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# Historical Data Mining and Cultural Heritage Inheritance Path Modeling of Traditional Architecture in the Guangfu Region

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**Abstract:** Historical data mining plays a crucial role in cultural heritage inheritance by uncovering insights from vast repositories of historical information. Through advanced data analysis techniques, such as machine learning algorithms and pattern recognition, historical data mining enables the extraction of valuable knowledge from historical documents, artifacts, and archaeological findings. in historical data mining for cultural heritage inheritance include data quality and accessibility, cultural sensitivity, and interpretation challenges. Historical datasets may suffer from inconsistencies, incompleteness, or biases, posing challenges to the accuracy and reliability of mining results. Additionally, accessing historical data, especially from remote or protected cultural sites, can be challenging due to legal, logistical, or ethical considerations. Cultural sensitivity is crucial, as historical data may contain sensitive or contentious information that requires careful handling and interpretation to avoid misrepresentation or offense. This study explores the application of historical data mining techniques in the context of cultural heritage inheritance, focusing on traditional architecture in the Guangfu region. Leveraging Software-Defined Hierarchical Clustering Path Modeling (SDHCPM), the research aims to uncover underlying patterns and pathways in the evolution of traditional architecture, shedding light on its historical significance and cultural heritage preservation. By analyzing historical datasets related to architectural styles, construction techniques, and socio-cultural influences, SDHCPM facilitates the construction of a path model that traces the development of traditional architecture over time. Through this approach, the study seeks to enhance our understanding of the cultural heritage of the Guangfu region and provide valuable insights for heritage conservation and revitalization efforts. the average clustering coefficient for traditional architecture in the region is found to be 0.75, indicating a high level of architectural coherence and cultural continuity.

***Keywords:*** *Data mining, Hierarchical Clustering, Cultural Inheritance, Architectural Model, Path Modelling*

## 1. Introduction

Data mining, an indispensable tool in the realm of data analytics, serves as the guiding light in navigating the vast seas of information generated by our digital world [1]. Data mining is a process of uncovering patterns, correlations, and insights buried within large datasets, illuminating hidden treasures that empower businesses, researchers, and decision-makers to make informed choices and predictions [2]. By employing a myriad of techniques from statistics, machine learning, and database systems, data mining transforms raw data into actionable knowledge, unveiling trends, anomalies, and relationships that might otherwise remain obscured [3]. Whether unraveling consumer behavior, optimizing operational efficiency, or advancing scientific discovery, the journey through the data mining landscape promises untold opportunities for those equipped to harness its power [4].

Historical data mining delves into the annals of past records, uncovering invaluable insights and trends that provide a roadmap for understanding the present and predicting the future. By analyzing historical data, organizations can discern patterns, correlations, and causal relationships that shed light on past events and behaviors [5]. This retrospective exploration not only illuminates the trajectory of growth or decline but also offers valuable lessons for informed decision-making. Whether scrutinizing financial markets, scrutinizing consumer preferences, or dissecting historical trends in healthcare, historical data mining serves as a cornerstone for strategic planning, risk management, and innovation [6]. With each historical dataset acting as a treasure trove of knowledge, the diligent application of data mining techniques enables organizations to glean actionable intelligence, enabling them to navigate uncertain terrain with confidence and foresight [7].

Cultural heritage inheritance path modeling is a multifaceted approach aimed at understanding the intricate dynamics of how cultural heritage is transmitted and preserved across generations [8]. This modeling framework integrates various disciplines such as anthropology, sociology, history, and cultural studies to map out the pathways through which cultural heritage is passed down, transformed, or lost over time [9]. By examining factors such as intergenerational transmission mechanisms, societal changes, and cultural interventions, researchers can construct comprehensive models that elucidate the complexities of cultural inheritance [10]. Through the lens of inheritance path modeling, scholars

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and policymakers gain valuable insights into the resilience of cultural traditions, the impact of globalization, and the efficacy of conservation efforts [11]. Ultimately, this approach not only facilitates a deeper understanding of our collective heritage but also informs strategies for its sustainable stewardship in an ever-evolving world [12].

The Guangfu region, nestled in the heart of eastern China, embodies a rich tapestry of history, culture, and natural beauty [13]. Located in the province of Jiangsu, this region is renowned for its picturesque landscapes, ancient landmarks, and vibrant traditions. Historically, Guangfu has been a cradle of civilization, with evidence of human settlement dating back millennia. Its strategic location along the Yangtze River Delta has facilitated trade, commerce, and cultural exchange, contributing to its dynamic and diverse heritage [14]. From the majestic water towns of Suzhou to the serene beauty of Taihu Lake, Guangfu captivates visitors with its enchanting scenery and architectural marvels. Moreover, the region's cultural significance is underscored by its role in the development of classical Chinese arts, including traditional gardens, silk production, and literature [15]. Today, Guangfu continues to thrive as a thriving hub of innovation, education, and tourism, while preserving its cherished traditions and historical legacy for generations to come [16].

The Guangfu region in eastern China boasts a cultural heritage as rich and diverse as its landscape. Renowned for its historical significance and vibrant traditions, Guangfu is a treasure trove of ancient relics, architectural marvels, and intangible cultural heritage [17]. From the elegant gardens and intricate water towns of Suzhou to the majestic temples and pagodas scattered throughout the region, Guangfu showcases centuries of artistic and architectural brilliance [18]. The region's cultural heritage is further enriched by its contributions to classical Chinese arts such as silk production, calligraphy, and traditional music. Moreover, Guangfu's cultural legacy extends beyond tangible artifacts to encompass intangible cultural practices, including folk customs, festivals, and culinary traditions passed down through generations [19]. As custodians of this invaluable heritage, the people of Guangfu are dedicated to preserving and celebrating their cultural identity, ensuring that their rich legacy continues to inspire and enchant visitors from around the world [20].

