Machine Learning in Geotechnical Engineering

Soil Layering by Pile Driving Records

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1. Introduction

Geotechnical information is fundamental for foundation design in civil engineering. Due to the inherent spatial variations in soil strata, the soil properties within a given area of interest typically change with depth. To support effective foundation design, geotechnical engineers often partition soil strata into a finite number of discrete layers, each assumed to exhibit sufficient homogeneity to be assigned constant soil properties. This process, known as soil layering, relies on geotechnical data obtained during subsurface investigation phase. The most commonly used data sources include standard penetration test (SPT) blow counts, soil classifications, and tip and sleeve resistances recorded during the cone penetration tests (CPT).

However, subsurface investigation locations, particularly in the initial phases of a project, are often spatially sparse. For example, soil boring spacing requirements can be as large as 150 ft for sites with relatively simple geotechnical conditions. Additionally, SPT blow counts are typically recorded at 5-ft intervals starting at a depth of 10 ft, resulting in considerable vertical gaps in data. Consequently, soil layering based on solely on such sparse data may fail to accurately to capture the complexity of soil conditions. Therefore, it is advantageous to explore supplementary data sources for soil layering.

One promising data source is the incremental blow counts recorded during pile installation. Incremental blow counts, which reflect the number of hammer blows required to advance a pile by a unit depth (e.g., per foot), are generally positively correlated with the stiffness or strength of the soil layers encountered. As a common form of deep foundation, driven piles are typically installed in groups with small horizontal spacing. For quality assurance purposes, geotechnical professionals record incremental blow counts for each pile, creating a more densely spaced dataset in both horizontal and vertical directions compared to SPT data. Moreover, pile driving records are routinely documented to verify that the pile installation complies with design specifications, ensuring the availability and reliability of these records. Thus, incremental blow counts have the potential to reveal both native and modified soil conditions in practical applications.

This project studies the feasibility of applying machine learning algorithms to incremental blow counts for automated soil layering. The findings aim to enhance the accuracy and efficiency of geotechnical designs by providing a data-driven approach to soil stratification.

This project is implemented using Jupyter Notebooks within Visual Studio Code environment. The Python interpreter version is 3.9.19. The major external libraries utilized include Scikit-learn, Numpy, Pandas, and Matplotlib. Detailed instructions for running the code are provided below:

- The dataset can be found in https://github.com/Drzyjiang/ML-in-Geotechnical-Engineering/tree/main/Soil%20Layering%20by%20Pile%20Driving%20Records
- The source code can be found in https://github.com/Drzyjiang/ML-in-Geotechnical-Engineering/tree/main/Soil%20Layering%20by%20Pile%20Driving%20Records
- Run source code Soil Layering by Pile Driving Records.ipynb in Visual Studio Code or Jupyter Lab.

2. Methodology

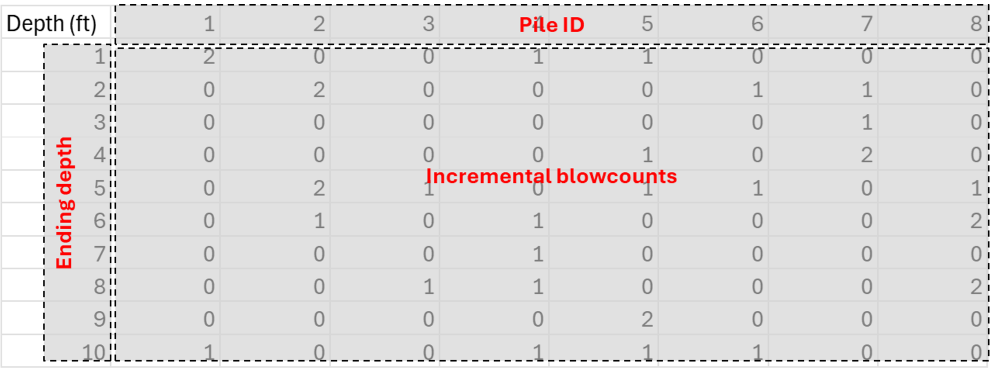
2.1 Problem statement

Given the incremental blow counts of multiple piles recorded during pile installation, the objective is to partition the soil strata into a predefined number of layers such that soils within each layer exhibit maximum homogeneity. This task can be framed as a clustering problem with a continuity constraint. Specifically, soils with similar incremental blow counts should be grouped together, while ensuring that the layers remain contiguous in terms of depth. In other words, a cluster cannot overlap with or span across another cluster.

2.2 Dataset

The dataset used in this project consists synthetic pile driving records for a total of 34 piles. This dataset is selected because of its representation of various common geotechnical soil conditions encountered at numerous project sites.

The dataset contains 76 rows and 35 columns. The first row indicates the pile IDs, ranging from 1 to 34. The first column of the remaining rows represents the ending depth for each increment, while the rest of entries correspond to incremental blow counts. The maximum depth recorded is 75 ft. An illustration of the dataset is shown in Figure 1. It is important to note that some piles were terminated at depths less than 75 ft, and any missing incremental blowcounts are noted as #N/A.



Depth (ft)	1	2	3	4	5	6	7	8
1	2	0	0	1	1	0	0	0
2	0	2	0	0	0	1	1	0
3	0	0	0	0	0	0	1	0
4	0	0	0	0	1	0	2	0
5	0	2	1	0	1	1	0	1
6	0	1	0	1	0	0	0	2
7	0	0	0	1	0	0	0	0
8	0	0	1	1	0	0	0	2
9	0	0	0	0	2	0	0	0
10	1	0	0	1	1	1	0	0

Figure 1 Explanation of dataset format

2.2 Preparation

2.2.1 Statistical analysis of raw data

Since the incremental blow counts were recorded at the same ending depths for all piles, the arithmetic mean and the standard deviation of each depth are calculated and are presented in Figure 2.

