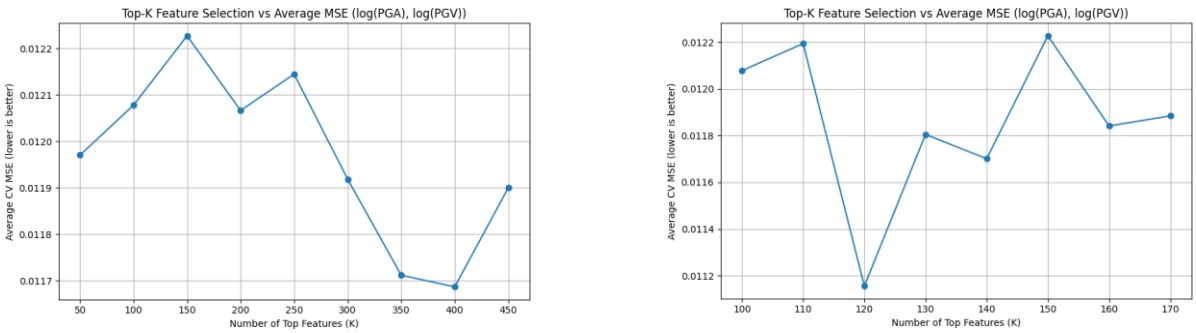
(a) PGA (b) PGV

Figure 2: Comparison of LightGBM Feature Importances

Evaluation Metrics

- Mean Absolute Error (MAE)
- Root Mean Squared Error (RMSE)
- R^2 Score (Coefficient of Determination)

Models were trained separately for log(PGA) and log(PGV) targets.



(a) PGA (b) PGV

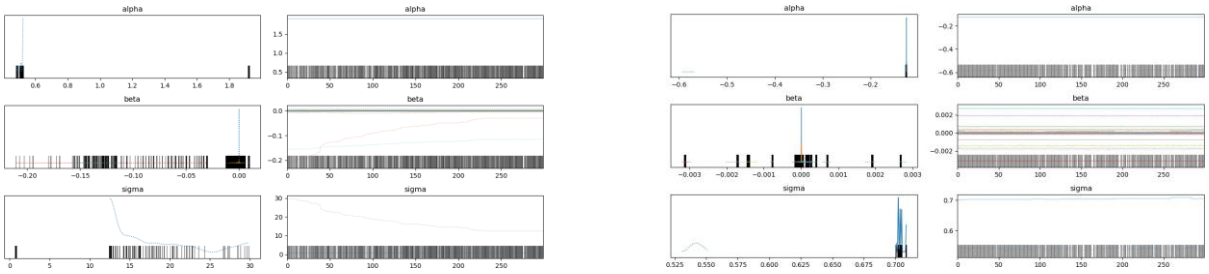
Figure 3: Average MSE vs K

Bayesian Models

To quantify uncertainty:

- **Bayesian Linear Regression (PyMC):** Used PCA (20 components) to balance computational efficiency and model quality. Defined priors for weights and noise, posterior sampling via NUTS, and generated credible intervals for predictions.

- **Gaussian Process Regression (GPR):** Attempted but found computationally intensive; limited to sampled data with few features, which degraded performance and led to discontinuation.