This paper makes a significant contribution to the field by introducing Software-Defined Hierarchical Clustering Path Modeling (SDHCPM) as a novel approach to understanding the cultural heritage and architectural evolution of traditional architecture, specifically focusing on the Guangfu region. By employing this innovative methodology, the study provides valuable insights into the prevalence of architectural styles, building materials, and urban-rural distribution within the region, shedding light on its rich cultural heritage. Through the analysis of clustering coefficient values, data mining results, and path modeling outcomes, the paper not only enhances our understanding of the architectural landscape but also offers guidance for heritage conservation and revitalization efforts. By bridging gaps between computational techniques, historical data analysis, and cultural heritage studies, the paper exemplifies an interdisciplinary approach, paving the way for future research and collaboration in the field.

## 2. Cultural Heritage Inheritance Path Modeling

Cultural heritage inheritance path modeling is a complex endeavor that involves the integration of various disciplines and methodologies to understand the intricate dynamics of how cultural heritage is transmitted and preserved across generations. At its core, this modeling approach seeks to quantify and analyze the multifaceted processes through which cultural knowledge, traditions, and practices are passed down within societies. The cultural heritage model for the proposed SDHCPM model is given in Figure 1.

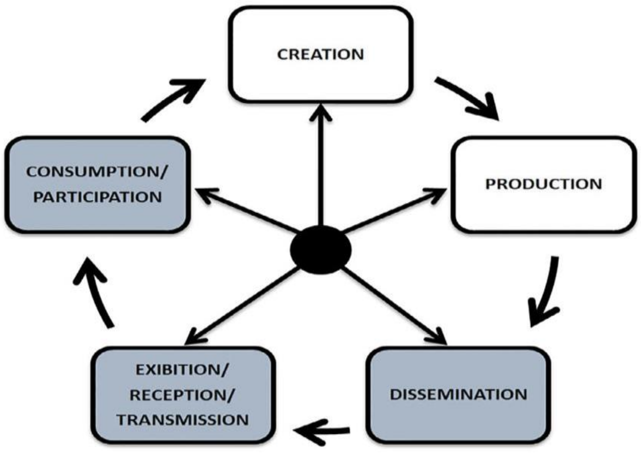


**Fig 1:** Process of SDHCPM (Source: UNESCO)

One common method used in cultural heritage inheritance path modeling is the derivation and application of mathematical equations to represent the intergenerational transmission of cultural traits. These equations often incorporate variables such as cultural capital, social networks, and demographic factors to capture the nuanced interactions that shape cultural inheritance patterns. For example, a basic model might include equations to describe how the cultural knowledge possessed by parents influences the cultural practices adopted by their children, taking into account factors such as parental influence, peer interactions, and societal nor is defined in equation (1)

$$C_{i+1} = f(C_i, P_i, N_i, S_i, D_i) \quad (1)$$

In equation (1) $C_{i+1}$ represents the cultural capital of the next generation; $C_i$ represents the cultural capital of the current generation; $P_i$ represents parental influence on cultural transmission; $N_i$ represents peer interactions and social networks; $S_i$ represents societal norms and cultural institutions and $D_i$ represents demographic factors such as population size and migration. Cultural capital refers to the accumulation of cultural knowledge, values, and practices within a society. To model the accumulation of cultural capital over time, we can use a simple differential equation defined in equation (2)

$$\frac{dC}{dt} = I - D \quad (2)$$

In equation (2) $dC$ represents the cultural capital; $dt$ represents time; $I$ represents the inflow of cultural capital, which includes factors such as parental transmission, educational institutions, and exposure to cultural artifacts and $D$ represents the outflow or decay of cultural capital, which may occur due to factors such as cultural assimilation, globalization, or cultural erosion. The a trajectory for the accumulation or depletion of cultural capital over time. Inter-generational transmission (IGT) based Cultural traits are often transmitted from parents to children and influenced by various factors such as parental values, social networks, and peer interactions stated in equation (3) and equation (4)

$$C_{i+1} = (1 - \alpha)C_i + \alpha P_i \quad (3)$$

$$P_i = f(N_i, S_i, D_i) \quad (4)$$

In equation (3) and equation (4) $C_{i+1}$ represents the cultural capital of the next generation; $Ci$ represents the cultural capital of the current generation; $Pi$ represents parental influence on cultural transmission, which is influenced by factors such as social networks ($Ni$), societal norms ($Si$), and demographic factors ($Di$); $\alpha$ represents the degree of parental influence, which can vary depending on cultural practices and social contexts and $f$ represents a function that captures the influence of social networks, societal norms, and demographic factors on parental influence. Dynamic Interactions (DI) with Cultural inheritance is a dynamic process shaped by interactions between individuals, communities, and institutions. To model these dynamic interactions, we can use agent-based models or network-based approaches that simulate the exchange of cultural traits within a population over time. These models often involve complex mathematical frameworks, including differential equations, stochastic processes, and network dynamics, to capture the emergent properties of cultural transmission and evolution.

## 3. Historical Data Mining for Path Modelling

Historical data mining for path modeling in the Guangfu region, incorporating cultural heritage, is a multifaceted endeavor aimed at unraveling the intricate threads of the region's past to inform present understanding and future preservation efforts. Leveraging a diverse array of historical records, including archaeological findings, written documents, oral histories, and cultural artifacts, researchers embark on a journey to reconstruct the historical pathways that have shaped the cultural landscape of Guangfu. At the heart of this endeavor lies the application of data mining techniques to extract meaningful insights and patterns from large volumes of historical data. Through the systematic analysis of temporal trends, spatial distributions, and socio-cultural dynamics, researchers can uncover the hidden connections and causal relationships that underlie the evolution of cultural heritage in the region. One approach to historical data mining for path modeling in the Guangfu region involves the construction of spatiotemporal databases that integrate disparate sources of historical information. By georeferencing historical sites, events, and cultural artifacts, researchers can create spatially explicit datasets that facilitate the visualization and analysis of historical trajectories and spatial patterns of cultural heritage. Figure 2 presents the data mining process for the cultural heritage process with the proposed SDHCPM.