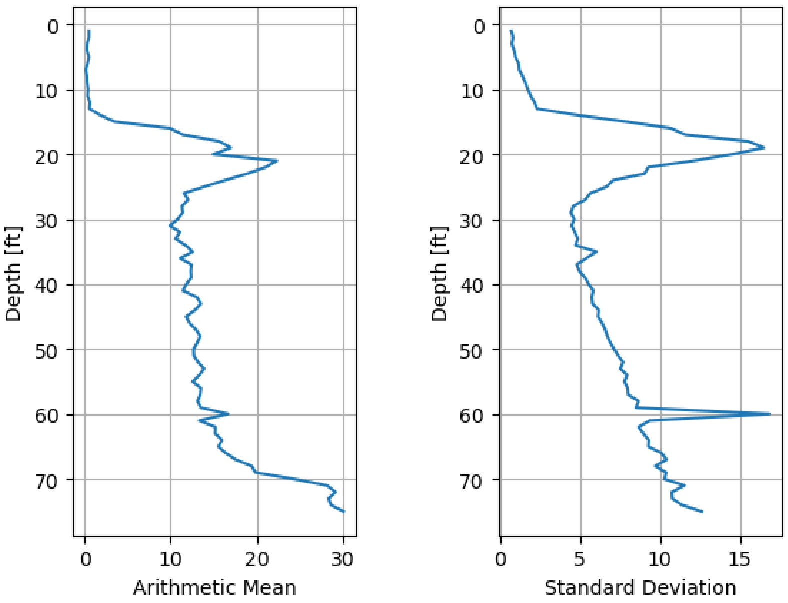


Figure 2 Arithmetic mean and standard deviation of incremental blow counts in terms of depth

The statistical analysis reveals key trends in the data. For the uppermost 13 ft of soils, the mean incremental blow counts are predominantly zero, indicating minimal resistance during pile installation. Between depths of 13 ft and 26 ft, the mean value initially rise to a local maximum of 22 before declining to approximately 12. From 26 and 60 ft, the mean values exhibit a slow yet steady pace. Beyond 65 ft, the mean values escalate sharply, reaching a peak of 30 at the maximum depth.

The standard deviation profile mirrors the mean trend, suggesting greater variability in blow counts at deeper layers. Notably, while the mean values rise sharply beyond 65 ft, the standard deviation displays a more gradual upward trajectory, imply that deeper soils not only offer greater resistance but also exhibit more consistent incremental blow counts across piles.

2.2.2 Data preprocessing

To develop a site-wide layering model using all pile driving records, the data from all piles are aggregated together into {depth, incremental blow count} pairs, disregarding pile IDs. This aggregation yielded a total of 2,550 data pairs. After excluding pairs with missing incremental blow counts (#N/A), the remaining 2,527 pair of data points are valid points remained for analysis. The preprocessed dataset is shown in Figure 3.

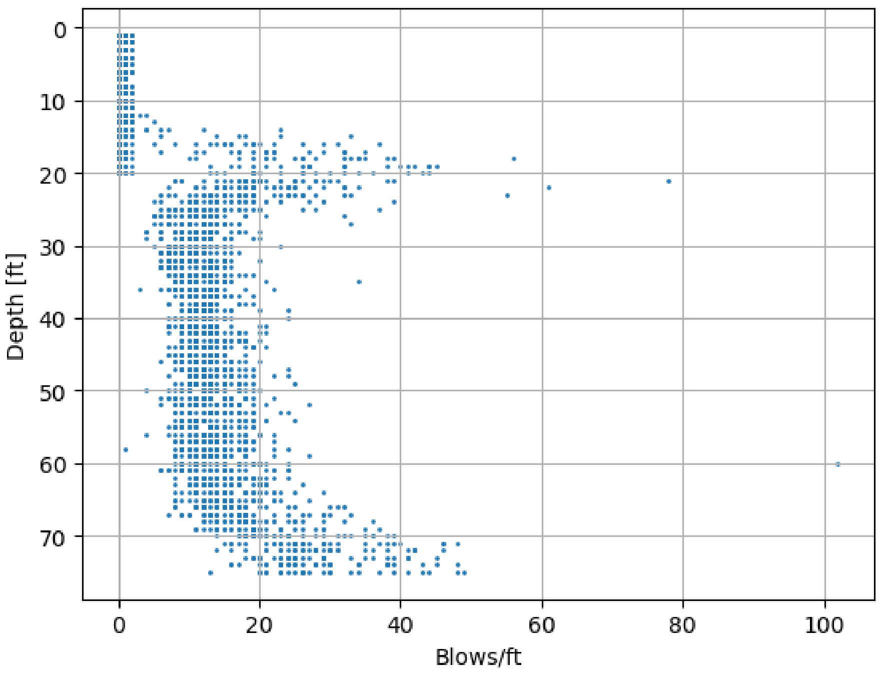


Figure 3 Dataset after preprocessing

Due to the overlap of data points from 34 piles in Figure 3, it is challenging to clearly visualize the distribution of incremental blow counts at each depth. To address this, Figure 4 represents the 25th and 75th percentile blow count profiles at each depth, offering a clearer depiction of the spread of data.

