Volume 7 (2) (2024): 41-49

The Indonesian Journal of Social Studies

Available at https://journal.unesa.ac.id/index.php/jpips/index

Iconographic analysis of ancient roof tiles using a data science approach

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Abstract— In archaeology, typological research methods have long been used as a reliable methodology to estimate the relative ages of artifacts and clarify their genealogical relationships. There is, however, a disadvantage to typological research methods—the researcher's subjectivity cannot be eliminated during the analysis process. This study aimed to provide an objective typological index by applying data science to typological research. Techniques known as "feature extraction" and "unsupervised learning" were used to recognize the patterns and visualize the data. Thereby, the study is expected to help clarify the laws hidden in the iconographic data of tiles. An experiment was performed to analyze the patterns on the eaves tiles of ancient Japanese roof tiles (from Fujiwara and Heijo Palace), which are the authors' specialty. Results revealed that matching local features focusing on edges was effective in detecting similarities between tiles and extracting differences in the general framework of the pattern structure. Furthermore, the multidimensional scaling method and phylogenetic tree were utilized to estimate the age and place of origin of each tile, which is a crucial task in archaeology. In general, the results obtained were in accordance with those of previous studies.

Keywords—Archaeology; Typology; Ancient Japanese Roof Tiles; Figure of Patterns; Data Science Approach

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e-ISSN 2615-5966 (Online)

1. Introduction

In the field of archaeology, typological analysis has traditionally been employed as a valuable and efficient method for establishing the relative ages of artifacts and illuminating their phylogenetic connections. In studies on roof tiles, the authors analyzed the pattern alterations in *nokimaru* (round eaves) and *nokihira* (flat eaves) tiles through a typological viewpoint, with the aim of recording sequencing and construction methods at specific sites such as temples and palaces. Studies based on the antecedent relationship of tiles, the transmission of building construction, handicraft production techniques between central and local regions, and their historical significance have been the mainstay of archaeological research.

However, current typological research methods have several limitations, including subjectivity. First, the analysis may be subject to divergent interpretations as different investigators focus on distinct parts of an artifact. Moreover, there is no clear indicator for determining the process of stylistic degeneration or the formalization of changes in artifacts.

This study seeks to address these issues by employing a data science approach to mechanically extract and categorize features, thereby providing a different index of stylistic change rather than relying on manual analysis by researchers. In detail, we used the techniques of feature extraction[1] and unsupervised learning (which have been explored in the domain of data science) to uncover the latent principles concealed within the patterns observed in the data.

The authors are currently engaged in research on the data-driven classification of archaeological artifacts, with a focus on the 3D analysis of Sue pottery and the use of artificial intelligence (AI) to determine type and identify provenance[2]. Additionally, the works of Fujita, Yamamoto, and others[3] are also being pursued in this arena. The relationship between typological research methods and data science approach is marked by a strong affinity as both disciplines engage in data analysis and benefit from mutual feedback regarding findings. Collaboration in this manner may enable the construction of a more objective and comprehensive typology.

However, a challenge that has arisen in the employment of AI in archaeology is the difficulty of differentiating between minute variations, such as those caused by burnt distortion, and the maker's habitual techniques. To address this issue, the application of a data-driven approach to the typological analysis of tiles, with a well-defined classification criterion for "mold," holds great promise for yielding more precise and comprehensive results rather than pottery.

2. What is typology?

In this section, we explain the concept of typology, which serves as a preliminary methodology for the analysis of materials in the field of archaeology.

The Encyclopedia of Japanese Archaeology describes typology as follows[4]:

> A main method for classifying archaeological materials. Initially, the categorization of archaeological materials entails organizing them into broader and more specific classifications, with the classification unit being determined by style, form, or type. Subsequently, the materials are arranged in a chronological order on a vertical timeline and a horizontal spatial plane, serving as the initial basis for reconstructing past human activities through archaeological research.

In the field of archaeology, a standard approach involves categorizing numerous excavated materials from archaeological sites based on their distinct characteristics and comparing these classified materials to derive important insights such as chronological sequences or phylogenetic connections. The methodological correlation between this approach and the data science approach (which identifies explicit and latent patterns in data and evaluates them for similarities) is considered extremely high.