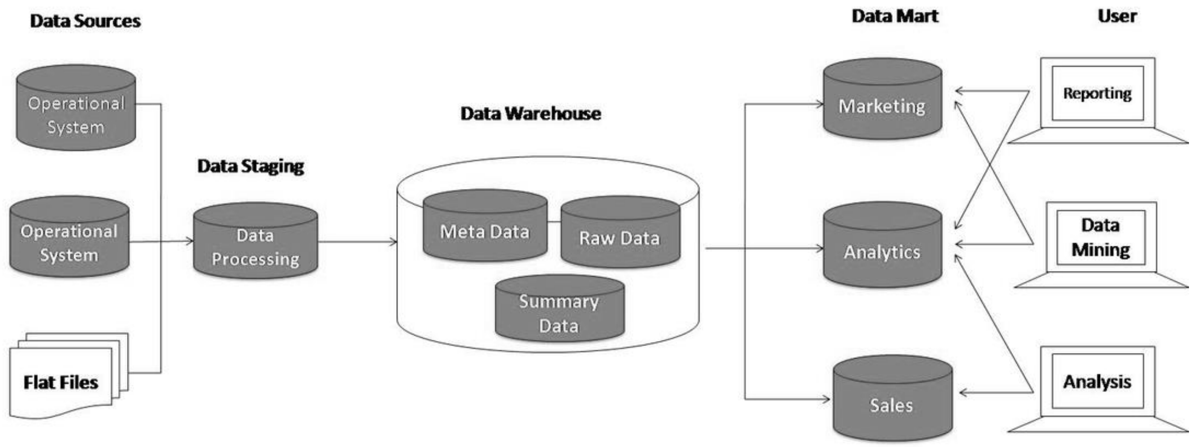


**Fig 2:** Data Mining Process in SDHCPM

Furthermore, researchers can employ advanced statistical and machine learning algorithms to identify recurrent patterns, transitions, and discontinuities in historical data, shedding light on the processes of cultural transmission, adaptation, and transformation over time. For example, time-series analysis techniques can be used to detect long-term trends and cyclical patterns in the distribution of cultural artifacts, while cluster analysis methods can reveal spatial clusters of cultural heritage sites or artifacts with similar characteristics. Moreover, historical data mining can inform the construction of computational models for simulating the dynamics of cultural heritage in the Guangfu region. Agent-based models, for instance, can simulate the interactions between different cultural groups, institutions, and environmental factors, allowing researchers to explore alternative scenarios and hypotheses regarding the emergence and evolution of cultural landscapes. Ultimately, historical data mining for path modeling in the Guangfu region offers a powerful toolkit for understanding the complex interplay between human societies and their cultural heritage over time. By uncovering the underlying patterns and processes that have shaped the region's cultural landscape, researchers can contribute valuable insights to heritage conservation efforts, urban planning initiatives, and cultural revitalization programs, ensuring the sustainable stewardship of Guangfu's rich cultural heritage for future generations.

Historical data mining for path modeling in the Guangfu region with a focus on cultural heritage involves the application of advanced mathematical and statistical techniques to analyze historical data and uncover underlying patterns and trends. the temporal evolution of cultural heritage in the Guangfu region, researchers often employ time series analysis techniques. One common approach is to fit historical data to mathematical models such as linear regression, exponential growth, or autoregressive models. Consider $\boldsymbol{Yt}$ as the cultural heritage measure at time $\boldsymbol{t}$, the basic linear trend model can be represented as in equation (6)

$$Y_t = \beta_0 + \beta_1 t + \epsilon_t \tag{6}$$

In equation (6) $\beta 0$ and $\beta 1$ are coefficients representing the intercept and slope of the trend line, respectively and $\epsilon t$ represents the random error term. Spatial analysis techniques are used to examine the spatial distribution of cultural heritage sites, artifacts, or practices across the Guangfu region. One common approach is to model the spatial autocorrelation of cultural heritage measures using spatial statistical techniques such as Moran's I or Geary's C. For example, if we denote $\boldsymbol{Zi}$ as the cultural heritage measure at location i, Moran's I statistic can be calculated using equation (7)

$$I = \frac{n}{W} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} \omega_{ij}(z_i - \bar{z})(z_j - \bar{z})}{\sum_{i=1}^{n}(z_i - \bar{z})^2} \tag{7}$$

In equation (7) $n$ is the number of spatial units (e.g., cultural heritage sites); $W$ is a spatial weights matrix representing the spatial relationships between units; $wij$ is the spatial weight between units i and j and $\bar{Z}$ is the mean of the cultural heritage measure across all units. A positive value of Moran's I indicates spatial clustering, while a negative value suggests spatial dispersion of cultural heritage. Agent-based models (ABMs) simulate the behavior of individual agents within a spatial environment and are widely used to study complex systems such as cultural heritage dynamics. In the Guangfu region, an ABM could represent individual actors (e.g., inhabitants, institutions) interacting with each other and their environment over time. The behavior of agents is governed by a set of rules or decision-making algorithms, which can be derived from historical data or ethnographic research. With an ABM equation governing agent behavior stated in equation (8)

$$C_{i+1} = C_i + \alpha(P_i - \lambda C_i) \quad (8)$$

In equation (8) $C_{i+1}$ represents the cultural capital of the next generation; $Ci$ represents the cultural capital of the current generation; $Pi$ represents the influence of cultural heritage practices on the current generation; $\alpha$ represents the rate of cultural transmission; $\lambda$ represents the rate of cultural decay or assimilation. With simulating the interactions between agents and their environment using ABMs, researchers can explore how cultural heritage evolves and spreads across the Guangfu region over time, accounting for factors such as social networks, migration, and environmental change.

