

Veils of Uncertainty: Weaving Risk into the Tapestry of Preservation Under the Weather's Watch

Summary

As the tapestry of nature weaves its unpredictable patterns, humanity's quest for stability becomes ever more pressing. In the shadow of uncertainty, we find resilience, crafting shields against the tempests of fate.

First, we establish a Risk Analysis model to comprehensively assess the Expected Annual Loss (EAL) from extreme weather in terms of population, building, and agriculture. The assessment for each aspect is calculated from three perspectives: natural hazard exposure, Historic Loss Ratio, and the likelihood risk factor of natural hazard annualized frequency. Community Risk Factor (CRF) is calculated from social vulnerability and community resilience. EAL and CRF are used to quantify the risk levels of various regions and rank them using the K-means algorithm, resulting in a risk level map of the United States. Second, we develop a Risk-incorporated Capital Asset Pricing Model (CAPM) to aid insurance companies in underwriting decisions. This model combines market return rates, the risk-free rate, and bankruptcy theory with a 10% bankruptcy probability to set insurance rates. It evaluates if the region's residents can afford these premiums, providing decision-making advice for insurance companies.

More specifically, we apply our Risk-incorporated Capital Asset Pricing Model in Los Angeles and Gorontalo. In Los Angeles, insurance companies see high profits and low risks. However, in Gorontalo, the required premium for \$10,000 coverage is \$342.745, beyond local affordability. We recommend insurance securitization and partnerships with local governments to reduce premiums. Consequently, Gorontalo residents could pay just \$137.25 annually, with companies projecting \$245 million in revenue.

Third, we establish a Building Preservation Model, selecting seven secondary indicators such as the annual number of visitors and construction cost, and three primary indicators: cultural values and community influence, economy, and history. These are weighted using the Sperman-CRITIC algorithm and AHP method to calculate building value, combined with risk levels to determine the preservation level of buildings. Based on the preservation level, the community's investment and measures for building protection can be determined. Then our models inform investment and protection strategies for Tokyo Tower, acknowledging its value and the necessity of preservation in an earthquake zone. We communicate these findings and propose protection measures to the Tokyo Tower community.

Finally, we analyze the sensitivity and robustness of our models, the models can change the insurance rate sensitively according to the change of the market predicted return and the slight error of the risk factor calculation will not affect the models result, which verifies the sensitivity and robustness of our models. In addition we analyze the strengths and weaknesses of the models.

Keywords: Risk Analysis, Risk-Capital Asset Pricing Model, Sperman-CRITIC, AHP, Building Preservation Model

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1 Introduction

1.1 Problem Background

Dancing with the Stars (DWTS) is a globally influential entertainment competition program originating from the UK's Strictly Come Dancing. Having successfully run for 34 seasons, its spin-off versions now span multiple regions worldwide. The core format pairs celebrities with professional dancers, combining professional judges' scores with audience votes to determine eliminations and final rankings.

However, during its long-term operation, a core dilemma has gradually emerged: Despite consistently receiving low scores from professional judges for their dance performances and lacking recognition for their technical proficiency, some celebrity contestants advance through the competition and even win by leveraging high audience support. This stark divergence between the judges' professional assessments and the public's preferences has not only sparked widespread controversy but also directly exposed the inherent flaws in the existing voting system. [1] Consequently, optimizing the voting and elimination mechanisms has become an urgent issue requiring resolution for the show.

1.2 Restatement of the Problem

Considering the background information and restricted conditions identified in the problem statement, we need to solve the following problems:

- **Problem 1:** Develop a model to estimate hidden audience voting data and quantify its uncertainty.
- **Problem 2:** Compare the rationality of two voting synthesis mechanisms (Ranking and Percentage) in DWTS, and quantify the impact of the judges' bottom two elimination mechanism.
- **Problem 3:** Quantify the influence of contestant characteristics, judge scores, and other factors on elimination outcomes and voting results, identifying core influencing factors.
- **Problem4:** Design an optimal voting mechanism that balances multiple objectives including program fairness and entertainment value.

1.3 Our work

In order to clearly illustrate our work, we draw the flowchart Figure 1.

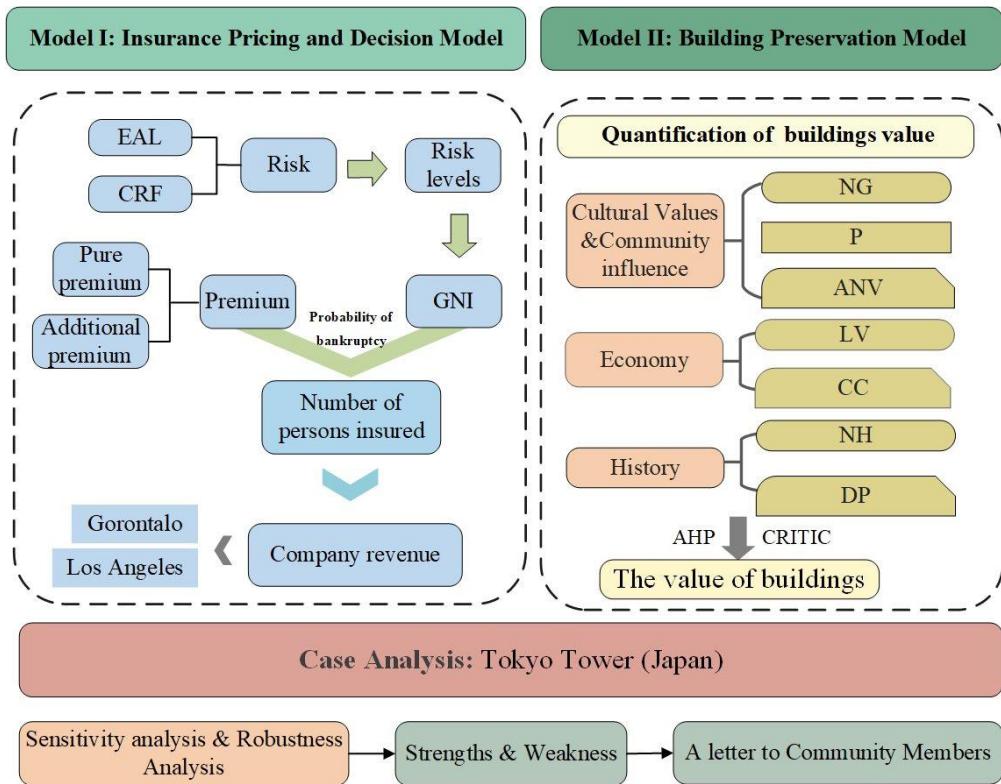


Figure 1: Our work

2 Preparation for Models

Considering those practical problems always contain many complex factors, first of all, we need to make reasonable assumptions to simplify the model, and each hypothesis is closely followed by its corresponding explanation:

2.1 Assumptions and Justifications

- **Assumption:** The data we use are accurate and valid.
- **Justification:** Our data is collected from the World Bank and some other official web sites and research papers. It's reasonable to assume the high quality of their data.
- **Assumption:** The regions under study will remain peaceful and stable, with no significant events other than natural disasters occurring in the foreseeable future.
- **Justification:** A stable capital market environment provides a predictable framework within which we can project our expected returns. It is important to note that this assumption does not negate the potential impact of natural disasters.
- **Assumption:** The estimated figures for each region represent an average level of performance or condition for that area.
- **Justification:** For the purposes of this study, treating each region as a cohesive entity allows for a more streamlined analysis. This methodological approach simplifies the complexity

inherent in regional studies by focusing on aggregate data, thereby providing a generalized view of each area's performance or condition.