The Encyclopedia of Japanese Archaeology also stipulates that "the acquisition of 'useful information' from archaeological materials necessitates the selection of suitable attributes, which, in turn, enables the generation of useful information through analysis." It is important to emphasize that merely conducting a blind analysis of data does not guarantee the attainment of archaeologically relevant "useful information." It is important to determine and refine suitable data analysis techniques based

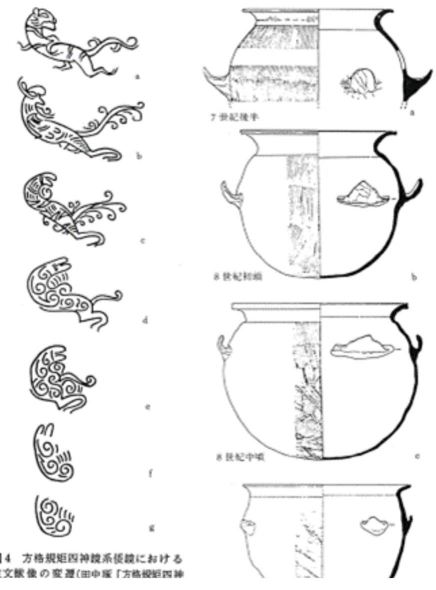

Figure 1. An example of type transition. (Yokoyama, 1985)

[1] A method for detecting similarity by extracting local features for each of two arbitrary images.
[2] Inoue et al., 2020
[3] Fujita et al., 2021
[4] Morimoto, 2002

on the properties of the materials and the archaeological inferences to be drawn.

3. Research methods

We employed a formal approach to analyze and discuss the findings.

1. The *nokimaru* and *nokihira* tiles unearthed from the Fujiwara and Heijo palaces served as primary sources of information (Figure 2). We used these data for the following reasons: (1) The detailed excavation sites and points of excavation were uncovered through excavation surveys. (2) The Nara National Research Institute for Cultural Properties in Nara Prefecture and other research institutes have already conducted extensive chronological and genealogical studies; for example, the research carried out by Morimitsu and Hanatani[5] is particularly valuable for comparison with data-driven analysis as it provides a valuable case study for examination and evaluation. (3) The Nara National Research Institute for Cultural Properties released a comprehensive catalog of rubbings in the form of standardized visual data.
2. We subjected the image data of all varieties of tiles obtained from the Nara National Research Institute for Cultural Properties to data-driven analysis by using feature extraction and unsupervised learning.
3. Note that the genealogical relationship between tiles should not be based solely on the tile pattern but also on the production technique, the set relationship with ordinary round and flat tiles, the excavation site, the excavation context, quantity ratios, and other factors. We confirmed these relationships using both analytical methods and an aggregate of existing research.
4. We aimed to improve accuracy by feeding the results back into the data science process.