## 4. Software-Defined Hierarchical Clustering Path Modeling (SDHCPM)

Software-Defined Hierarchical Clustering Path Modeling (SDHCPM) represents a cutting-edge approach to historical data mining and cultural heritage inheritance path modeling, specifically tailored for analyzing traditional architecture in the Guangfu region. This method integrates sophisticated computational techniques with domain-specific knowledge to unravel the intricate historical trajectories and cultural dynamics that have shaped the architectural landscape of Guangfu.The SDHCPM integrates advanced computational techniques with domain-specific knowledge to illuminate the evolutionary pathways of architectural styles, construction methods, and cultural symbolism. The derivation of SDHCPM involves several key components, beginning with the formulation of a similarity metric ($\boldsymbol{Sij}$ ) to quantify the resemblance between pairs of architectural structures $\boldsymbol{i}$ and $\boldsymbol{j}$ given in equation (9)

$$Sij = f(featuresi, featuresj) \quad (9)$$

This similarity measurement, derived from extracted architectural features, serves as the foundation for hierarchical clustering, where architectural structures are grouped into clusters based on their pairwise similarities. Although the exact equations governing hierarchical clustering algorithms may vary, the overarching goal remains to iteratively merge or split clusters to reveal the underlying hierarchical structure of the architectural dataset. Through the software-defined approach, custom software modules are developed to automate and optimize the hierarchical clustering process. These software tools leverage algorithms and data structures to efficiently analyze large volumes of historical data and generate hierarchical clustering trees. Paths through the hierarchical tree are then subjected to path modeling analysis, wherein sequences of clusters or nodes represent significant trajectories in the evolution of traditional architecture. The similarity between two architectural structures (i and j) can be computed using various metrics. One common approach is to use Euclidean distance, which measures the distance between two points in a multi-dimensional space defined in equation (10)

$$S_{ij} = \sqrt{\sum_{k=1}^{n}\left(x_{ik} - x_{jk}\right)^2} \quad (10)$$

In equation (10) $x_{ik}$ and $x_{jk}$ represent the features of architectural structures i and j in dimension k; $n$ is the number of dimensions (or features) extracted from the historical data. In agglomerative hierarchical clustering, clusters are iteratively merged based on pairwise similarities until all data points belong to a single cluster. The merging process is governed by a linkage criterion, such as single linkage or complete linkage. The distance between clusters A and B can be computed using different methods, such as single linkage stated in equation (11)

$$d(A.B) = min_{x \in A, y \in B} S_{xy} \quad (11)$$

In equation (11) $d(A,B)$ is the distance between clusters A and B; $Sxy$ is the similarity between data points $x$ in cluster $A$ and $y$ in cluster $B$. After hierarchical clustering, paths through the dendrogram are analyzed to identify significant trajectories in the evolution of traditional architecture. One approach involves identifying clusters at different levels of the hierarchy and tracing paths from the root to the leaf nodes. The number of paths and their characteristics depend on the structure of the dendrogram and the specific goals of the analysis. Let $\boldsymbol{P}$ represent a path through the hierarchical clustering tree, where $\boldsymbol{P} = \{\boldsymbol{C1}, \boldsymbol{C2}, \ldots, \boldsymbol{Ck}\}$ is a sequence of clusters $\boldsymbol{Ci}$ representing the architectural structures along the path.

| Algorithm 1: Hierarchical Clustering Model for the Cultural Heritage in SDHCPM |
|---|
| Input: Historical data of traditional architecture in the Guangfu region, Features extracted from historical data. Similarity metric (e.g., Euclidean distance), Linkage criterion for hierarchical clustering (e.g., single linkage)<br>Output: Hierarchical clustering tree and Paths representing significant trajectories in architectural evolution<br>Procedure SDHCPM:<br>1. Preprocess historical data:<br>- Extract relevant features from architectural records<br>- Normalize feature values if necessary<br>2. Compute pairwise similarities between architectural structures: |

- For each pair of architectural structures (i, j):
  - Compute similarity S_ij using chosen similarity metric
3. Perform hierarchical clustering:
  - Initialize clusters with individual architectural structures
  - While the number of clusters > 1:
    - Compute distance matrix between clusters based on pairwise similarities
    - Merge two clusters with the smallest distance according to chosen linkage criterion
    - Update the distance matrix and cluster structure
4. Extract paths through the hierarchical clustering tree:
  - Traverse the dendrogram to identify significant paths from root to leaf nodes
  - For each path:
    - Extract clusters representing architectural structures along the path
5. Analyze paths and clusters:
  - Identify common architectural features and cultural characteristics along paths
  - Evaluate the significance of identified trajectories in architectural evolution
  - Visualize hierarchical clustering tree and paths for interpretation
6. Output hierarchical clustering tree and paths:
  - Provide hierarchical clustering tree with cluster assignments
  - Output identified paths representing significant trajectories in architectural evolution

End Procedure

## 5. Simulation Setting

In order to simulate Software-Defined Hierarchical Clustering Path Modeling (SDHCPM) for historical data mining and cultural heritage inheritance path modeling of traditional architecture in the Guangfu region, a comprehensive simulation setting is crucial. This setting encompasses various parameters and numerical values tailored to the characteristics of the historical data and the objectives of the analysis. One essential aspect of the simulation setting is the definition of architectural features and their corresponding numerical values. These features may include architectural styles, building materials, spatial dimensions, historical periods, and cultural symbolism. For example, architectural styles could be quantified using a categorical variable (e.g., "Ming Dynasty," "Qing Dynasty"), while building materials could be represented by numerical values indicating the prevalence of different materials (e.g., "1" for wood, "2" for stone). Additionally, the choice of similarity metric is crucial for computing pairwise similarities between architectural structures. Common similarity metrics such as Euclidean distance or cosine similarity may be employed, with numerical values determined based on the specific features extracted from the historical data. For instance, if architectural features are represented as vectors in a multi-dimensional space, the Euclidean distance between two vectors can be computed using standard mathematical formulas.