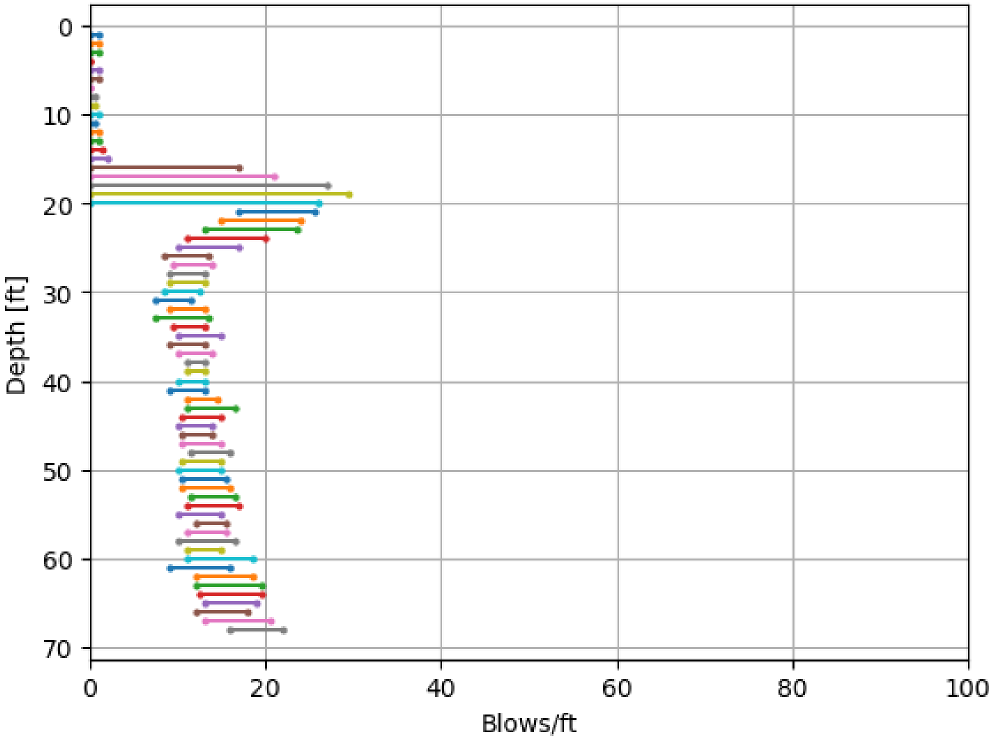


Figure 4 25th and 75th percentile blow count profiles

The incremental blow count profiles suggest the presence of distinct soil layers: a very soft or loose layer above 20 ft, a thin and very stiff soil layer, a relatively homogeneous intermediate layer with moderate strength, and a stiff bottom layer. Based solely on these profiles, an experienced geotechnical engineer might subjectively divide the strata into four or five layers. Guided by these observations, subsequent analyses in this study focus on partitioning the soil into five layers for simplicity and consistency.

3. Clustering

Multiple clustering techniques are examined for their applicability in the following sections.

3.1 Agglomerative clustering

Agglomerative clustering and divisive clustering are two types of hierarchical clustering. While divisive clustering adopts a top-down approach, agglomerative clustering builds clusters in a bottom-up manner. The iterative process of agglomerative clustering can be summarized as follows: initially each data point is treated as an individual cluster. At each iteration, the two clusters with shortest distance between them are merged, reducing the total number of clusters by one. This process repeats until the number of clusters equals the specified value – the number of soil layers in this study.

The distance between two clusters, known as the linkage criterion, can be defined in several ways:

- *Ward's minimum variance*: based on normalized distance between two cluster centroids.

$$\Delta(C_i, C_j) = \frac{|C_i||C_j|}{|C_i| + |C_j|} \left\| \overline{x_\imath} - \overline{x_\jmath} \right\|^2$$

where $|C_i|$ and $|C_j|$ are number of points of clusters i and j, and $\overline{x_\imath}$ and $\overline{x_\jmath}$ denote their.

- *Complete linkage:* defined by the maximum distance between any pair of points in the two clusters.

- *Average linkage*: based on the average distance between all pairs of points across clusters.

- *Single linkage*: uses the minimum distance between any pair of points across clusters.

In this project, the Ward's minimum variance criterion is adopted. Agglomerative clustering is employed as it proves feasible given the nature of the data. As shown in Figure 3, the distance between two data points depends on the differences in depths and incremental blow count values. A small difference in depth implies spatial proximity of the soils, while a small difference in incremental blow count values suggests similar soil strength or stiffness.

However, a challenge arises when a data point exhibits significantly higher or lower incremental blow counts value compared to its adjacent points. In such cases, the small difference in depth may overshadow the variation in blow count values, leading to a scenario where the upper and lower points bypass the middle point and directly link together. This violates the continuity requirement. To mitigate the impact resulting from the range disparity between incremental blow count values (ranging from 0 to 100+) and incremental depths (fixed at 1), both variables are normalized to [0,1], as illustrated in Figure 5.