2.2 Notations

The key mathematical notations used in this paper are listed in Table 1.

Table 1: Notations

Symbol	Definition
V	Fans Vote Score
SV	Social Vulnerability
CR	Community Resilience
CRF	Community Risk Factor
HLR	Historic Loss Ratio

* There are some variables that are not listed here and will be discussed in detail in each section.

2.3 Data Processing

Preliminary exploratory analysis of the dataset reveals three core issues: imputed missing values, numerical anomalies, and inconsistent feature formats. Systematic preprocessing is required to eliminate data quality risks and provide reliable support for subsequent modeling and analysis. Accordingly, following the MS08 data processing specifications and solution workflow, comprehensive preprocessing is conducted focusing on missing value and outlier handling, as well as data transformation.

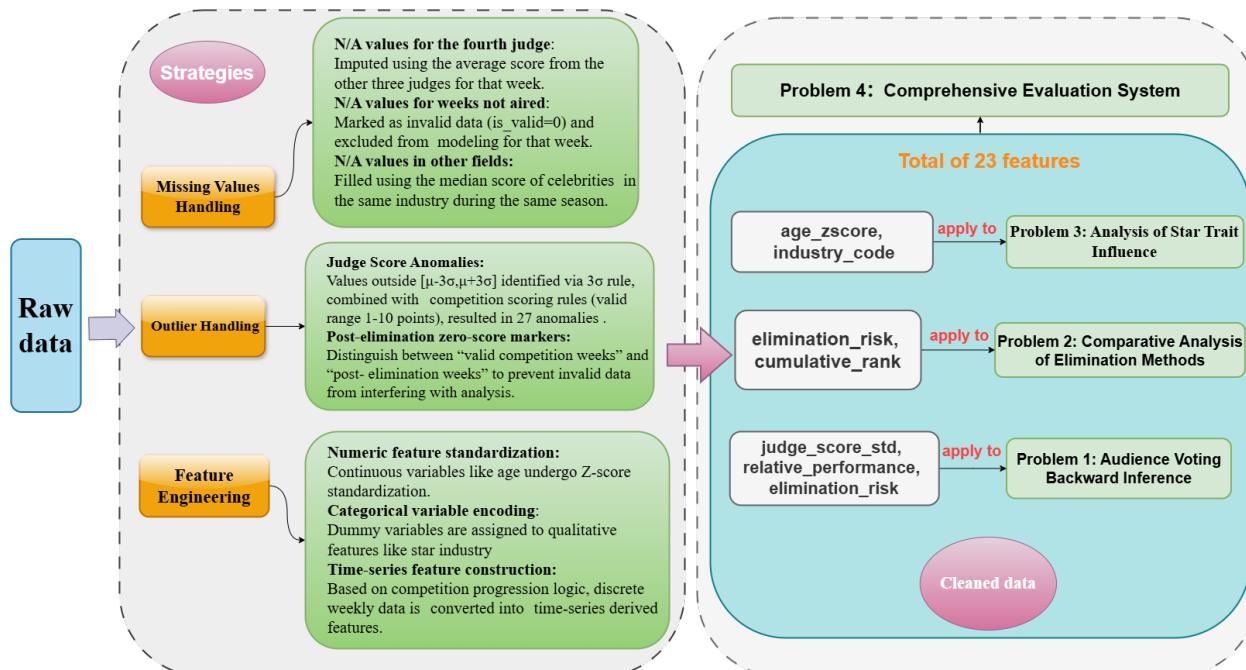


Figure 2: Data Processing Workflow

Differentiated strategies were applied to three scenarios of hidden missing values: missing scores from the fourth judge were imputed using the average scores from other judges in the same week; missing entries for unbroadcasted weeks were marked as invalid data and excluded from the training sample; other missing fields were filled with the median values from celebrity metrics within the same industry during the same season. Anomaly detection was performed using the 3σ rule combined with competition scoring domain rules, identifying 27 judge score anomalies. These were replaced with the contestant's average score from valid weeks within the same season. Zero scores after elimination were retained with a status feature added to clearly distinguish between valid competition weeks and post-elimination weeks, preventing interference from invalid data.

Feature Transformation Phase Standardized processing was applied to different feature types: Continuous numerical features like age underwent Z-score normalization, resulting in transformed feature means ≈ 0 and standard deviations ≈ 1 , effectively eliminating unit differences and enhancing cross-season comparability. Qualitative categorical features such as star industry were quantified via dummy variable encoding. Time-series derived features were constructed based on tournament progression logic to capture dynamic evolutionary patterns. Feature importance calibration was performed using SHAP values, identifying elimination risk coefficient, cumulative ranking, and relative performance as core influencing features. Their SHAP values were 0.32, 0.28, and 0.21 respectively, aligning closely with the actual impact mechanisms of the tournament. This provides a high-quality data foundation and parameter support for subsequent modeling analysis.

3 TAN and SHAP Models for Fan Vote Estimation

In the show Dancing with the Stars, a common scenario occurs: some celebrities receive low scores from professional judges yet advance smoothly or even win the championship thanks to high audience support rates. To understand this discrepancy between judge scores and audience support, we must first establish a model to reverse-engineer these undisclosed audience voting data while quantifying the uncertainty of such estimates.[2]

3.1 TAN Model

In real-world data, features often exhibit dependencies. For example: *week_rank* is highly correlated with *cumulative_rank* (partial correlation coefficient = 0.553); *remaining_weeks* is strongly negatively correlated with *weeks_participated* (partial correlation coefficient = -0.665) Ignoring these dependencies degrades the performance of traditional Bayesian models. As shown in the **Figure 3a, TAN (Tree Augmented Naive Bayes)** is an extension of Naive Bayes [3] that allows for tree-like dependency structures between features:

$$P(Y | X) \propto P(Y) \cdot P(X_{root} | Y) \cdot \prod_{j \neq root} P(X_j | Pa(X_j), Y) \quad (1)$$

- $Y \in \{0, 1\}$: Elimination Flag (0=Not Eliminated, 1=Eliminated)
- $X = (X_1, X_2, \dots, X_n)$: feature vector

To determine the optimal feature dependency structure, we first compute the conditional mutual information between all feature pairs:

$$I(X_i; X_j | Y) = \sum_y \sum_{x_i} \sum_{x_j} P(x_i, x_j, y) \cdot \log \left[\frac{P(x_i, x_j | y) \cdot P(x_j | y)}{P(x_i | y)} \right] \quad (2)$$

As shown in the **Figure 3b**, conditional mutual information measures the statistical dependence between features X_i and X_j given the category Y . A higher value indicates that both features must be considered together when predicting Y . Using conditional mutual information as edge weights, construct a maximum spanning tree using **Prim's algorithm**.