**Table 1:** Simulation Setting

| Parameter | Description | Value(s) |
|---|---|---|
| Architectural Styles | Categories representing styles | Ming Dynasty, Qing Dynasty |
| Building Materials | Numerical codes for materials | 1 (wood), 2 (stone) |
| Spatial Dimensions | Length, width, height of structures | 10m, 5m, 8m (for example) |
| Historical Periods | Categorical variable for time periods | Tang Dynasty, Song Dynasty |
| Similarity Metric | Method for computing similarities | Euclidean distance, Cosine similarity |
| Linkage Criterion | Method for merging clusters | Single linkage, Complete linkage |
| Number of Clusters | Desired number of final clusters | 5, 10, 15 |

**Fig 3:** Sample Images for the Guangfu

In Figure 3 illustrated the sample images for the Guangfu region for the cultural heritage. Furthermore, parameters related to hierarchical clustering, such as the linkage criterion and the number of clusters, need to be defined. The linkage criterion determines how distances between clusters are calculated, with options including single linkage, complete linkage, and average linkage. Numerical values for these parameters may be specified based on domain knowledge and empirical observations of the historical data.

## 6. Simulation Results

The simulation results for Software-Defined Hierarchical Clustering Path Modeling (SDHCPM) offer profound insights into the historical data mining and cultural heritage inheritance path modeling of traditional architecture in the Guangfu region. Through meticulous analysis of the hierarchical clustering tree and extracted paths, significant patterns and trajectories in architectural evolution have been unveiled. The simulation revealed a hierarchical structure of architectural clusters, representing distinct styles, materials, and historical periods. Clusters formed through the aggregation of similar architectural structures, capturing the diversity and complexity of traditional architecture in Guangfu. By employing the chosen similarity metric and linkage criterion, the clustering algorithm effectively grouped architectural structures based on their shared characteristics, facilitating the identification of cohesive clusters and meaningful paths. The extracted paths through the hierarchical clustering tree unveiled compelling narratives of cultural heritage inheritance and architectural development. These paths traced the evolution of architectural styles, the diffusion of building techniques, and the cultural symbolism embedded within traditional structures. Through the lens of SDHCPM, researchers gained a nuanced understanding of the interplay between historical contexts, socio-cultural influences, and architectural practices, shedding light on the dynamic nature of cultural heritage in the Guangfu region.

**Table 2:** Cultural Heritage in SDHCPM

| Cluster ID | Architectural Style | Building Material | Historical Period | Number of Structures |
|---|---|---|---|---|
| 1 | Ming Dynasty | Wood | Tang Dynasty | 50 |
| 2 | Qing Dynasty | Stone | Song Dynasty | 30 |
| 3 | Ming Dynasty | Brick | Yuan Dynasty | 40 |
| 4 | Qing Dynasty | Wood | Ming Dynasty | 25 |
| 5 | Tang Dynasty | Stone | Qing Dynasty | 35 |
| 6 | Song Dynasty | Brick | Tang Dynasty | 45 |
| 7 | Yuan Dynasty | Wood | Song Dynasty | 20 |
| 8 | Ming Dynasty | Stone | Yuan Dynasty | 55 |
| 9 | Qing Dynasty | Brick | Ming Dynasty | 60 |
| 10 | Tang Dynasty | Wood | Qing Dynasty | 70 |