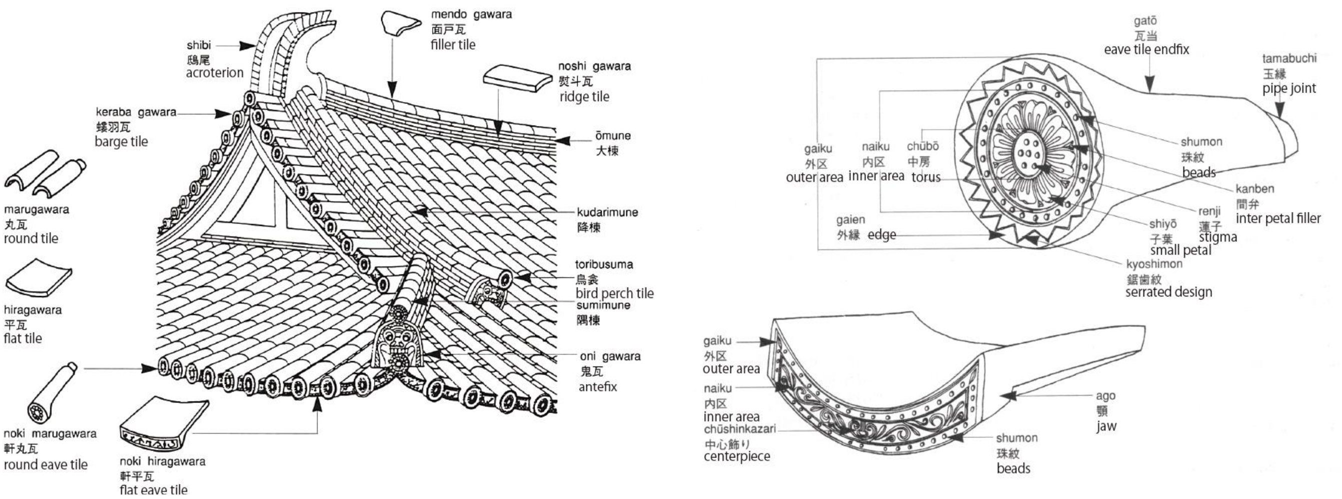

Figure 2. Round eave title, flat eave tile, and their partial names (Yamamoto, 2001, 198-201, author's addition).

4. Analysis methods

Figure 3 outlines the analysis process. Initially, we detected the keypoints of each tile, followed by matching similar keypoints based on their features between any two tiles. Subsequently, we computed the distance of any two tiles using the information obtained from the feature-matching approach. Finally, we employed multi-dimensional scaling (MDS; Kruskal, 1964) and phylogenetic tree (PT; Kitching et al., 1998) to create an overview of the similarities and depict the evolutionary links between the tiles, respectively.

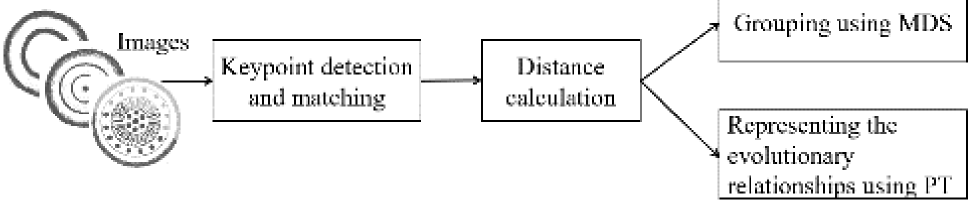

Figure 3. Analysis process. MDS is multi-dimensional scaling, and PT is phylogenetic tree.

[5] Morimitsu and Hanatani, 1991

4.1 Keypoint detection and matching

The main components of keypoint detection and matching include (1) identifying the interest point or feature point, which is the point at which the direction of the boundary of the observation changes abruptly, or it is the intersection point between two or more edge segments; (2) describing each feature point using a specific vector, known as a descriptor; and (3) identifying similar features by comparing descriptors across any two images. We employed the scale-invariant feature transform (SIFT; Lowe, et al., 2004) to detect and describe feature points and develop the fast library for approximate nearest neighbors (FLANN) to perform feature matching.

SIFT is widely utilized for keypoint detection and matching because of its ability to identify distinctive and invariant features in images. The final output of keypoint detection and feature extraction is a set of feature vectors that represent the keypoints and their descriptors. The steps are as follows:

1. *Scale-space extrema detection*: The first step is identifying potential keypoint locations in an image across multiple scales. This is achieved by creating a scale space representation of an image using Gaussian blurring at different levels.
2. *Key point localization:* Once potential key points are identified, representative keypoints are selected by using several criteria. Mainly, keypoints located on borders are selected.
3. *Orientation assignment:* An orientation is assigned to each key point based on local image gradients. This step renders the algorithm invariant to image rotation.
4. *Feature description:* Finally, a feature descriptor for each keypoint that describes the local image gradients and their distributions around that keypoint is computed. The descriptor is robust to changes in illumination, rotation, and scale.

After obtaining the feature vectors of the keypoints, FLANN was used to find the nearest neighbors in the feature space. Although FLANN supports various algorithms to approximate the nearest-neighbor search, we employed commonly used randomized k-d trees based on the Euclidean distance. For each query keypoint, we found top two closest keypoints. We matched each query to the first nearest keypoint, and considered a match as good match if the ratio $r = d_1/d_2$ of distance d_1 of the first nearest keypoint to the distance d_2 of the second nearest keypoint is smaller than 0.7.