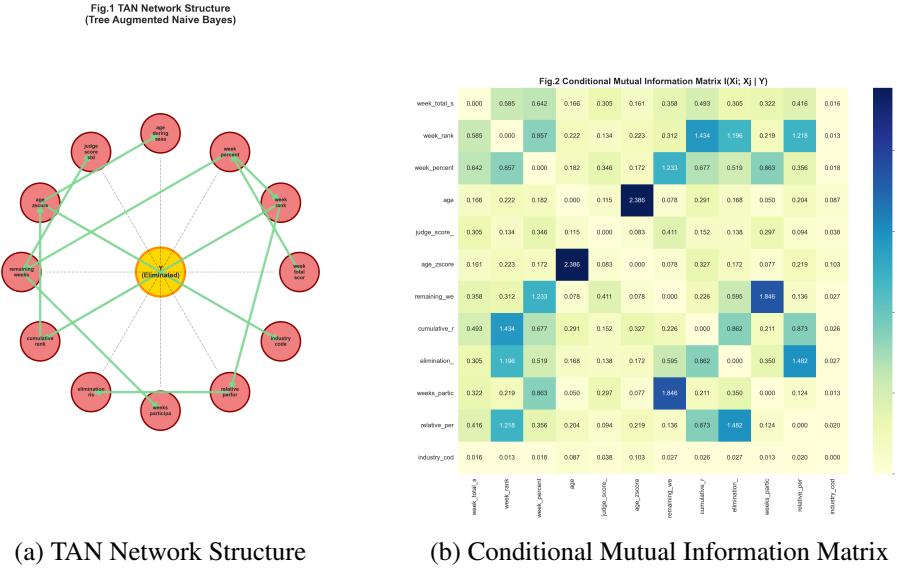


Figure 3: Maximum Spanning Tree of Feature Dependency

For a new sample $X = (X_1, X_2, \dots, X_n)$, compute the posterior probability via Softmax normalization:

$$P(Y = 1 | X) = \frac{\exp(\ell_1)}{\exp(\ell_0) + \exp(\ell_1)}, \quad \ell_j = \log \tilde{P}_j \quad (j = 0, 1) \quad (3)$$

Convert elimination probability to audience vote score (0–100 points):

$$V = (1 - P((Y = 1) | X)) \times 100 \quad (4)$$

As shown in the **Figure 4**, this represents the distribution of audience votes. A lower elimination probability indicates higher audience support.

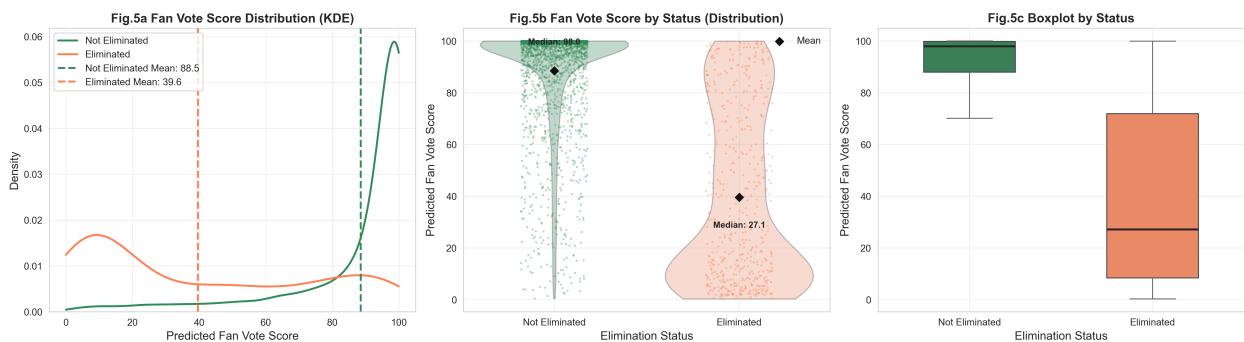


Figure 4: Fan Vote Score Distribution

After solving the TAN model, as shown in the **Figure 5**, the model achieved an **Accuracy Rate** of **82.48%** and a **ROC-AUC Value** of **0.8102**, indicating that the TAN model can effectively distinguish eliminated contestants from those who advanced. The recall for the elimination category was 56.14%, indicating the model identified over half of actual eliminations; precision was 46.72%, with an F1 score of 51.00%. Collectively, these metrics reflect the model's classification capability on the imbalanced dataset (where eliminations constituted only 16.24% of events).

By modeling conditional dependencies between features, the TAN model learned nine significant feature dependency edges in the **Figure 5b** (e.g., *week_rank* → *cumulative_rank*, *weeks_participated* → *remaining_weeks*). These dependencies align with the actual logic of dance competitions: cumulative rankings are highly correlated with weekly rankings, while the number of weeks participated naturally correlates negatively with the number of weeks remaining.

