Problem Chosen	2024 HiMCM/MidMCM Summary Sheet	Team Control Number
A		15885

An Olympic Games Events Evaluation Based on Modeling of Weighted SVM

Summary

We comprehensively considers six core criteria and establishes an evaluation model as a tool for the IOC to decide on the addition or removal of sports.

For Problem 1, We extract key influencing factors from the criteria and **normalizes** them to achieve unified dimensions.Keyword search frequency and venue capacity measures Popularity and Accessibility; gender equality is quantified using the gender ratio of participants; sustainability is evaluated through nine composite indicators ; inclusiveness is assessed by the number of participating countries.

For Problem 2, we build three models based on the factors extracted in Problem 1 to score SDEs align. Considering the high subjectivity of the Analytic Hierarchy Process (AHP), we switched to using **SVM** for classifying Olympic sports, achieving an initial accuracy of 75.17%. To further improve accuracy, weights were assigned to each factor, and **Bayesian optimization** was used to enhance computational efficiency, increasing the model's accuracy to 85.52%. T**he top five ranked Olympic sports** identified are Weightlifting, Rowing, Judo, Wrestling Greco-Roman, and Aquatics Swimming.

For Problems 3 and 4, we tested the model from Problem 2 on 3v3 Basketball, Karate, Softball, Weightlifting, Athletics, and Cycling to verify its broad applicability and conducted predictions for future sports. Using the **ARIMA** model, we predicted data for **esports and cricket** and combined it with the weighted SVM model to estimate their potential inclusion probabilities for the 2032 Olympics.

For Problem 5, we analyzed the model from the perspectives of sensitivity and factors. Using **cross-validation**, the average cross-validation accuracy is 0.8157, and the cross-validation accuracy standard deviation is 0.0181, indicating good model stability as verified by the histogram. Analyzing the three factors with the highest weights reveals the following: gender equality enhances the social value and global influence of the Olympics, but achieving gender equality in some traditional sports may require long-term efforts; inclusiveness ensures the Olympics covers more countries and regions, but high inclusiveness demands for emerging sports may limit their participation; popularity and accessibility directly increase the number of spectators and participants, ensuring the sustainable development of the event, but an overemphasis on popular sports may neglect niche or emerging sports, thereby affecting the diversity of Olympic events.

Keywords: Weighted SVM Bayesian Optimization Olympic Align

Contents

1 Introduction

1.1 Background

Orginated from ancient Greece over two thousand years ago, Olympic Games is the largest multi-sport event in the world Due to the Olympic values, the International Olympic Committee (IOC) makes adjustments to the sports, disciplines, or events (SDEs).For instance, take karate, which made its Olympic debut in 2020, will not be part of the events at the Paris 2024 Olympic Games.

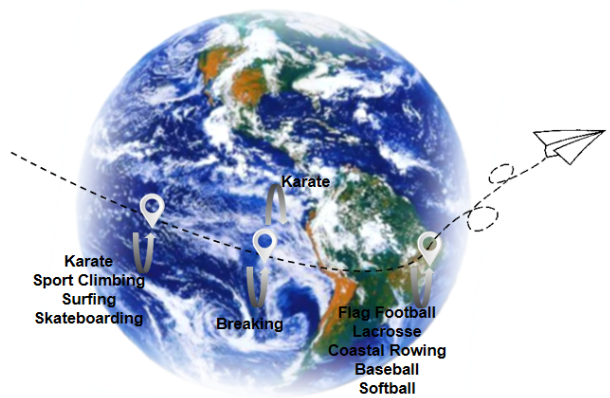


Figure 1: Recent Changes in Olympic SDEs

To aid in judgement, the following eligibility criteria have been set for each sport:

- Universality and Accessibility:Minimize additional costs while boosting the global attractiveness of the Olympic Games.
- Gender Equity:Guarantee that everyone has an equal opportunity to take part in the competition, regardless of gender.
- Sustainability:Shoulder the responsibility for the environment and society
- Diversity： encourage widespread global Involvement.
- Inheritance and Innovation： Preserve the past ,embrace the future.
- Security and Equity： Strict requirements for Safeguarding and anti-doping.

1.2 Restatement of the problem

In the near future, the Olympics will take place in Brisbane, Australia.To support the IOC in the assessment of the SDEs for 2032,We need to complete the following tasks in sequence:

1.List the factors related to the IOC standards and prove their justification.

2.Develop a model based on the above factors to assess the SDE(s).

3.Conduct tests on at least three SDEs hat have been modified in the latest Olympic Games as well as at least three SDEs that have been consistently featured in the Olympic

Games since the early Olympic period.The above tests should emphasize the model's Broad applicability.Deliberate on how your model verifies the current Olympic status of these SDEs.

4.Confirm three SDEs that will be added in 2032 and rank them according to their scores.Meanwhile forecast the Prospective Admission of SDE(s) in an Olympic Games for 2036 and future editions.

5.Undertake a sensitivity analysis on the model to strengthen the robustness.Evaluate which aspects exhibit high sensitivity and determine whether the aspect reflect advantages or disadvantages.