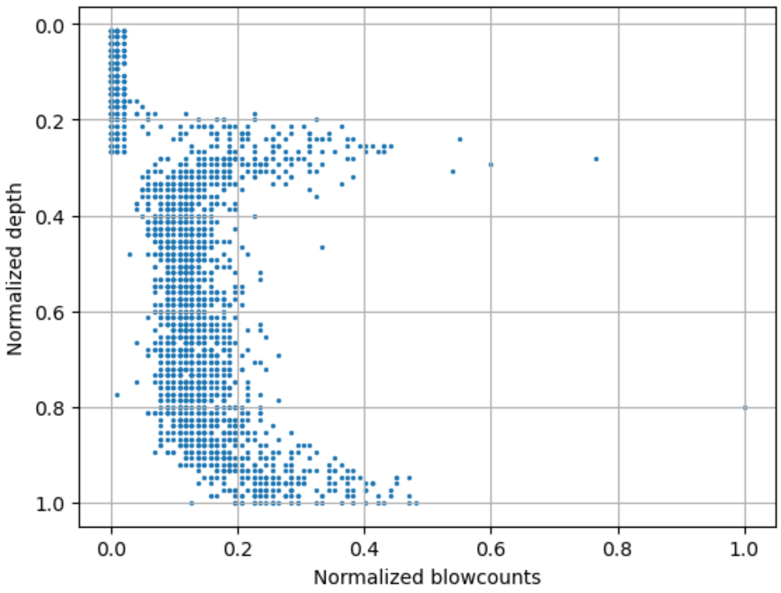


Figure 5 Normalized dataset

The agglomerative clustering result is presented in Figure 6. Overall, the clustering outcome appears to be reasonable. The first layer spans from 0 to 20 ft, capturing the very soft layer at top. The second layer extends from 14 to 35 ft, representing the thin and stiff layer. The third and fourth layers reflect relatively homogeneous strata with constant stiffness. Finally, the last layer ranges from 59 to 75 ft, representing the stiff bottom layer. Notably, the clusters have noticeable overlap in depth. For instance, there is a 10-ft overlap between layer 2 and layer 3. This overlap is justifiable, as transitions between soil layers in practice tend to be gradual rather than abrupt. However, the extent of overlap is substantial, necessitating additional steps to further delineate the transition zones and refine the cluster boundaries.

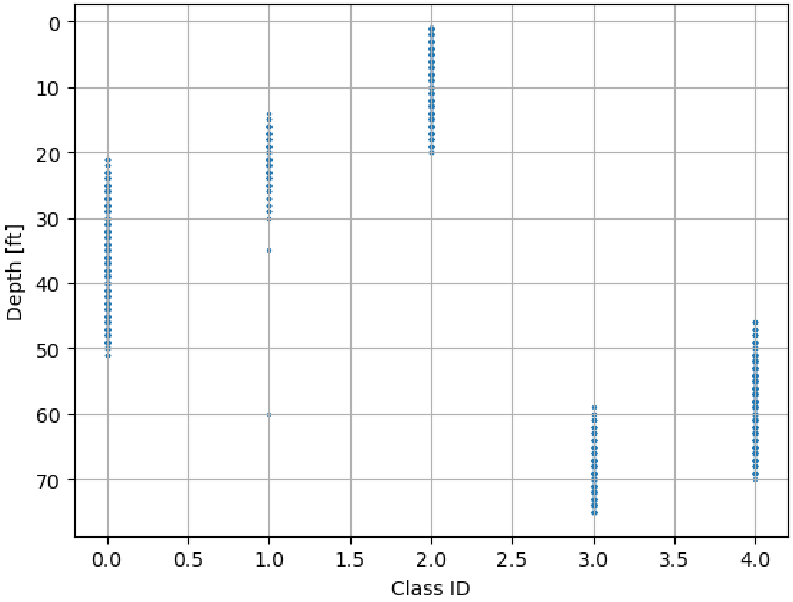


Figure 6 Results of agglomerative clustering

3.2 K-Means clustering

K-Means is another distance-based clustering technique widely used for partitioning data into a fixed number of clusters, denoted as K. The primary objective of K-Means is to minimize the sum of squared distances between each point and the centroid of its assigned cluster. Mathematically, this objective function is expressed as:

$$J = \sum_{n=1}^{N} \sum_{k=1}^{K} \delta_{n,k} \| x_n - \mu_k \|^2$$

where x_n denotes data point n, a vector corresponding to a location in the vector space;
μ_k denotes the centroid of cluster k;
$\delta_{n,k}$ is the Dirac delta function, defined as:

$$\delta_{n,k} = \begin{cases} 1, if data\ point\ n\ belongs\ to\ cluster\ k \\ 0, otherwise \end{cases}$$

The goal is the iteratively determine $\delta_{n,k}$ and μ_k. The K-Means algorithm follows these steps:

1. Initialize by randomly selecting K data points as the initial cluster centroids;
2. For each remaining data point, calculate its distance to all cluster centroids and assign it to the nearest cluster;
3. Update each cluster centroid as the mean of all points assigned to that cluster;
4. Repeat steps 2 and 3 until either the cluster assignments ($\delta_{n,k}$) and centroids (μ_k) converge, or a predefined maximum number of iterations is reached.

Unlike agglomerative clustering, which builds clusters incrementally by merging the closest points one-by-one case. Therefore, K-Means simultaneously assigns all points to clusters, reducing the bias towards the initially closest points. The clustering results obtained using K-Means are shown in Figure 7. Compared to agglomerative clustering, K-Means produces less overlap between adjacent layers, facilitating clearer layer delineation.

However, K-means has certain limitations. The clustering outcome is sensitive to the random initialization of cluster centroids, which may lead to inconsistent results. Thin soil layers near the ground surface and bottom (depth = 0 and 75) may be incorrectly merged, while homogeneous soil layers may be split into multiple clusters.