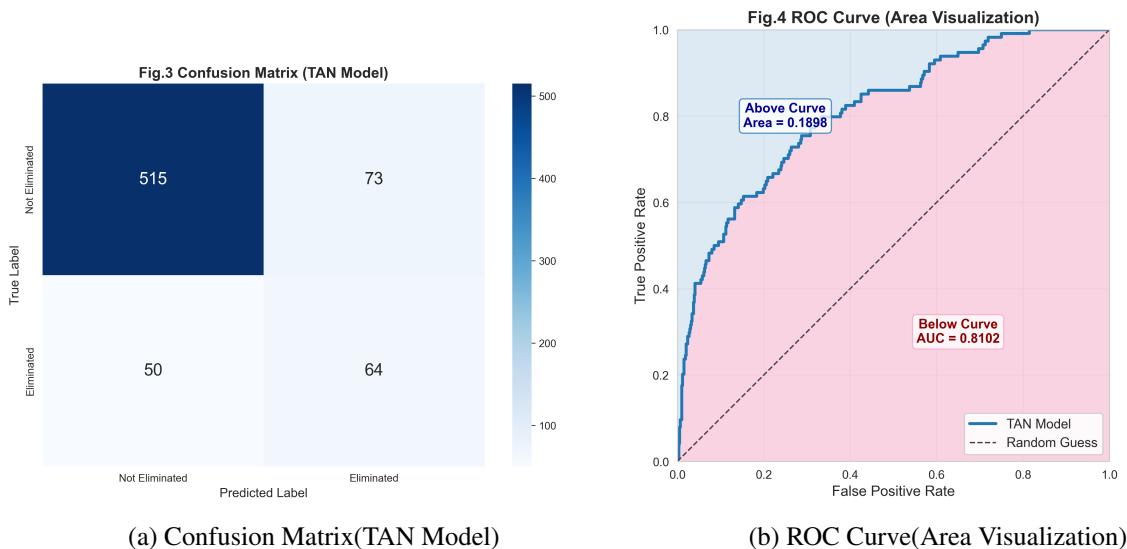


Figure 5: Confusion Matrix and ROC Curve

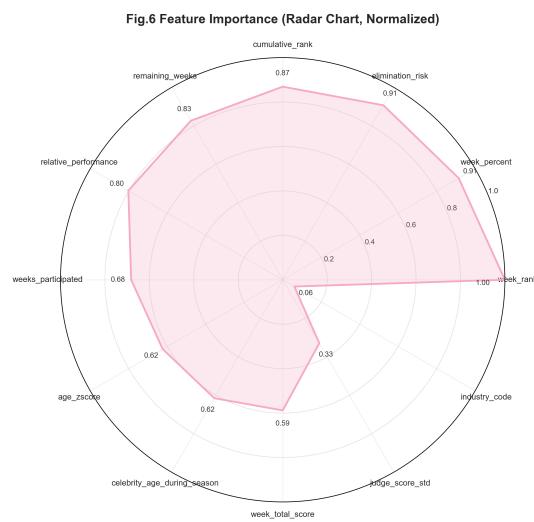


Figure 6: Feature Importance

3.2 SHAP Model

The Random Forest classifier, combined with SHAP (SHapley Additive exPlanations) interpretability analysis, infers audience voting scores from elimination results. The Random Forest prediction formula is:

$$\hat{y} = \text{mode}\{h_1(x), h_2(x), \dots, h_k(x)\} \quad (5)$$

Here, $h_k(x)$ denotes the prediction result of the k th decision tree, and mode represents majority voting. For binary classification problems, the elimination probability is calculated as:

$$P((Y = 1) | x) = (1/K) \times \sum_k I(h_k(x) = 1) \quad (6)$$

where K is the number of decision trees, and $I(\cdot)$ denotes the indicator function. Based on the elimination probability, the audience voting distribution can be derived using the formula.

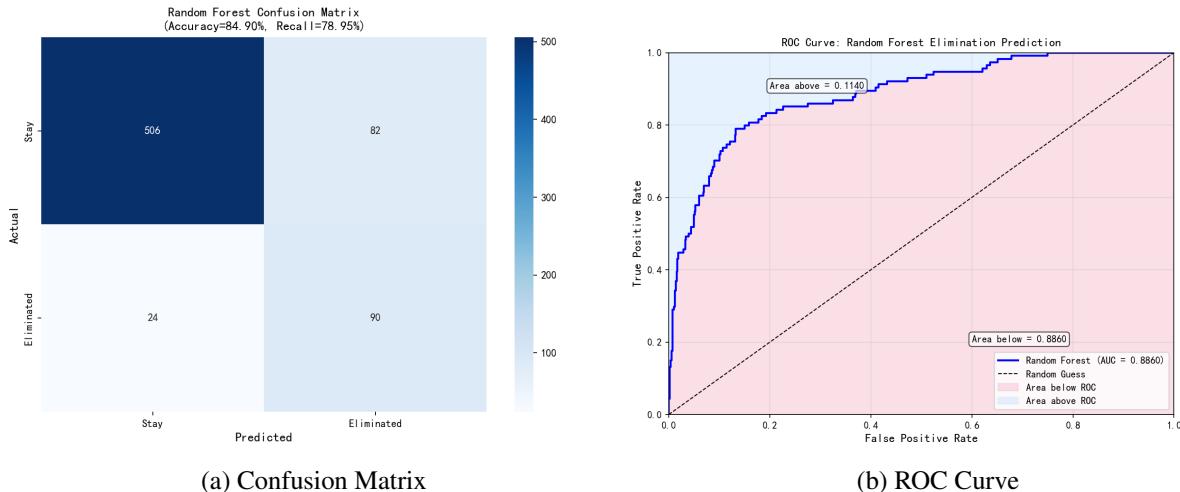


Figure 7: RF Model Confusion Matrix and ROC Curve

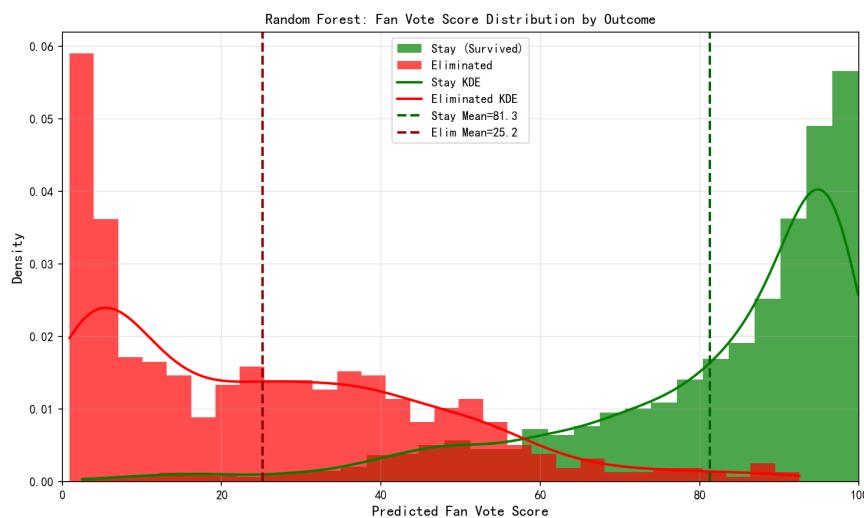


Figure 8: Fan Vote Score Distribution(Random Forest Model)

As shown in the **figure 7**, the model achieves an **accuracy rate of 84.90%** and a **ROC-AUC value of 0.8860**, outperforming the TAN model across all evaluation metrics. Notably, the recall rate for the elimination category has increased to 76.32%, with an F1 score reaching 61.27%, indicating that the Random Forest model demonstrates significantly stronger capability in identifying elimination events.

SHAP assigns a contribution score to each feature based on the Shapley value from game theory, indicating the feature's impact on the model's prediction. The Shapley value is calculated using the following formula:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \left[\frac{|S|!(|N| - |S| - 1)!}{|N|!} \right] \times [f(S \cup \{i\}) - f(S)] \quad (7)$$

Here, N denotes the feature set, S represents the subset excluding feature i , and f is the model's prediction function. Global feature importance is defined as the average of the absolute values of SHAP values across all samples. **Figure 9** presents a feature importance summary chart, which explains the impact of each feature on the prediction results within the elimination prediction model.