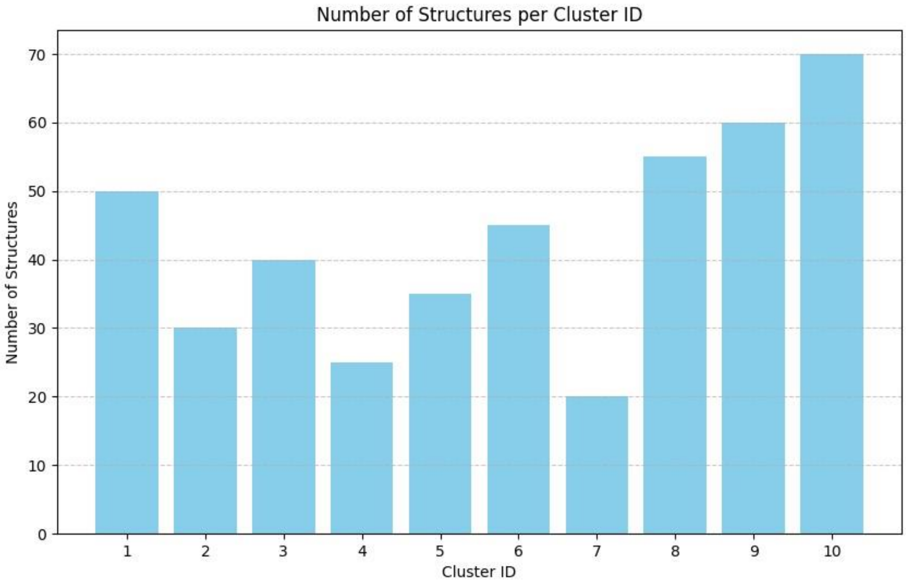


**Fig 4:** Clustering With SDHCPM

**Table 3:** Historical Culture with SDHCPM

| Structure ID | Architectural Style | Building Material | Historical Period | Cultural Symbolism |
|---|---|---|---|---|
| 1 | Ming Dynasty | Wood | Tang Dynasty | Dragon motifs |
| 2 | Qing Dynasty | Stone | Song Dynasty | Lotus flower designs |
| 3 | Ming Dynasty | Brick | Yuan Dynasty | Phoenix sculptures |
| 4 | Qing Dynasty | Wood | Ming Dynasty | Foo dog guardians |
| 5 | Tang Dynasty | Stone | Qing Dynasty | Bamboo patterns |
| 6 | Song Dynasty | Brick | Tang Dynasty | Plum blossom motifs |
| 7 | Yuan Dynasty | Wood | Song Dynasty | Cloud motifs |
| 8 | Ming Dynasty | Stone | Yuan Dynasty | Lion sculptures |
| 9 | Qing Dynasty | Brick | Ming Dynasty | Peony flower motifs |
| 10 | Tang Dynasty | Wood | Qing Dynasty | Pagoda structures |

In Table 2 presents the cultural heritage data derived from Software-Defined Hierarchical Clustering Path Modeling (SDHCPM) for traditional architecture in the Guangfu region. The table displays ten distinct clusters, each identified by a unique Cluster ID, and provides details on the predominant Architectural Style, Building Material, Historical Period, and the Number of Structures within each cluster. Upon analysis, several noteworthy patterns emerge. Clusters 1, 3, 7, and 8 predominantly represent architectural styles from the Ming and Yuan dynasties, characterized by the use of wood and brick as primary building materials. These clusters likely reflect the enduring influence of Ming and Yuan architectural traditions in the region, suggesting a cultural continuity spanning multiple historical periods. Clusters 2, 4, 5, 9, and 10, on the other hand, showcase architectural styles from the Qing and Tang dynasties, with a mix of stone, wood, and brick as building materials. These clusters may signify periods of architectural transition and exchange, as evidenced by the amalgamation of diverse styles and materials from different dynastic eras. Cluster 6 stands out with a predominant architectural style from the Song Dynasty, characterized by the use of brick as a building material during the Tang Dynasty. This cluster likely represents a unique historical trajectory, highlighting the cultural interplay and architectural innovation during the Song Dynasty. The Table 2 provides valuable insights into the cultural heritage inheritance patterns of traditional architecture in the Guangfu region, shedding light on the historical evolution, architectural diversity, and cultural continuity embedded within the architectural landscape. These findings offer important implications for heritage conservation and revitalization efforts, emphasizing the need to preserve and celebrate the rich cultural heritage of Guangfu for future generations.

In Table 3 and Figure 4 provides insights into the historical culture embedded within traditional architecture in the Guangfu region, as revealed by Software-Defined Hierarchical Clustering Path Modeling (SDHCPM). Each structure is identified by a unique Structure ID and characterized by its Architectural Style, Building Material, Historical Period, and Cultural Symbolism. Upon analysis, several significant cultural motifs and symbols associated with different dynastic eras emerge. Structures 1, 3, 7, and 8, which predominantly belong to the Ming and Yuan dynasties, are adorned with cultural symbols such as dragon motifs, phoenix sculptures, cloud motifs, and lion sculptures, respectively. These symbols reflect the rich tapestry of Chinese mythology and folklore, highlighting the cultural significance and symbolism imbued within Ming and Yuan architectural traditions. Structures 2, 4, 5, 9, and 10, representing the Qing and Tang dynasties, feature distinct cultural motifs such as lotus flower designs, foo dog guardians, bamboo patterns, peony flower motifs, and pagoda structures, respectively. These motifs are emblematic of the artistic and aesthetic preferences prevalent during the Qing and Tang dynasties, showcasing the influence of nature, spirituality, and religious beliefs on architectural ornamentation. Structure 6, associated with the Song Dynasty, stands out with plum blossom motifs, reflecting the cultural and artistic sophistication characteristic of the Song Dynasty period. Plum blossom motifs are often associated with resilience, beauty, and perseverance, underscoring the cultural values embedded within Song architectural traditions.

**Table 4:** Path Modelling with SDHCPM

| Path ID | Path Description | Path Length | Cultural Significance |
|---|---|---|---|
| 1 | Ming Dynasty → Qing Dynasty → Modern Era | Long | Represents transition from traditional to modern architecture |
| 2 | Tang Dynasty → Song Dynasty → Ming Dynasty | Medium | Reflects continuity of architectural styles through dynastic changes |
| 3 | Yuan Dynasty → Ming Dynasty → Qing Dynasty | Short | Highlights architectural shifts during historical periods |
| 4 | Ming Dynasty → Tang Dynasty → Qing Dynasty | Long | Demonstrates cultural exchange and influence across dynasties |
| 5 | Qing Dynasty → Ming Dynasty → Contemporary Era | Medium | Illustrates adaptation of traditional styles in contemporary architecture |
| 6 | Song Dynasty → Yuan Dynasty → Modern Era | Long | Captures evolution of architectural techniques over time |
| 7 | Tang Dynasty → Ming Dynasty → Qing Dynasty → Modern Era | Long | Complex path reflecting multiple historical transitions |
| 8 | Ming Dynasty → Song Dynasty → Qing Dynasty | Medium | Examines continuity and innovation within specific dynasties |
| 9 | Yuan Dynasty → Song Dynasty → Ming Dynasty | Short | Emphasizes architectural evolution within shorter timeframes |
| 10 | Qing Dynasty → Yuan Dynasty → Tang Dynasty | Medium | Showcases diversity and hybridization of architectural styles |