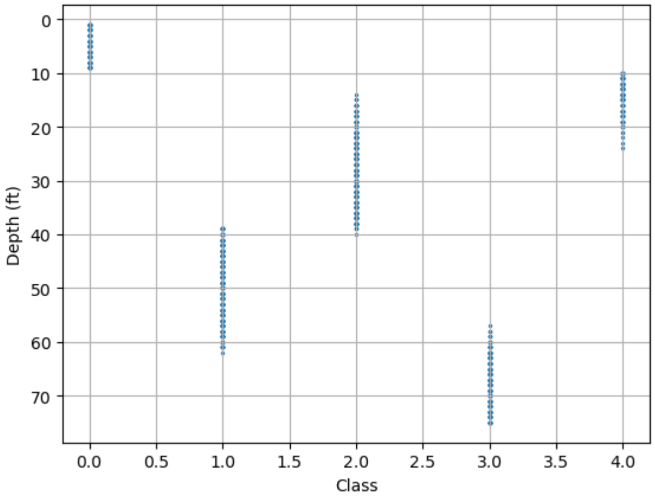


Figure 7 Results by K-Means clustering

3.3 Bisecting K-Means clustering

Bisecting K-Means clustering is a variation of the K-Means clustering that combines elements of divisive hierarchical clustering with K-Means. At each iteration, among all existing clusters, the one with highest total sum of squared errors is selected for further division using the “2-Means” approach. Consequently, the total number of clusters increases by one in each step. This procedure is repeated until the specified number of clusters is reached.

Compared with K-Means, bisecting K-Means is more stable due to the use of a smaller cluster count (K=2) at each stage, which helps mitigate the sensitivity to initial conditions. Additionally, bisecting K-Means does not require a predetermined number of clusters, offering greater flexibility during the clustering process. However, the primary drawback is its computational cost, as each step only increases number of clusters by one, requiring more steps to reach the final clustering configuration.

The clustering results obtained by bisecting K-Means are showing in Figure 8. The results are generally similar to those produced by standard K-Means, with the primary difference being a lower depth for Lay 1.

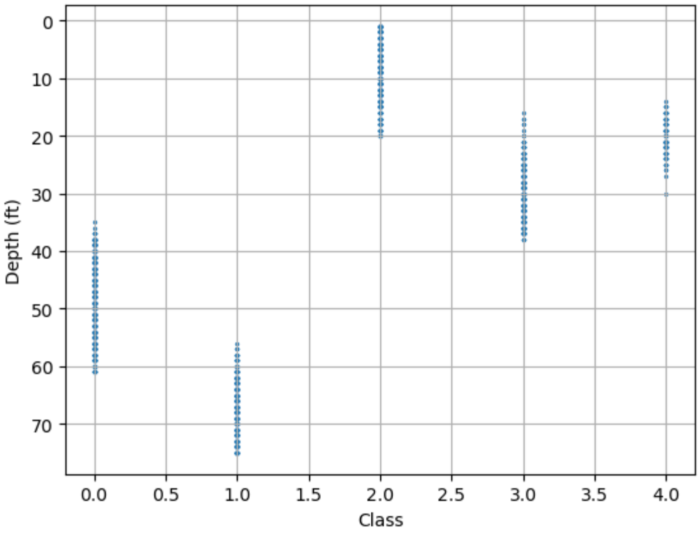


Figure 8 Results of Bisecting K-Means

3.4 Gaussian mixture model

Gaussian Mixture Model (GMM) is a model-based clustering technique that assumes data is generated from a mixture of multiple Gaussian distributions. The probability density function of a data point is a modeled as:

$$f(\boldsymbol{x}) = \sum_{k=1}^{K} \pi_k \, f_k(\boldsymbol{x}|\theta_k)$$

where $f(\boldsymbol{x})$ is the probability density function for all data points;

K represents the number of Gaussian components; each corresponding to a cluster;

$f_k(\boldsymbol{x}|\theta_k)$ is the probability density function of the k-th Gaussian component, parameterized by θ_k;

π_k is the weight for the k^{th} Gaussian distribution component, $\sum_{k=1}^{K} \pi_k = 1$

Gaussian Mixture Models are commonly solved by the Expectation-Maximization (EM) algorithm, which iteratively refines the parameters to maximize the likelihood of the data given the model.

The clustering results obtained using the Gaussian Mixture Model are shown in Figure 9. Class 2 captures the very soft top layer, while Class 4 identifies the thin and stiff layer at 20 ft deep. Class 0 and Class 3 together represent the homogeneous layer between 20 and 65 ft, and Class 1 corresponds to the bottom stiff layer.

The outcome of the Gaussian mixture model closely resembles those of agglomerative clustering, with notable overlaps between layers. For example, Class 4 can be entirely replaced by Class 2 and Class 0. In addition, some data points with gaps between them are assigned to the same cluster, indicating that the model accounts for underlying probabilistic distributions rather than strictly enforcing spatial continuity.

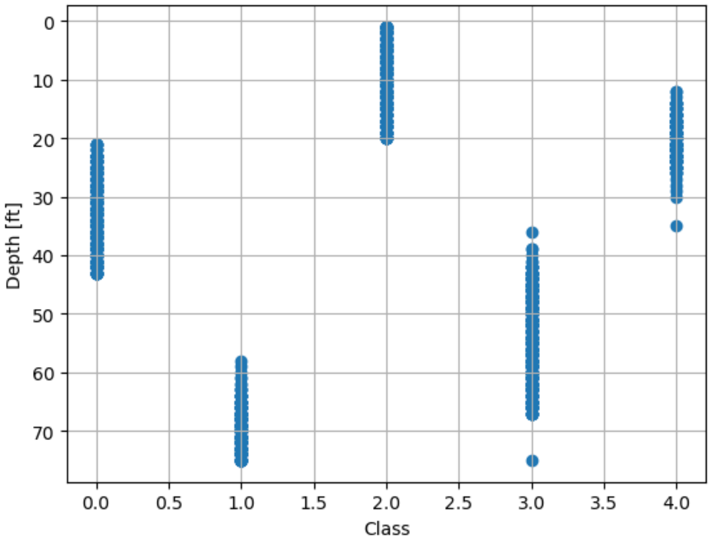


Figure 9 Result by the Gaussian mixture model

3.5 Decision tree regression

A decision tree is a hierarchical model that partitions data using a sequence of splitting rules, forming a tree-like structure. It consists of both non-leaf nodes, which represents decision rules, and leaf nodes, which correspond to clusters. Decision trees can be used for classification or regression. At each non-leaf node, a splitting rule is determined by evaluating a subset of candidate features, selecting the one that maximizes information gain or minimizes variance. Given the continuous nature of the incremental blow counts, a regression tree is more suitable for capturing the underlying data distribution.