4.2 Distance computation between images

We then define a distance metric for computing distances to all images for each image. The metric consists of three metrics: 1) average distance m_1 of matched keypoints d_1, 2) averaged ratio m_2 of the distances of the first nearest keypoint d_1 to the second nearest keypoint d_2, 3) good match ratio m_3 of the number of good matches to the number of total matches. Let d_{xy} represents the distance between *x* and *y* as

$$d_{xy} = m_1 * m_2 \,/\, m_3 \ . \tag{1}$$

The smaller d_{xy} is, the more similar *x* and *y* are to each other.

As the outcome of the FLANN is affected by the pre-specified target observation, d_{xy} is generally different from d_{yx}. For computing a symmetric distance between *x* and *y*, we re-describe the feature of a sample *x* by using distances to the rest images other than *x* and *y*. We used symmetrical chi-square distance (SChi). The symmetrical chi-square distances of images *x* and *y* are computed as

$$\mathrm{SChi}(x, y) = \sqrt{2 \ \sum_{z \in X¥\{x,y\}} \left(\frac{d_{xz} - d_{yz}}{d_{xz} + d_{yz}}\right)^2}, \tag{2}$$

where $X¥\{x, y\}$ is a set of images except the input *x* and *y*. By computing this between all the pairs of images, we obtained a distance matrix for the given images.

4.3 MDS

MDS is a well-known technique used in statistics and data visualization to analyze the similarity or dissimilarity of observations in a high-dimensional space and to represent them in a lower-dimensional space. Observations that are more similar are closer in the graph than are those that are less similar.

Let $\boldsymbol{D}$ be the similarity matrix, where d_{xy} denotes the similarity between observations *x* and *y*. The inner product matrix $\boldsymbol{B}$ is computed as follows:

$$\boldsymbol{B} = -\frac{1}{2}\boldsymbol{HDH}, \tag{3}$$

where **H** is the centering matrix, which is an $n \times n$ matrix with all elements $h_{xy} = \delta_{xy} - \frac{1}{n}$, and δ_{xy} is the Kronecker's delta.

Then, decompose $\boldsymbol{B}$ using $\boldsymbol{B} = \boldsymbol{V\Lambda V^T}$, where $\boldsymbol{\Lambda}$ is a diagonal matrix whose diagonal elements are eigenvalues and $\boldsymbol{V}$ is a matrix consisting of the corresponding eigenvectors. The eigenvectors corresponding to the k largest eigenvalues are then used to determine the coordinates of the observations in the lower-dimensional space using $\boldsymbol{X} = \boldsymbol{V_k \Lambda_k^{1/2}}$.

4.4 PT

A PT represents the evolutionary relationships among a group of organisms. The branches of the tree represent the lineages of the organisms, and the points where the branches split (nodes) indicate common ancestors.

The construction of a PT consists of two steps: (1) building a distance matrix by calculating the pairwise distances between observations, and (2) determining the distance between sets of observations using a proper linkage criterion. We applied the “ward.D2” criterion. The “D2” in “ward.D2” refers to the squared Euclidean distance, which is presented in Equation 4. The algorithm calculates the increase in the sum of the squared differences that would result from merging two clusters compared to merging all other possible pairs of clusters, and the decision to merge two clusters is based on minimizing the sum of the squared differences within all clusters. Ward.D2 is reported to be capable of producing compact spherical clusters. Moreover, it is sensitive to cluster shape and size and is less likely to produce clusters of unequal variance than other linkage criteria.

$$\text{Euclidean}(x, y) = \sqrt{\sum_{i=1}^{n} |x_i - y_i|^2} \qquad (4)$$

5. Results

5.1 Results of the overall trend

Figure 4 depicts the outcomes of MDS. The upper portion of the figure shows the *nokimaru* tiles, whereas the lower portion depicts the *nokihira* tiles. For the *nokimaru* tiles, the distribution of the concentric circle patterns (6009–6018) was distinct from that of the other groups, and a fundamental dissimilarity in pattern composition between the concentric circle and lotus patterns was evident. Furthermore, the group of double-petaled lotus patterns (6200–6369) comprised three distinct categories of tiles: those with a bare edge (6200–6229), those with bare edges and an outer beads band (6231–6249), and those with serrated edges and an outer beads band (6269–6320). We confirmed the validity of the data pertaining to the pattern structures of the edges and outer areas.