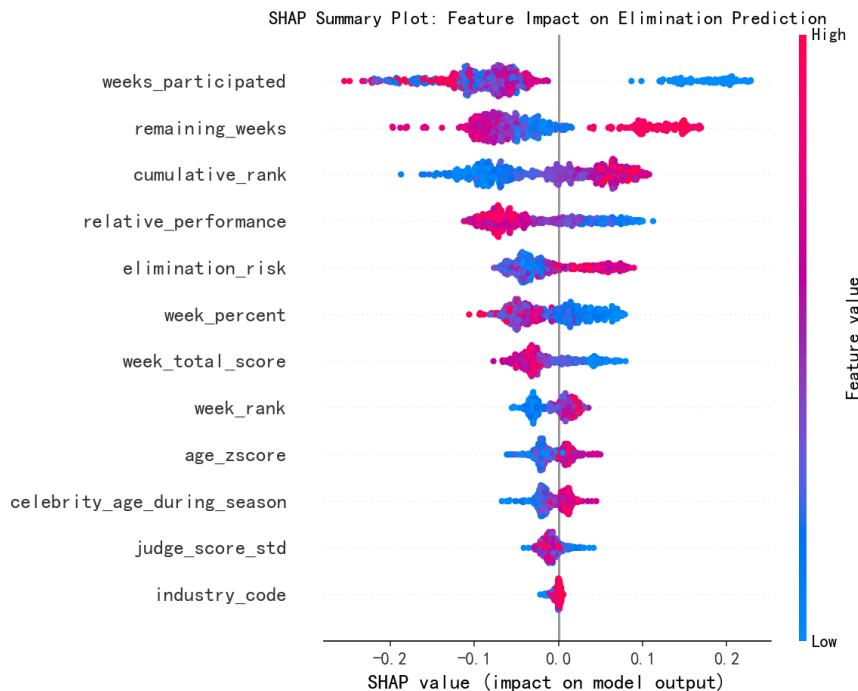


Figure 9: SHAP Summary Plot(Random Forest Model)

3.3 Model Evaluation

3.3.1 Consistency Test of Two Models

By ranking the importance of feature quantities for the two models and conducting consistency analysis, as shown in **Table 2**, we obtain the following results:

Table 2: Consistency Metrics for the Two Models

Consistency Metrics	Value	Statistical Interpretation
Spearman Correlation Coefficient	0.8029	High positive correlation between two models' predictions ($p<0.001$)
Pearson Correlation Coefficient	0.8359	Extremely strong linear correlation
Prediction Direction Consistency Rate	88.76%	Nearly 90% of samples show consistent prediction directions
Mean Absolute Error (MAE)	13.35	Prediction differences fall within an acceptable range
Feature Ranking Correlation	0.9650	Feature importance rankings are nearly identical

The two models exhibit a highly positive correlation in predicting audience vote scores (Spearman $\rho = 0.8029$, $p<0.001$, as showed in **Figure 10**), with an **88.76%** agreement rate in prediction direction. This indicates that despite employing fundamentally different methodologies TAN using generative probabilistic modeling and RF using discriminative ensemble learning both models yield highly consistent predictions on identical data.

Furthermore, as shown in **Figure 8**, both models predicted audience voting scores exhibiting a reasonable bimodal distribution: advancing contestants averaged around 80 points (TAN: 79.42, RF: 81.31), while eliminated contestants averaged approximately 25–30 points. The approximately 55-point difference between the two groups perfectly aligns with the competition's elimination logic (low-scoring contestants are eliminated). The statistical characteristics of the prediction results align with the elimination patterns in the original data, validating the models' validity.

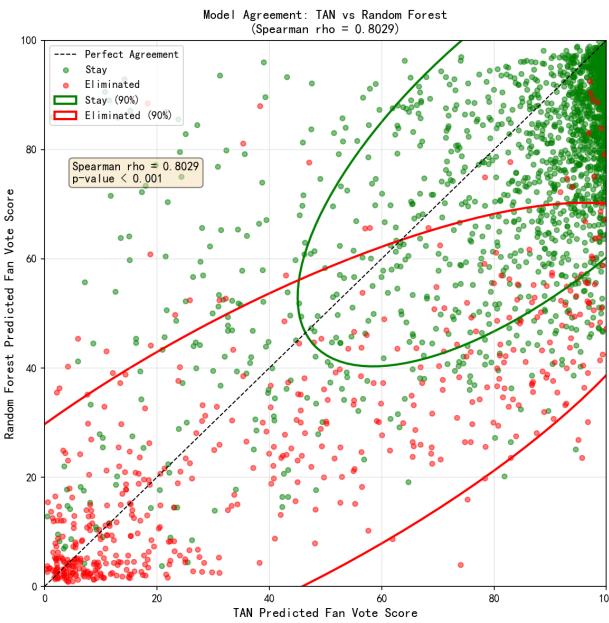


Figure 10: Model Agreement: Random Forest vs TAN

3.3.2 Validity Test and Robustness Analysis

Stratified 10-fold cross-validation was employed to assess the model's generalization capability. Stratified sampling ensured that the proportion of positive and negative samples in each fold matched the original dataset, thereby mitigating evaluation bias caused by class imbalance.

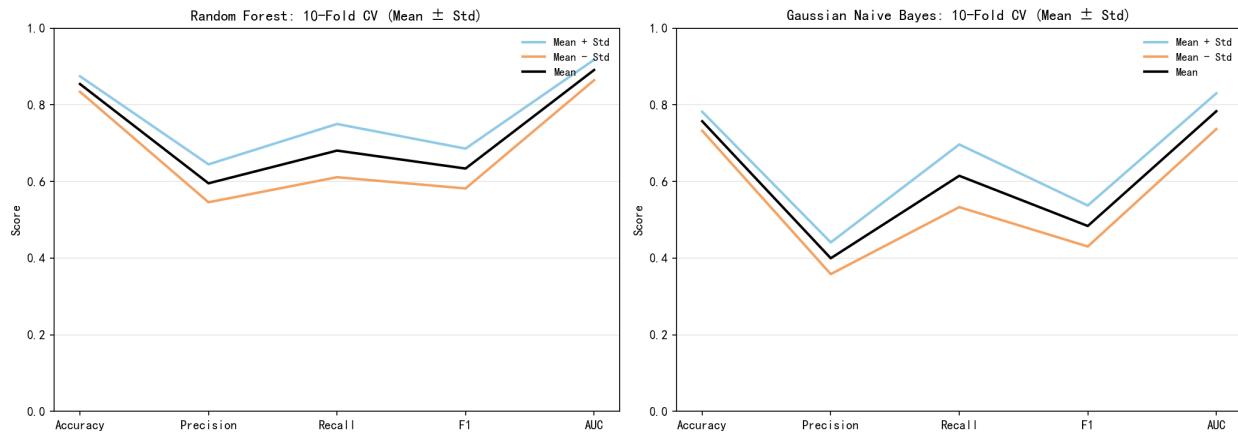


Figure 11: Cross-validation Boxplot

As shown in **Figure 11**, the average accuracy of the random forest model with 10-fold cross-validation is 0.8524, with a standard deviation of only 0.0213. This indicates the model exhibits stable performance across different data partitions and possesses strong generalization capabilities. The ROC-AUC reaches 0.8906, demonstrating the model's excellent ability to distinguish classification boundaries. Recall (0.6766) exceeds precision (0.5898), indicating the model tends to identify more rejected cases aligning with the early warning system's design objectives.

Next, robustness testing is conducted by adding Gaussian noise at varying levels (1%-20%) to the input features to assess the model's stability when data contains minor errors. Noise is added proportionally to each feature's standard deviation to simulate measurement errors encountered during actual data acquisition.