The goal is to minimize the total variance after split:

$$Variance(Var) = \frac{1}{n}\sum_{i=1}^{n}(y_i - \bar{y})^2$$

$$\text{Total variance after split} = \frac{n_L}{n}Var(y_L) + \frac{n_R}{n}Var(y_R)$$

where n_L and n_R are sizes of left and right cluster sizes, respectively; n is the total size. Then the average value of all data points at a leaf node is assigned as the predicated value for that node.

In this project, depth is used as feature, while incremental blow counts serve as the label. By structuring the decision tree in this manner, clusters are strictly segregated by depth without any overlap. Since each data point has only one feature (depth), feature selection randomness does not apply in this context.

The clustering results obtained using the decision tree method are shown in Figure 10. The first very soft layer extends from 0 to 15 ft, followed by a thin and stiff layer from 16 ft and 24 ft. A homogeneous layer spans 25 to 63 ft, while the fourth layer is from 63 to 70 ft. The bottom stiff layer is from 70 to 75 ft.

Decision trees tend to maximizes the thickness of the homogeneous layers before identifying transition zones. Unlike other clustering techniques, decision trees clearly delineate layers without overlap.

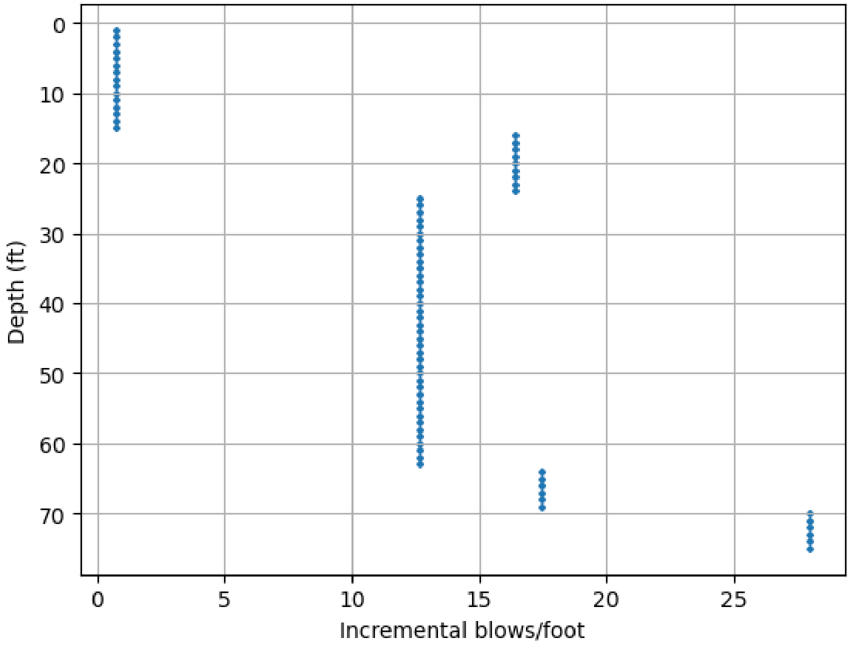


Figure 10 Clustering results by decision tree

3.6 Random forests regression

Random forests extend decision trees by employing an ensemble learning approach, where multiple decision trees are trained on different subsets of the data. This method is effective for both classification and regression tasks. The key distinction between a single decision tree and the random forests lies in the use of bootstrap aggregation (bagging), which reduces variance and improve model robustness.

Bootstrap aggregation involves constructing multiple datasets by randomly sampling with replacement from the original dataset. Given an initial dataset of N points, each bootstrap dataset is generated by randomly selecting a data point and reinserting it, repeating this process N times. Due to this random selection, each decision tree in the ensemble is trained on a slightly different dataset, leading to diverse predictions. The final output by the random forest regression is obtained by averaging the predictions from all individual trees:

$$\hat{y} = \frac{1}{B}\sum_{i=1}^{B} y_i$$

where B is the number of decision trees; y_i is the prediction by the i$^{\mathrm{th}}$ tree; $\hat{y}$ is the final aggregated prediction.

In this study, the size of random forest is specified as 10. The regression results are depicted in Figure 11. Although the figure presents regression results rather than explicit clustering, distinct layers can still be identified, including the very soft top layer, the thin and very stiff layer, the homogeneous layer, and the bottom very stiff layer.