In contrast, the distribution of single-petaled lotus patterns (6129–6162) almost overlapped with that of double-petaled lotus patterns. The specific distinctions noted by archaeologists through their observations were not effectively distinguished based on the features we used.

Furthermore, despite the similarities in their serrated edges, beads bands, and double-petaled lotus patterns, we successfully distinguished the tiles excavated at Fujiwara Palace (6269–6281) and those used at Heijo Palace (6282–6320). Given the absence of any conspicuous stylistic variations between the serrated edges of the two groups, particularly with respect to the presence of convex or linear serrations, it is intriguing to observe the characteristics of the data science approach identified as significant as well as the criteria employed for pairing these features in the classification process.

The *nokihira* tiles featured a group of multiple contour patterns (6572–6575) that could be considered as a separate and distinct classification from the others. Furthermore, the inner area group was clearly distinguished into two unique categories: (1) the one-way arabesque group (6640-6654) and (2) the symmetrical arabesque group (6655–6775). However, the extraction of the outer area pattern from the *nokihira* tiles was unsatisfactory, indicating that the method we employed was insufficient for accurately identifying the outer distinct pattern. Furthermore, similar to the *nokimaru* tiles, we were unable to differentiate minor variations in the design within the overall Arabidopsis pattern.

These findings suggest that although the fundamental design elements of the patterns—such as concentrated circles, lotus motifs, multiple contours, one-way arabesques, and symmetrical arabesques—can be discerned, the subtle variations typically used by archaeologists to distinguish between different patterns are not readily apparent. In particular, the pattern structures of the edge and outer areas of the *nokimaru* tiles were distinctively recognizable.

The ramifications of these results extend to the cognitive aspects of tile patterns, particularly areas of focus among individuals. In his examination of *nokimaru* tiles, Fujisawa[6] discovered that the configurations of the edges and outer areas, rather than the inner areas, changed with age. He referred to this phenomenon as the chronological category and utilized it to determine the age of the tiles. In fact, the design of the edge and outer area patterns of *nokimaru* tiles has undergone transformations throughout various historical periods, from a rudimentary configuration to the bare edge,

[6] Fujisawa,1941

then to concentrated circles, to the sawtooth pattern, and finally to the development of an outer beads band. This implies that people's understanding of the pattern of *nokimaru* tiles was primarily influenced by the outer edge, rather than the inner area. Thus, the application of data science techniques can be considered indicative of the significance of individuals by focusing on the arrangement of the tile patterns.

5.2 Analysis of individual tile types

This section attempted to classify a group of archaeologically studied tiles using data science methods that match both established archaeological classifications and the corresponding phenomena.

Tiles excavated at Fujiwara Palace were provided by multiple places in the workshop. During the early phase of the construction of Fujiwara Palace, tiles were provided from local kilns situated in distant provinces, such as Omi and Sanuki, as well as the Hidakayama kilns, which is located in close proximity to the palace. These tiles were primarily used for the outer mud walls around the palace. Later, the supply from local kilns was disrupted, and tile production was relocated to kilns in the Yamato Basin. The production site moved from the Hidakayama kilns to the Kodai kilns, which was situated near Fujiwara Palace. These tiles were specifically used in the inner-central region of the palace. Figure 5 illustrates the correlation of the tiles used at Fujiwara Palace, which indicates the potential of employing data science techniques to discern variations in production sites and supply stages.