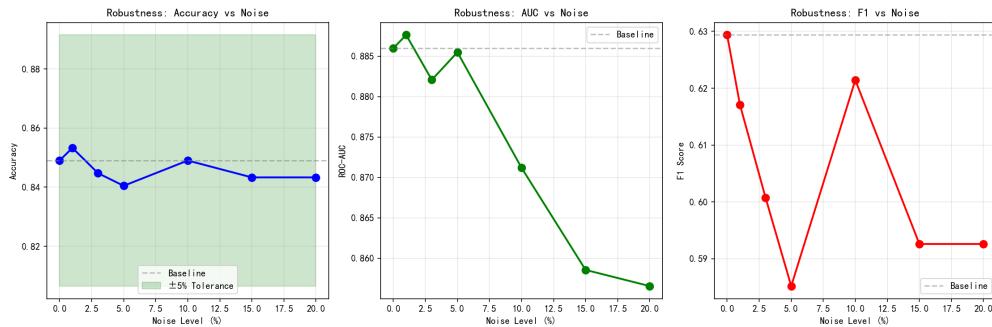


Figure 12: Robustness Analysis: Noise Injection

After adding 5% noise to the data, the model's accuracy changed by only 0.43%, and the ROC-AUC changed by 0.0060. After adding 10% noise, the accuracy changed by +1.00%. This indi-

cates that the model possesses strong robustness against interference and can still reliably output stable results even when actual data contains minor measurement errors.

4 Building Preservation Model

4.1 Building Value Quantification

Building value is measured in terms of the building's cultural value and community influence, economic value, and historical value. Therefore, we take these three main aspects as primary indicators.

4.1.1 Indicators Determination

For the cultural value and community influence, we synthesized various factors, such as geography and network, and finally selected the three most representative secondary indicators to construct our model. Similarly, for the economic and historical value, we selected two secondary indicators each to improve the model. The specific description and indicators selected are shown in Table 3.

Table 3: Indicators

Object	Indicators	Description
Cultural Values and Community influence	NG	Number of Google search terms
	P	Participation in events held around the building
	ANV	Annual number of visitors
Economy	LV	Land value
	CC	Construction cost
History	NH	Number of historical research documents
	DP	Degree of preservation

- Cultural Value and Community Influence

- Global Visibility

The cultural value of a building depends to a large extent on its global visibility. So we quantify its global visibility through two metrics, “Number of Google search terms” (NG) and “Annual number of visitors” (ANV). This approach balances online and offline, making the measurement of cultural values more quantifiable and accurate.

- Impact on the Community

Buildings have a strong connection with local communities. When measuring the value of a building, we take into account its impact on the local community. Research has shown that the more influence a building has on the local community, the more the value of the landmark itself will increase. Besides, it will further promote the increase of influence, realizing a positive feedback loop. Therefore, we choose “Participation in events held around the building” (P) to quantify the building’s influence on the community. We calculate P as follows:

$$P = \frac{1}{N} \times \sum_{i=1}^N \frac{NCMP_i}{NTC_i} \quad (8)$$

where $NCMP_i$ represents “Number of community members participating in activities” at the i th activity, NTC_i means the total number of people in the community at the time of the i th activity and N means the total number of activities conducted around the building.

- Economy Value

For economic value, we mainly consider the value of the building in terms of its construction. Therefore, we considered the value of the land it occupies. And it is measured by the indicator “Land value” (LV).

$$LV = P_c \times Area \quad (9)$$

where P_c represents the current price of the land and Area represents the area occupied by the building. Meanwhile, for the value created during the construction of the building itself, we use “Construction cost” (CC) for quantitative assessment. Taking inflation into account, we define Construction cost as all costs involved in the implementation of that construction project under this year’s Engineering News-Record (ENR) benchmark for the region. Both the LV and CC metrics are expressed in U.S. dollars.

- Historic Value

- Historical Research Value

The historical value of a building is largely dependent on its place in historical research. So we quantify its visibility and importance in the academic world through NH. NH refers to the number of historical research documents related to the building, including but not limited to books, papers, reports, etc. This indicator reflects the building’s attention and depth of research in the historical community. The higher NH value means the building has a higher historical research value.

- The Preservation Condition

The historic value of a building is also affected by its state of preservation. We use “Degree of preservation” (DP) to measure the extent to which a building has been preserved from its original state. It includes aspects such as structural integrity, exterior preservation, and interior decoration. The assessment of DP can be based on expert review, preservation grade, and comparative analysis with the original state. Highly preserved buildings not only better transmit history and culture, but also provide rich materials for future research.

4.1.2 Weight Calculation

CRITIC is an objective assignment method based on data volatility. The idea of this method was based on two indicators, contrast intensity and correlation indicators. When calculating the weights, we need to multiply the contrast intensity with the correlation indicator and then normalize to get the final weights.

- Contrast intensity refers to the magnitude of the difference in values between evaluation programs for the same indicator, expressed as a standard deviation. The larger the standard deviation, the greater the fluctuation . That is, the larger the difference in the values taken between the programs, the higher the weight will be.
- The Sperman correlation coefficient is used to express the correlation between indicators. If there is a strong positive correlation between two indicators, it means that the less conflicting they are, the lower the weight will be.

1) There are n samples to be evaluated and p evaluation indicators to form the raw indicator data matrix.

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{pmatrix}$$

where x_{ij} represents the value of the j th evaluation indicator for the i th sample.

2) In order to remove the effect of the scale each indicator is normalized. The indicators we selected are of benefit attributes type, so the normalization formula:

$$X_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}$$

where X_{ij} is normalized to obtain a numerical matrix.

3) Then we calculate the contrast intensity of the indicator:

$$\begin{cases} \bar{x}_j = \frac{1}{n} \sum_{i=1}^n x_{ij} \\ S_j = \sqrt{\frac{\sum_{i=1}^n (x_{ij} - \bar{x}_j)^2}{n-1}} \end{cases}$$

where S_j represents the strength of comparison of the j th indicator.

The larger the S_j , the greater the difference in values for that indicator. The more information the indicator reflects, the stronger the evaluation strength of the indicator itself and the more weight should be assigned to it.

4) Calculation of the conflicting nature of the indicators

$$\begin{cases} d_i = \text{rank}(x_{ij}) - \text{rank}(x_{ik}) \\ r_{jk} = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \\ R_j = \sum_{k=1, k \neq j}^p (1 - r_{jk}) \end{cases}$$

where R_{jk} denotes the Sperman correlation coefficient between evaluation indicators j and k . R_j denotes the conflictual of the j th indicator.

The Sperman correlation coefficient is used to express the correlation between indicators. The stronger the correlation between two indicators, the less they conflict, the more they reflect the same information, and the more repetitive the content of the evaluation is. To a certain extent, the evaluation strength of the indicator is weakened and the weight assigned to it should be reduced.

5) Calculation of the amount of information:

$$C_j = S_j \times R_j$$

6) Based on the amount of information, we calculate the weights of each indicator defined w_j :

$$w_j = \frac{C_j}{\sum_{j=1}^p C_j}$$

7) The score for each indicator is:

$$Score_{object} = \sum_{j=1}^p w_j s_j$$

where $object$ represents “Cultural values and community influence”, “Economy”, “History”, s_j denotes the value of the j th secondary indicator.

Applying the CRITIC weighting method for each level 1 indicator separately, the objective weights for each level 2 indicator were obtained as shown in the following Table 1.