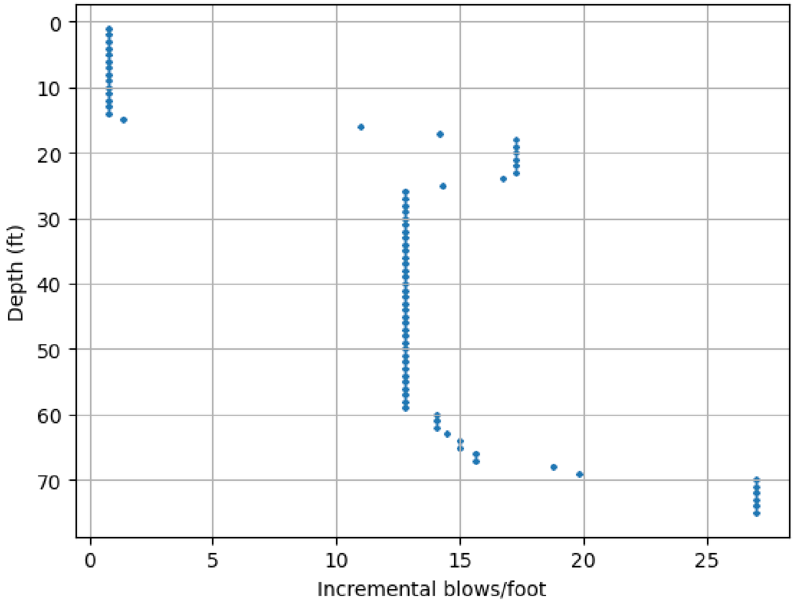


Figure 11 Regression results by random forest

To further illustrate the clustering pattern learned by individual trees, the splitting criteria stored at each non-leaf nodes are extracted and shown in Figure 12. These criteria represent depth-based interfaces between different layers. Notably, most trees identify consistent transition depths at approximately 15 ft (between Layer 1 and Layer 2) and 70 ft (between Layer 4 and Layer 5). However, greater variability is observed in the interfaces between Layer 2 and 3, as well as between Layer 3 and 4, with some trees selecting depths of approximately 17 and 24 ft, while others prefer 25 and 60 ft. This divergence originates from variations in the original dataset, as indicated by the standard deviation in Figure 2, which propagate through the bootstrapped datasets.

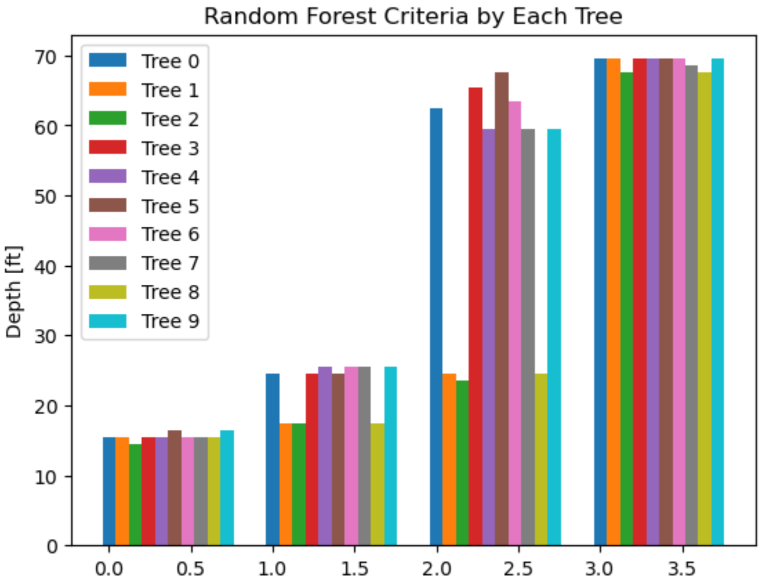


Figure 12 Clustering results by random forest

To evaluate the performance of decision tree and random forest regression, the coefficient of determination is used as a metric:

$$R^2 = 1 - \frac{RSS}{TSS}$$

where RSS (Residual Sum of Squares) is given by:

$$RSS = \sum_{I} (y_i - f_i)^2$$

TSS (Total Sum of Squares) is computed as,

$$TSS = \sum_{I} (y_i - \hat{y})^2$$

y_i is observed data; $\hat{y}$ is the mean of observed data; f_i is fitted data.

A sensitivity study is performed to study the influence of number of clusters (leaf nodes) on the R^2 determination. The results are shown in Figure 13. Coefficient of determination R^2 increases as the number of clusters increases from 2 to 6. However, beyond six clusters, no significant improvement is observed for either the decision tree or random forest models. When compared to a cluster count of fie, which was determined based on the domain knowledge, using machine learning demonstrates potential for enhancing engineering design. Overall, random forests achieve slightly higher R^2 than the decision tree, indicating superior predictive accuracy.

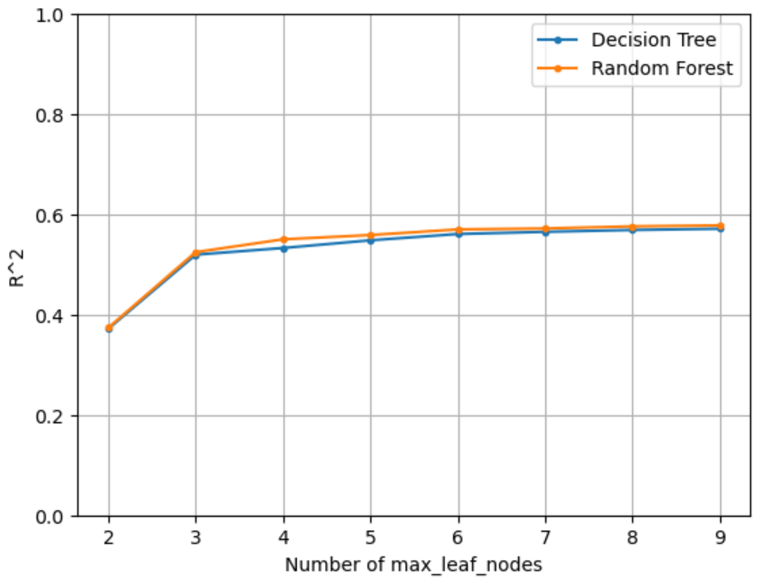


Figure 13 Results of sensitivity analysis on number of clusters for decision tree and random forests

4. Verification and Application

In the previous section, six clustering and regression techniques are evaluated for their applicability to pile driving records. The resulting soil layering outcome are compared in Table 1. Some outliers are manually excluded when determining the upper and lower depths of each layer.