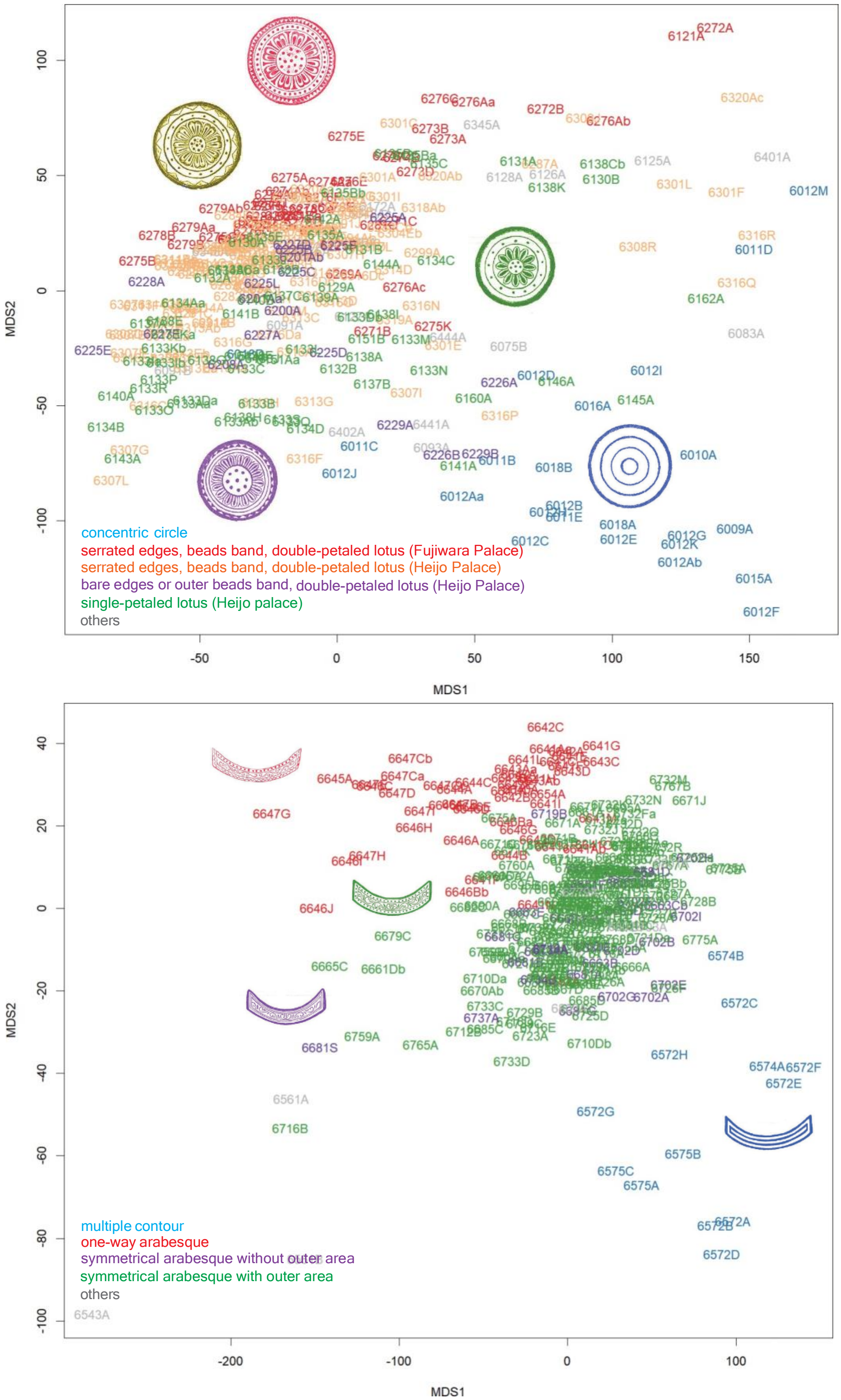

Figure 4. Results of MDS of *nokimaru* and *nokihira* tiles from Fujiwara and Heijo Palace.