4.1.3 Quantitative Results of Building Values

In order to assign weights to these three level 1 indicators to get the final building value, we use hierarchical analysis to construct a judgment matrix to get the weights of the three level 1 indicators:

$$\theta = (0.4432, 0.3873, 0.1694)$$

where the consistency ratio of the judgment matrix = 0.017591, and the consistency is acceptable. Ultimately, our building impact score is calculated as follows:

$$V_{score} = \sum_{i=1}^3 \theta_i Score_{object} \quad (10)$$

Table 4: The weight of indicators

Object	Weight	Indicators	Weight
Cultural Values and Community influence	0.4432	NG	0.1698
		P	0.4429
		ANV	0.3873
Economy	0.3873	LV	0.4272
		CC	0.5728
History	0.1694	NH	0.6286
		DP	0.3714

4.2 Determination of protection measures

4.2.1 Measure Score

In Model 1, we obtained a composite risk score R_{score} of each region by analyzing 18 natural hazards. Next, in the above section, we quantified the value of the building to get the score V_{score} . By multiplying the risk score and the value score, M_{score} is obtained, which is used to assess the conservation priority of the building and the extent and scale of conservation measures that need to be taken.

$$M_{score} = V_{score} \times R_{score} \quad (11)$$

A higher M_{score} indicates a higher value of the building, along with a higher risk of exposure to natural hazards. Therefore, more urgent and comprehensive protection measures are needed. Based on the statistical distribution of M_{score} , we set reasonable thresholds to recognize low, medium, and high grades, and the values of the specific thresholds need to be set based on expert recommendations and industry standards.

4.2.2 Score of Protection Measures

- **Low:** For low-grade M_{score} buildings, basic conservation measures, such as routine maintenance and inspections and, where necessary, minor repairs, are undertaken. The risk or value of these buildings is low, so the measures taken are mainly preventive and low-cost.
- **Medium:** For medium-grade M_{score} , moderate protection measures are implemented, including enhanced structural inspections, improved safety features, and disaster preparedness programs. These measures aim to increase the resistance and resilience of buildings and require moderate investment.
- **High:** For high-grade M_{score} , implement comprehensive and high-intensity protection measures. This may include comprehensive structural reinforcement, installation of advanced security systems, and customized risk management plans in cooperation with external experts. Given the high risk or value of these buildings, the goal of the measures is to minimize potential losses, even if this means higher initial costs.

Note that: The “one-size-fits-all” approach to disaster protection measures ignores the impact of regional differences, architectural characteristics and socio-economic factors, and can lead to poor protection and resource utilization. So specific protection measures still need to be derived from a thoughtful local analysis by natural disaster experts.

4.2.3 Mentoring for Community Leaders

Our model provides a quantitative and systematic framework for community leaders to help them determine the extent and priority of preservation measures based on a building’s risk

and value scores. The model makes the decision-making process more scientific and accurate by combining risk scores (which consider threats such as natural hazards) and value scores (which include historical, cultural, economic, and community importance). It promotes optimal allocation of resources and ensures that high-value or high-risk buildings are adequately protected, while also taking into account economic benefits. In addition, the model encourages community

involvement and support, improves disaster response capacity, and supports sustainable community development. Through this approach, community leaders are able to make more informed decisions to protect and maintain important buildings in their neighborhoods, contributing to the overall well-being and development of the community.

5 Landmark Case Analysis

We select Tokyo Tower in Japan as the landmark for evaluation and analysis.



Figure 13: Location of Tokyo Tower

5.1 Insurance Pricing for Tokyo Tower

Designed by Japanese architect Tachu Naito, the Tokyo Tower cost \$8.4 million to build at the time and was constructed to send broadcast signals in Tokyo. Currently, Tokyo's GNI per capita is \$36,964.96, and the Tokyo capital market is currently functioning well. The risk score for Tokyo is calculated to be 86. According to the insurance pricing model, the optimal insurance rate for an insurance company to issue catastrophe insurance in Tokyo is 3.8%. In view of the special historical value of the Tokyo Tower, the insurance company may appropriately increase the insurance rate. As a result, the Tokyo government spends approximately US \$319,200 per year on catastrophe insurance for the Tokyo Tower.

5.2 Architectural Value of Tokyo Tower

In 2011, a major earthquake struck northeastern Japan, and this earthquake caused some damage to Tokyo Tower, bending the antenna at the tip of the tower by 2 degrees, resulting in the end of the experimental broadcasting of terrestrial wave digital sound broadcasting, and the interruption of the transmission of the 24/7 terrestrial analog television signals. Tokyo Tower entered a maintenance period during which analog signals and FM broadcasting-related services also began to be transferred to Tokyo Skytree, so the proportion of Tokyo Tower's actual use gradually decreased. However, Tokyo Tower has attracted more than 3 million visitors as a tourist attraction and has accumulated more than 150 million visitors. It is also a symbol of Japan's post-war prosperity and has a remarkable historical significance for the Japanese people.

According to the calculations of the building conservation model, the Mscore of Tokyo Tower is located in a high conservation level area. Therefore, the government should consider purchasing catastrophe insurance for Tokyo Tower and strengthening its daily supervision and maintenance to

ensure that it can withstand natural disasters, such as earthquakes, and that its seismic treatment measures also need to be strengthened.

6 Sensitivity and Robustness Analysis

6.1 Sensitivity

In section 4.3, factor is introduced to estimate the parameters of the expected return of the market. Therefore, change the size of this parameter, that is, the capital market environment has changed. Below we analyze the sensitivity of this parameter. Gradual reduction of the parameter by 5%. The reason for considering only a decrease in r and not an increase in r is to reflect the worst-case scenario, i.e. a gradual decrease in capital market returns, and to see if our model is sensitive to the parameter.

Therefore, Re-simulate the calculation results and obtain 3 sets of curves as shown in Figure 14.

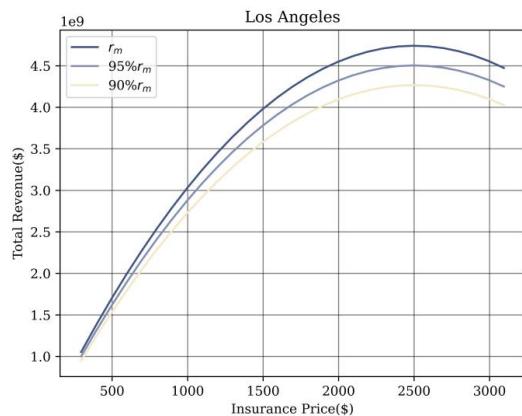


Figure 14: Sensitivity analysis of r_m

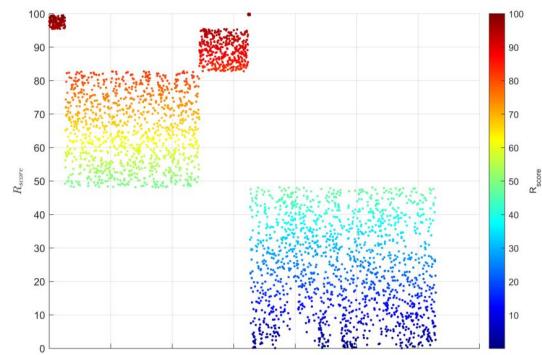


Figure 15: Robustness analysis of R_{value}

The results show that as r decreases, the profit gained by the insurance company if it sells the insurance company at the same price tends to decrease. This makes sense because lower capital market interest rates result in lower profits for insurance companies. The trend of the curve obtained by sensitivity test is consistent with the actual situation.