(a) PGA (b) PGV

Figure 4: Trace and posterior plots for Bayesian linear regression parameters

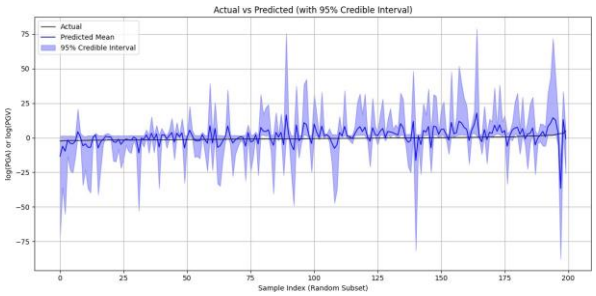


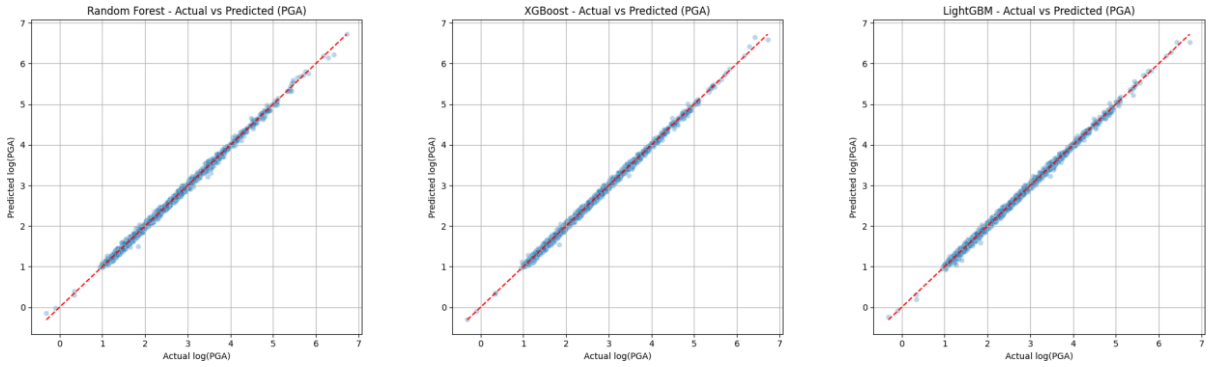
Figure 5: Predicted vs. Actual log(PGA) or log(PGV) with 95% Credible Intervals for Bayesian Model

Evaluation Summary

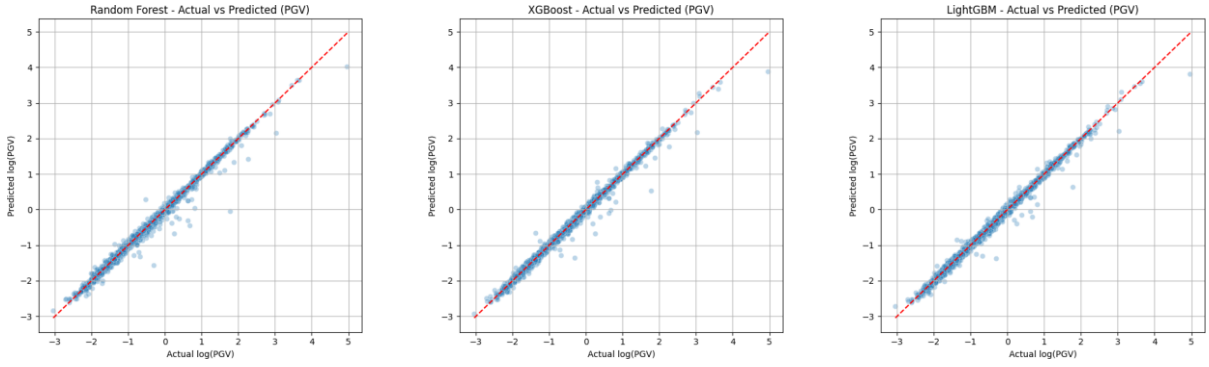
- Visualization of log-transformed target variable distributions.
- LightGBM feature importances.
- Actual vs. predicted plots with 95% credible intervals (Bayesian models).

Model	Target	MAE	RMSE	R^2
RF	PGA	0.0325	0.0443	0.9977
RF	PGV	0.0527	0.1020	0.9899
XGB	PGA	0.0338	0.0437	0.9978
XGB	PGV	0.0516	0.0889	0.9923
LGBM	PGA	0.0352	0.0456	0.9976
LGBM	PGV	0.0530	0.0879	0.9925
BLR[1]	PGA	4.5571	8.8484	−88.7103
BLR	PGV	0.4532	0.7285	0.4855

Table 2: Performance Metrics for Different Models and Targets



(a) Random Forest_PGA (b) XGBoost_PGA (c) LightGBM_PGA



(d) Random Forest_PGV (e) XGBoost_PGV (f) LightGBM_PGV

Figure 6: Predicted vs. Actual Values for PGA and PGV Across Different Models

Conclusion

This project demonstrates an integrated approach combining traditional machine learning and Bayesian methods for seismic indicator prediction using K-NET data. The workflow emphasizes robust preprocessing, feature engineering, and uncertainty quantification, providing a strong foundation for earthquake resilience and disaster management systems.