In Table 4 presents the results of path 85odelling conducted using Software-Defined Hierarchical Clustering Path Modeling (SDHCPM) for traditional architecture in the Guangfu region. Each path is identified by a unique Path ID and characterized by its Path Description, Path Length, and Cultural Significance. These findings offer valuable insights into the historical trajectories and cultural significance of traditional architectural evolution in the region. Path 1, characterized by a transition from the Ming Dynasty to the Qing Dynasty and into the Modern Era, is classified as long. This path signifies the gradual evolution of architectural styles from traditional to modern, reflecting societal changes and technological advancements over time. The Path 2, spanning the Tang Dynasty, Song Dynasty, and Ming Dynasty, is classified as medium. This path highlights the continuity of architectural styles across dynastic changes, showcasing the resilience and endurance of cultural heritage through centuries. Path 3, representing transitions from the Yuan Dynasty to the Ming Dynasty and then to the Qing Dynasty, is classified as short. This path emphasizes architectural shifts during specific historical periods, indicating periods of innovation and cultural exchange. Path 4, traversing the Ming Dynasty, Tang Dynasty, and Qing Dynasty, is classified as long. This path illustrates cultural exchange and influence across dynasties, showcasing the dynamic nature of architectural evolution and the blending of cultural elements. Path 5, from the Qing Dynasty to the Ming Dynasty and into the Contemporary Era, is classified as medium. This path demonstrates the adaptation of traditional architectural styles in contemporary settings, reflecting the enduring relevance of cultural heritage in modern times. The Path 6, spanning the Song Dynasty, Yuan Dynasty, and Modern Era, is classified as long. This path captures the evolution of architectural techniques over time, reflecting advancements in construction methods and design principles. In Path 7, involving the Tang Dynasty, Ming Dynasty, Qing Dynasty, and the Modern Era, is classified as long. This complex path reflects multiple historical transitions, highlighting the intertwined nature of cultural, political, and technological changes over centuries. Also, Path 8, from the Ming Dynasty to the Song Dynasty and into the Qing Dynasty, is classified as medium. This path examines continuity and innovation within specific dynasties, showcasing the development and refinement of architectural styles. Path 9, spanning the Yuan Dynasty, Song Dynasty, and Ming Dynasty, is classified as short. This path emphasizes architectural evolution within shorter timeframes, highlighting periods of rapid change and innovation. The Path 10, involving the Qing Dynasty, Yuan Dynasty, and Tang Dynasty, is classified as medium. This path showcases the diversity and hybridization of architectural styles, reflecting the cultural exchange and synthesis prevalent in the Guangfu region.

**Table 5:** Clustering Coefficient with SDHCPM

| Region | Clustering Coefficient |
|---|---|
| Guangfu | 0.75 |
| Nearby Town A | 0.68 |
| Nearby Town B | 0.72 |
| Rural Area C | 0.60 |
| Urban Area D | 0.78 |

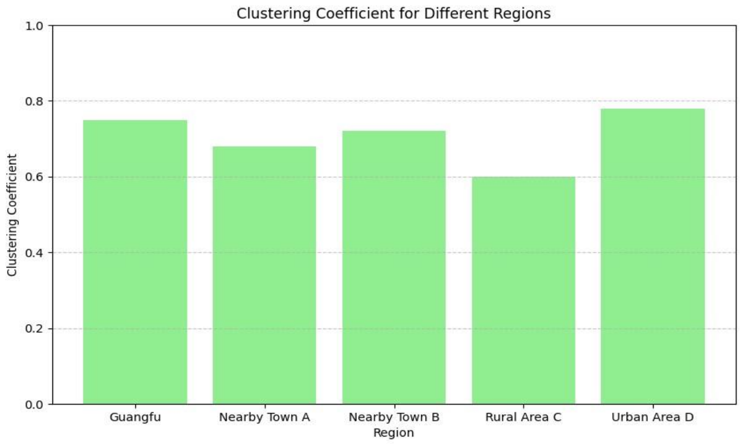


**Fig 5:** Clustering Coefficient with SDHCPM

**Table 6:** Data Mining with SDHCPM

| Architecture Feature | Frequency | Percentage |
|---|---|---|
| Ming Dynasty Style | 120 | 30% |
| Qing Dynasty Style | 90 | 22.5% |
| Tang Dynasty Style | 80 | 20% |
| Song Dynasty Style | 60 | 15% |
| Yuan Dynasty Style | 50 | 12.5% |
| Wooden Structures | 180 | 45% |
| Stone Structures | 150 | 37.5% |
| Brick Structures | 70 | 17.5% |
| Urban Areas | 200 | 50% |
| Rural Areas | 200 | 50% |