Among the six techniques, the random forests regression provides the most reliable clustering results. To verify these results, an experienced geotechnical engineer independently determines the soil layering using domain knowledge, which serves as the ground truth in this study. In addition, the layering derived from pre-production geotechnical investigations, including Standard Penetration Tests (SPTs) and Cone Penetration Tests (CPTs) are included for comparison. The random forests closely match the ground truth, with the primary discrepancy occurring at the interface between Layer 3 and Layer 4. This difference is, however, negligible, as the soil properties in these two layers exhibit similar incremental blow counts. Notably, the random forests also align well with the design layering. The geotechnical investigation allowed for further subdivision of Layer 2. More importantly, the blow counts profile captures a very stiff bottom layer, which is overlooked in the original design. These findings justify the use of machine learning-based clustering on blow count data to extract additional geotechnical insights.

Table 1 Comparison of machine learning results, ground truth, and design values

Technique	**Layer 1**	**Layer 2**	**Layer 3**	**Layer 4**	**Layer 5**
Agglomerative clustering	[0, 20]	[14, 30]	[21, 51]	[46, 70]	[59, 75]
K-Means clustering	[0, 9]	[10, 24]	[15, 40]	[39, 62]	[57, 75]
Bisecting K-Means clustering	[0, 20]	[16, 26]	[16, 38]	[35, 61]	[56, 75]
Gaussian mixture model	[0, 20]	[11, 30]	[20, 44]	[39, 68]	[58, 75]
Decision tree	[0, 15]	[16, 24]	[25, 63]	[64, 69]	[70, 75]
Random forests	[0, 15]	[16, 25]	[25, 59]	[59, 69]	[69, 75]
Ground truth	[0, 15]	[16, 24]	[25, 40]	[40, 67]	[67, 75]
Design (1)	[0, 17]	[17, 21], [21, 25]	[25, 46]	[46,75]	
	Predrilled depth	Native stratum improved by soil mixing	Native stiff soil	Native stiff soil	

Notes:
(1) Design is based on geotechnical investigations by SPTs and CPTs

After verification, the soil layering derived from the random forest model was applied to the original incremental blow counts data. For each identified layer, the incremental blow counts are consolidated using the mean value. The final layering, along with the corresponding simplified incremental blow counts, is overlaid on the original data, as presented in Figure 14. Overall, the simplified values of each layer align well with the observed dataset.

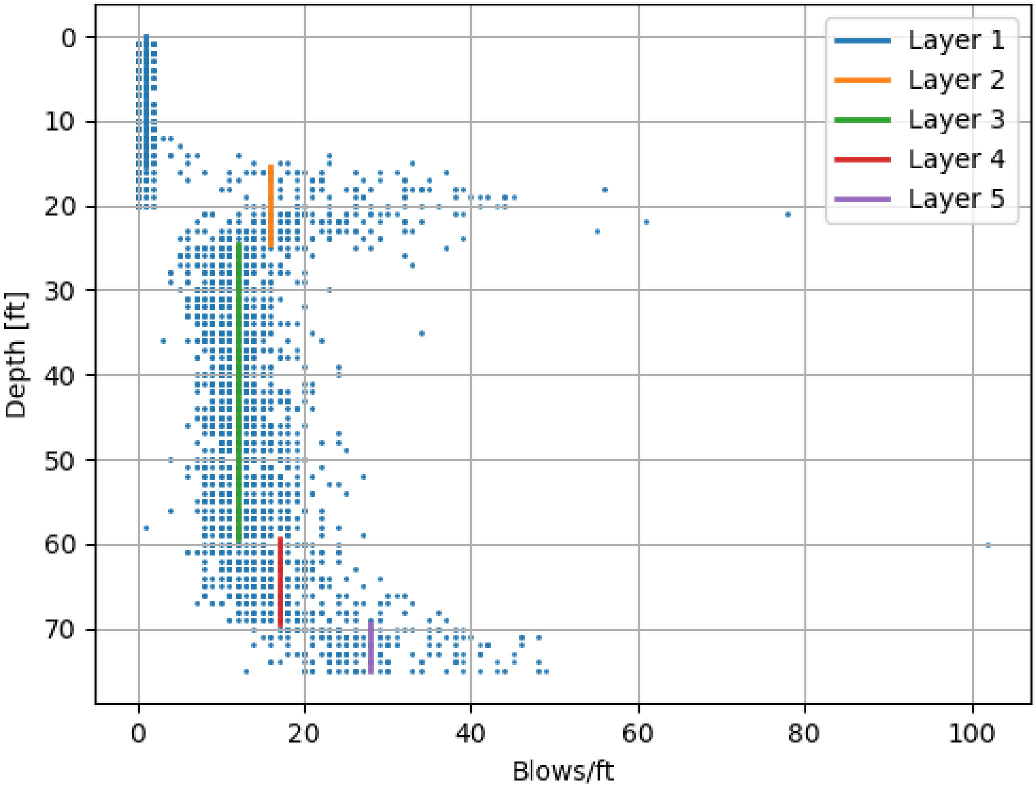


Figure 14 Final layering and the simplified incremental blow count values

5. Conclusions

Pile driving records of 34 piles are analyzed to characterize soil stratification. Six clustering and regression techniques are evaluated, including agglomerative clustering, K-Means clustering, bisecting K-Means clustering, Gaussian mixture modeling, decision tree regression, and random forests regression. Among these models, random forest regression demonstrated the highest accuracy in delineating soil layers. This study contributes to the application of machine learning techniques in geotechnical stratification and provides insights into clustering geotechnical data with high-dimensional geotechnical data.

6. References

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