6.2 Robustness

We verify the robustness of the model. Given the uncertainty of natural hazards, we may have errors in the calculation of Rvalue, which affects our grading of the risk indicators for each region. Randomly selecting some of the more than 3,000 counties in the United States and deviating its Rvalue by 5%, and again grading these areas, the results obtained are shown in Figure 15.

As can be seen from the figure, the grading of the original regions changes only slightly after randomly selecting regions to bias their measurements. This indicates that the small error in R does not cause large changes in the model results and our model is stable.

7 Model Evaluation

7.1 Strengths

Robustness and Flexibility: Our model demonstrates strong adaptability to various parameter variations through sensitivity analysis and robustness testing, and is able to provide reliable predictions under different scenarios.

Comprehensive consideration: Our model integrates social and economic factors, natural disaster risks, and provides a way to price insurance.

7.2 Weaknesses

Data Dependency: Although the model has a high demand for data quality, it reflects our scientific attitude of pursuing accuracy and real-time performance. By working with data providers, we can continuously optimize the data collection and processing process.[4]

Model Assumptions: The model relies on certain assumptions that may not hold true in

References

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A Letter to Community Members

Dear Esteemed Members of Tokyo Tower Community,

We are researchers dedicated to the study of architectural preservation. In order to realize the preservation of Tokyo Tower at a lower cost, please allow me to introduce our proposal on behalf of our team.

We have recently concluded a comprehensive analysis aimed at ensuring the future sustainability and preservation of our cherished Tokyo Tower. Our findings offer a strategic blueprint that prioritizes not only the physical well-being of this iconic structure but also its cultural and historical essence.

Recommendation Plan:

Our proposed plan encompasses innovative preservation techniques, structural enhancements, and community-centric initiatives designed to safeguard and celebrate the tower's legacy. We aim to implement cutting-edge solutions that address both current vulnerabilities and future challenges.

Implementation Timeline:

This ambitious project is scheduled over a five-year period, beginning with immediate preliminary assessments and followed by successive phases of structural upgrades and community engagement activities. This phased approach ensures meticulous attention to detail and the successful realization of our objectives.

Budget Overview:

The financial blueprint for this venture is estimated at \$320,000 per annum. This budget encompasses costs associated with structural reinforcements, preservation technology, and community enrichment programs. It represents a balanced investment in tower's longevity and its significance to our community.

We stand at a pivotal moment in the history of Tokyo Tower, poised to embark on a journey that not only secures its future but also reinvigorates its role within our community. We invite you to support this noble cause, ensuring that Tokyo Tower remains a symbol of resilience, heritage, and communal unity for countless years to come.

Sincerely yours,
Team #2400860

Appendices

Appendix A First Appendix

Input Python source:

```
import numpy as np

def fft(x):
    n = len(x)
    if n == 1:
        return x
    even = fft(x[0::2])
    odd = fft(x[1::2])
    T = [np.exp(-2j * np.pi * k / n) * odd[k] for k in range(n // 2)]
    return [even[k] + T[k] for k in range(n // 2)] + [even[k] - T[k] for k in
        range(n // 2)]
```

Input Matlab source:

```
function [t,seat,aisle]=OI6Sim(n,target,seated)
pab=rand(1,n);
for i=1:n
    if pab(i)<0.4
        aisleTime(i)=0;
    else
        aisleTime(i)=trirnd(3.2,7.1,38.7);
    end
end
```

Report on Use of AI

1. OpenAI ChatGPT [5] (Jan 25, 2024 version, ChatGPT-4)

Query1: Give me some brainstorming ideas for innovative data visualization techniques.

Output: Here are some innovative data visualization technique ideas:

(1) Interactive Dashboards: Develop dashboards that allow users to interact with the data, such as filtering, zooming, and selecting specific data points to see detailed information.

(2) Animated Visualizations: Use animations to show changes in data over time, helping to illustrate trends, cycles, or progressions.

(3) Augmented Reality (AR) Visualizations: Implement AR to overlay data on real-world objects or environments, enhancing understanding of spatial and contextual relationships.

(4) 3D Visualizations and Models: Employ 3D models to represent complex data structures, allowing exploration from different angles and perspectives.

(5) Narrative Visualizations: Combine data visualization with storytelling, guiding viewers through a narrative that explains the significance of the data in a compelling way.

(6) Real-time Data Streaming: Visualize data in real-time, updating visuals as new data comes in, ideal for monitoring and tracking systems.

(7) Data Sonification: Convert data points into audio signals, making it possible to “listen” to the data for patterns, trends, or anomalies.

These ideas can help present data in more engaging, insightful, and accessible ways.

2. OpenAI ChatGPT (Jan 25, 2024 version, ChatGPT-4)

Query1: What is Engineering News-Record? Give me a brief introduction.

Output: Engineering News-Record (ENR) is a prominent publication within the engineering and construction industry, providing news, analysis, commentary, and data vital for professionals in the field. The publication's roots can be traced back to two separate publications from the late 19th century, eventually merging into what we know today as ENR in 1917. It has evolved to offer a wide range of content including top design firms, construction companies, projects in the U.S. and around the world, and industry trends affecting business management, design, construction methods, technology, and more. ENR is recognized for its comprehensive rankings of the largest construction and engineering firms, based on gross revenues, and for its ENR Award of Excellence, which honors individuals who have made significant contributions to the industry. Today, ENR is owned by BNP Media and continues to serve as an essential resource for contractors, project owners, engineers, architects, and other industry stakeholders with its print and digital magazine, website, newsletters, webinars, and events.

3. OpenAI ChatGPT (Jan 25, 2024 version, ChatGPT-4)

Query1: What's the ENR for?

Output: The Engineering News-Record (ENR) serves several vital functions in the engineering and construction industry. It is recognized for:

(1) News and Analysis: ENR provides comprehensive news coverage, analysis, and commentary on various topics relevant to the construction industry, including major projects, industry trends, technological advancements, and issues affecting the sector such as safety, law, and labor.

(2) Rankings and Data: It publishes annual rankings of the largest construction and engineering firms based on gross revenues, including lists like the Top 400 U.S. General Contractors, Top 500 U.S. Design Firms, and Top 600 Specialty Contractors, among others. These rankings are widely respected and used as benchmarks within the industry.

(3) Awards and Recognition: ENR recognizes industry excellence through various awards, including the ENR Award of Excellence, which honors individuals and projects that have made significant contributions to the industry.

(4) Industry Insights: The publication offers insights on business management, project delivery, technology, workforce development, and other critical areas impacting the engineering and construction fields.

ENR serves as a key resource for professionals across the construction industry, including contractors, project owners, engineers, architects, and suppliers, connecting diverse sectors with coverage that addresses common challenges and opportunities.