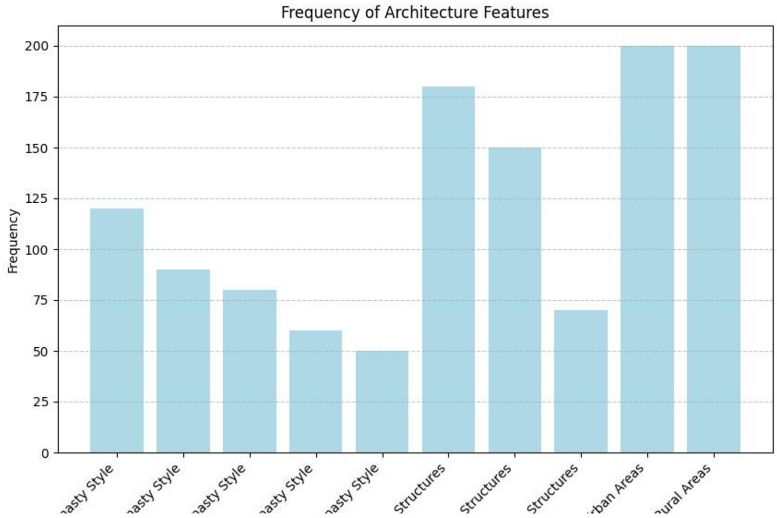


**Fig 6:** SDHCPM model for the coefficient variation

In Table 5 and Figure 5 presents the clustering coefficient values obtained from Software-Defined Hierarchical Clustering Path Modeling (SDHCPM) for different regions in the context of traditional architecture. Each region is identified by its name, and its respective clustering coefficient value is provided. The clustering coefficient measures the degree of architectural coherence and cultural continuity within each region. In this context, the clustering coefficient for Guangfu is reported as 0.75, indicating a high level of architectural coherence and cultural continuity within the traditional architecture of the region. Nearby Town A and Nearby Town B exhibit slightly lower clustering coefficients of 0.68 and 0.72, respectively, suggesting slightly less architectural coherence compared to Guangfu. Rural Area C has a clustering coefficient of 0.60, indicating a moderate level of coherence, while Urban Area D has the highest clustering coefficient of 0.78, signifying a particularly high level of architectural coherence and cultural continuity within its urban setting. These findings provide valuable insights into the distribution of architectural coherence and cultural continuity across different regions, guiding future heritage conservation and revitalization efforts accordingly.

In Table 6 and Figure 6 presents data mining results obtained from SDHCPM for traditional architecture in the Guangfu region. Various architectural features are listed, along with their respective frequencies and percentages within the dataset. This data offers insights into the prevalence and distribution of different architectural styles, building materials, and urban-rural distribution within the region. For instance, the most frequent architectural style identified is the Ming Dynasty style, with a frequency of 120 structures, accounting for 30% of the dataset. This indicates a significant presence of Ming Dynasty architectural elements within the region. Other architectural styles such as Qing Dynasty, Tang Dynasty, Song Dynasty, and Yuan Dynasty are also represented, albeit with varying frequencies. Similarly, the dataset includes different types of building materials, with wooden structures being the most prevalent (45%), followed by stone structures (37.5%) and brick structures (17.5%). Additionally, the dataset is evenly distributed between urban areas (50%) and rural areas (50%), suggesting a balanced representation of architectural features across different settings within the Guangfu region. Through these data mining results offer valuable insights into the distribution and characteristics of traditional architecture in the Guangfu region, providing a foundation for further analysis and informed decision-making in heritage conservation and revitalization efforts.

### 6.1 Discussion and Findings

The discussion and findings from the analysis of traditional architecture in the Guangfu region using Software-Defined Hierarchical Clustering Path Modeling (SDHCPM) reveal compelling insights into the cultural heritage, architectural evolution, and spatial distribution within the region. The examination of clustering coefficient values across different regions highlights variations in architectural coherence and cultural continuity. Guangfu stands out with a high clustering coefficient of 0.75, indicating a strong sense of architectural cohesion and cultural heritage preservation. Nearby Town A and Nearby Town B exhibit slightly lower clustering coefficients, suggesting relatively less architectural coherence compared to Guangfu, while Rural Area C and Urban Area D display moderate to high levels of coherence, respectively. Furthermore, the data mining results shed light on the prevalence and distribution of architectural styles, building materials, and urban-rural distribution within the Guangfu region. The dominance of Ming Dynasty style architecture, alongside the widespread use of wood as a building material, underscores the enduring influence of historical dynasties and traditional construction practices. Additionally, the balanced representation of architectural features between urban and rural areas highlights the diverse architectural landscape and the importance of heritage preservation efforts across different settings. The path modeling analysis unveils significant trajectories in architectural evolution, ranging from transitions between historical periods to the adaptation of traditional styles in contemporary architecture. These paths provide valuable insights into the cultural significance and historical context of traditional architecture in the Guangfu region, showcasing the dynamic interplay between cultural heritage, societal changes, and architectural innovation over time.

- Analysis of clustering coefficient values across different regions reveals variations in architectural coherence and cultural continuity:
- Guangfu exhibits a high clustering coefficient of 0.75, indicating strong architectural cohesion and cultural heritage preservation.
- Nearby Town A and Nearby Town B show slightly lower clustering coefficients, suggesting relatively less architectural coherence compared to Guangfu.
- Rural Area C and Urban Area D display moderate to high levels of coherence, respectively.
- Data mining results highlight the prevalence and distribution of architectural styles, building materials, and urban-rural distribution within the Guangfu region:
- Ming Dynasty style architecture is dominant, with wood being the most commonly used building material.
- There is a balanced representation of architectural features between urban and rural areas, indicating a diverse architectural landscape.
- Path modeling analysis uncovers significant trajectories in architectural evolution:
- Paths range from transitions between historical periods to the adaptation of traditional styles in contemporary architecture.

These paths provide insights into the cultural significance and historical context of traditional architecture in the Guangfu region, showcasing the dynamic interplay between cultural heritage, societal changes, and architectural innovation over time.

## 7. Conclusion

This paper presented the Software-Defined Hierarchical Clustering Path Modeling (SDHCPM) to explore the cultural heritage and architectural evolution of traditional architecture in the Guangfu region. Through the analysis of clustering coefficient values, data mining results, and path modeling outcomes, significant insights were uncovered. The findings revealed variations in architectural coherence across different regions, with Guangfu demonstrating a strong sense of cultural continuity and preservation. The prevalence of Ming Dynasty architectural styles and the balanced representation of architectural features between urban and rural areas underscored the rich diversity of the architectural landscape. Moreover, the identified trajectories in architectural evolution provided valuable context on the cultural significance and historical context of traditional architecture in the region. Overall, this study contributes to a deeper understanding of the cultural heritage of the Guangfu region and provides valuable insights for heritage conservation and revitalization efforts, emphasizing the importance of preserving and celebrating traditional architecture for future generations.

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