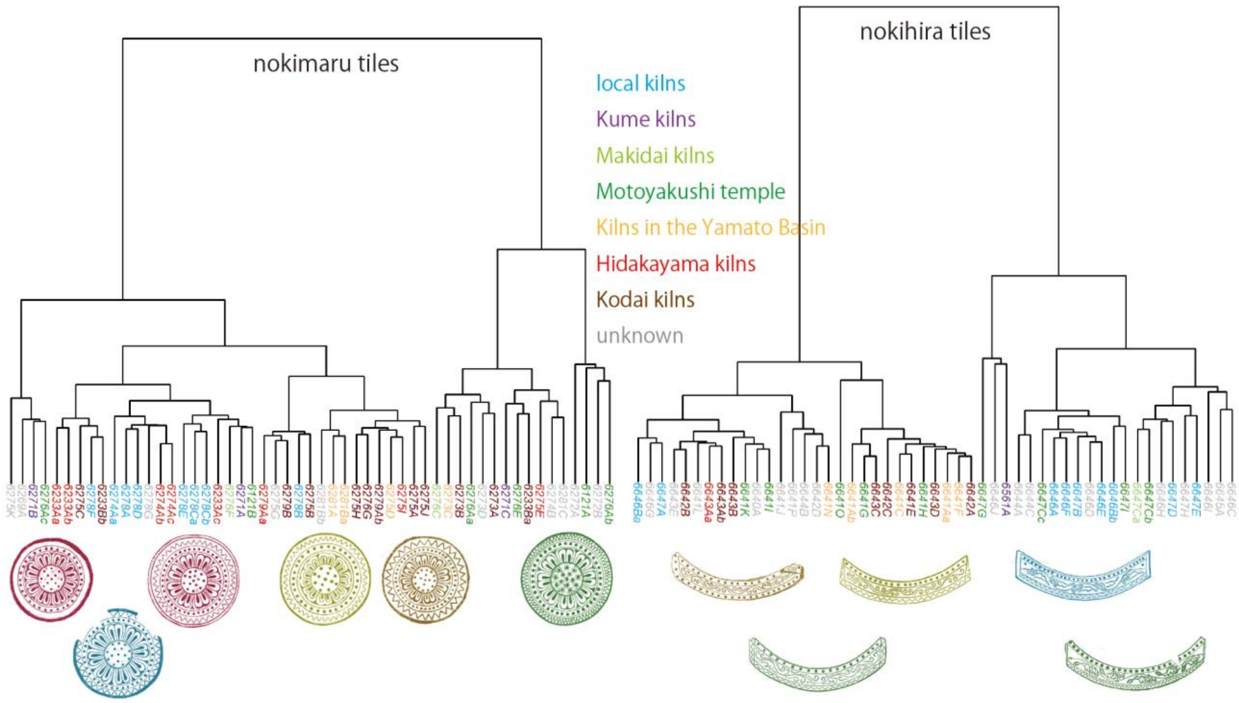

Figure 5. Correlation of the tiles used at Fujiwara Palace.

Figure 5 demonstrates that both the *nokimaru* and *nokihira* tiles are slightly mixed, but there are tiles from local kilns (e.g., the 6274 and 6278 series of the *nokimaru* tiles, and the 6646 and 6647 series of the *nokihira* tiles) and tiles from the Hidakayama kilns (e.g., the 6233 and 6274 series of the *nokimaru* tiles), which are from the early phase of construction of Fujiwara Palace. We recognized the late-phase tiles from the Yamato Basin (e.g., the 6281 series of the *nokimaru* tiles and the 6641 series of the *nokihira* tiles) and those from the Kodai kilns (e.g., the 6273, 6275, and 6279 series of the *nokimaru* tiles and the 6642 and 6643 series of the *nokihira* tiles) as approximate categories. Furthermore, we classified the *nokihira* tiles from the Motoyakushiji and Makidai kilns—which are considered to be the progenitors of these tiles—into two groups (series 6641 and 6647), whereas we did not observe a distinct pattern for the *nokimaru* tiles.

These results indicate that data science techniques can be employed to discern the provenance and production period of the Fujiwara Palace tiles with considerable accuracy. The application of data science techniques has proven highly effective in classifying *nokihira* tiles into two easily comprehensible patterns: one-way palmet arabesque and one-way normal arabesque. Furthermore, data science methods can clearly classify multiple patterns on *nokimaru* tiles, which are so similar that even researchers cannot distinguish them. It is intriguing to observe the manner in which the data science methodology discerns and arranges patterns.

6. Conclusions

This study demonstrates the potential of employing data science methods, specifically image similarity detection and edge feature matching, to differentiate patterns within the broader framework of the *nokimaru* tile configuration. Moreover, MDS and tree diagrams facilitated the identification of the age of each artifact and its place of origin to a certain extent. Notwithstanding, the data science methods we employed were insufficient to determine the typological transitions of tiles, a feature that has been achieved by archaeologists through meticulous analysis of minute alterations in the patterns. Figure 6 depicts a hierarchical representation of the approximate connections among the various types of Todaiji-style *nokihira* tiles, including the 6732 series. The diagram illustrates the relationships between these tile types in a structured and organized manner, providing a clear overview of their interconnections. Although it is commonly accepted that Todaiji-style plain tiles can be categorized into four distinct groups (Todaiji, Kofukuji, Saidaiji, and Heijo Palace) based on their intricate design variations and the locations from which they were excavated, we failed to separate them.

Although we were unable to attain the level of pattern subdivision typically pursued by archaeologists, one cannot say with certainty that the data science approach is ineffective for archaeology. Owing to the inherent relationship between data and methods, and the fact that no single method is consistently effective, a data science approach tailored to a specific pattern can be developed by implementing various techniques in the future.

This methodology can be broadly applied to diverse patterns and images including tile designs. Given that the potential application of data science techniques to the analysis of non-literary textual materials holds promise for uncovering objective and accurate chronological and genealogical relationships on a larger scale, we anticipate significant advancements in this area of research in the coming years.

This work was supported by JSPS KAKENHI (grant number:22H00712; 2022-2026), Cutting-Edge International Research Unit of Nagoya University (2019-2024), and Research Grant of Toyoaki Scholarship Foundation (2019-2020).

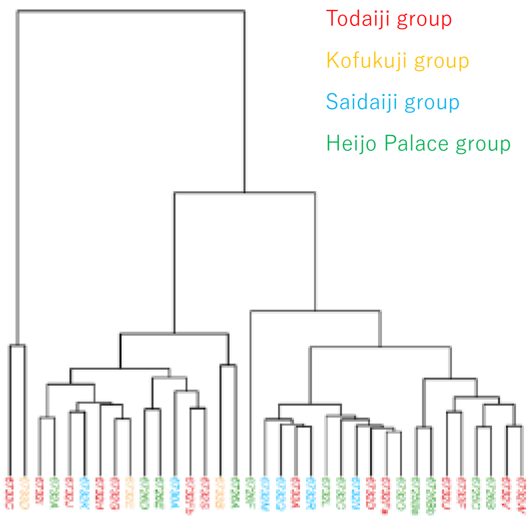

Figure 6. Correlation of the Todaiji-style tiles.

References

1. Inoue, H., Hori, R., Kawanishi, Y., Murase, H., Kajiwara, Y. (2020). The fundamental analysis of cross-sectioned Sueki pottery applied by machine learning of artificial intelligence. Papers and Proceedings of the Japan Association for Archaeoinfomatics, Vol.23, pp.66–71.
2. Fujita, H., Yamamoto, R., Itagaki, M., Ichikawa, K., Miyao, T., Kawahara, K. (2021). Validation of type and age classification criteria by deep learning cluster analysis of pottery 3D-RGB data. Proceedings of the 1st Workshop on Deep Learning of Archaeological and Cultural Properties, pp.1-4.
3. Morimoto, S. (2002). Typology. The Encyclopedia of Japanese Archaeology, pp.251-253. Sanseido.
4. Yokoyama, K. (1985). Typological theory. Iwanami Lecture Series:Japanese Archaeology, Vol.1, pp.43-78. Iwanami Shoten.
5. Yamamoto, T. (2001). Dictionary of Japanese Archaeological Terms.
6. Morimitsu, T., Hanatani, H. (1991). Roof tiles. The Nara Palace site Excavation Report, Vol.13, pp.251-369. Nara National Cultural Properties Reserch Institute (NABUNKEN).
7. Nara National Cultural Properties Reserch Institute (1996). List of Eaves Tile Types Excavated from Heijo and Fujiwara Palace.
8. Fujisawa,K. (1941). Studies of ancient roof tile excavated from Settsu, Kawachi, and Izumi. Buddhist Archaeology Journal.
9. Lowe, D.G. (2004). Distinctive image features from scale-invariant keypoints. International Journal of Computer Vision, Vol.60, pp.91-110. https://doi.org/10.1023/B:VISI.0000029664.99615.94.
10. Muja, M. and Lowe, D.G. (2009). Fast approximate nearest neighbors with automatic algorithm configuration. Proceedings of International Conference on Computer Vision Theory and Applications (VISAPP'09).
11. Kruskal, J.B. (1964). Multidimensional scaling by optimizing goodness of fit to a nonmetric hypothesis. Psychometrika, 29(1), pp.1-27. W. J. Ong, Orality and Literacy: The Technolizing of the World. New York: Methuen & Co Ltd.