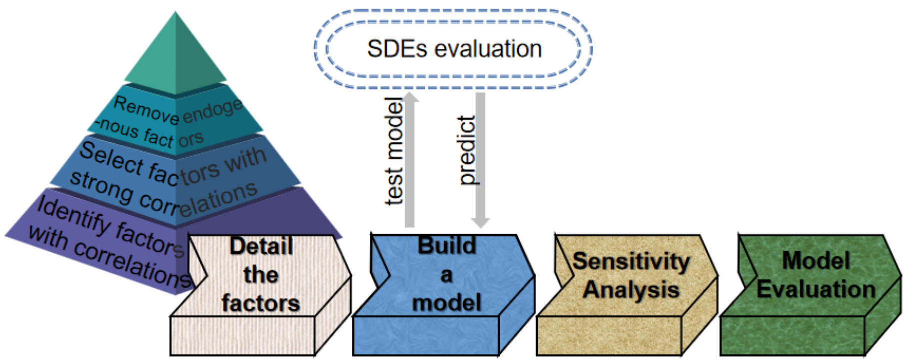


Figure 2

2 Assumptions

- Assume that the keyword search frequency on the three major global platforms can represent the keyword search frequency across all platforms.
- Assume that the per capita area within venues is equal.
- Assume that the popularity and accessibility of an Olympic event are positively correlated with the global audience size and search popularity.
- Assume that Gender equity in Olympic events can be measured by the gender ratio of participating athletes.
- Assume that sustainability can be evaluated by their environmental impact, such as carbon emissions and resource consumption.
- Assume that the inclusivity of an Olympic event can be measured by the level of participation across different continents and countries.

- Assume that the innovation of an Olympic event can be measured by the degree to which it attracts young audiences and athletes.

3 Notations and Glossary

3.1 Notations

Table 1: Notations and Definitions

Symbol	Definition
λ	Eigenvalue: Used for consistency check (CI)
v	Eigenvector: Used to calculate weights
RI	Random Consistency Index: Related to matrix order, used for consistency check
CI	Consistency Index: $CI = \frac{\lambda_{\max}-n}{n-1}$
X	Original data matrix (PCA variable)
W	Projection matrix: Used for dimensionality reduction (PCA)
α	Lagrange multipliers (SVM variable)
$K(x_i, x_j)$	Kernel function: RBF kernel in SVM
p	Autoregressive order (ARIMA parameter)
d	Differencing order (ARIMA parameter)
q	Moving average order (ARIMA parameter)
y_t	Time series: Dependent variable to be predicted

3.2 Glossary

Deterministic: processes that lead to a single, fixed outcome.

SDE: Sport, Discipline, or Event.

International Olympic Committee (IOC): a non-governmental global organization that oversees the Olympic Games and the Olympic Movement.

IOC's Olympic Programme Commission: an organization tasked with various responsibilities, including evaluating the programs for both the Summer and Winter Olympic Games.

Physical virtual sport: a type of sport that combines physical activity with virtual or digital components, typically utilizing technologies such as augmented reality (AR), virtual reality (VR), or esports platforms.

4 List Factor

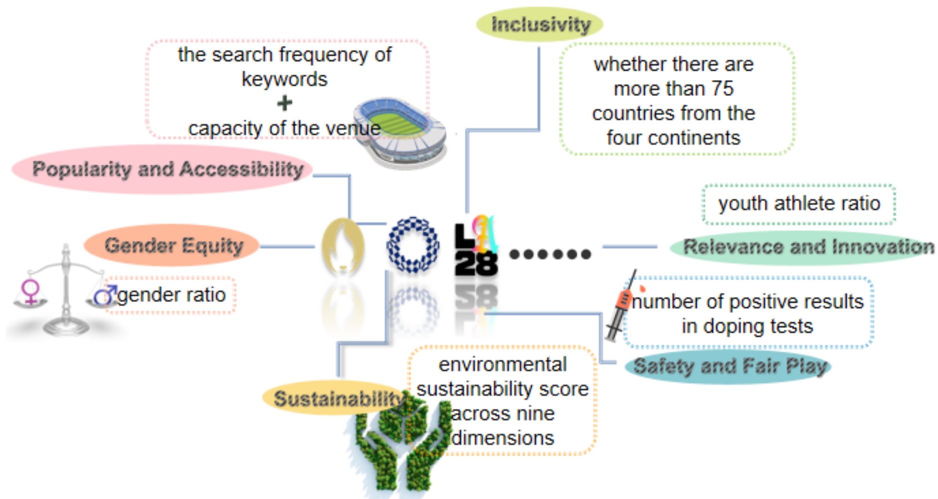


Figure 3

To avoid distortion of results and identify the relative contribution of different aspects, it is necessary to achieve a uniform dimension for data [1][2][3] [4][5][6]in each aspect, that is:

$$f_n(x)_{std} = \frac{f_n(x) - \mu}{\sigma} \tag{1}$$

- **Universality and Accessibility**

Regarding **Universality**, the appeal and popularity of an Olympic event can be reflected in the level of public discussion on the topic. Considering that daily discussions are difficult to record and modern internet technology has achieved near-global penetration, we can use keyword search frequencies on major platforms to characterize the data[7]. Based on the above assumption and to enhance the feasibility of data processing, it is feasible to focus solely on the keyword search frequencies from **the top five global platforms** and calculate their average.

Regarding **Accessibility**, cost accessibility is primarily reflected in the costs, and Olympic expenses are generally positively correlated with the venue area. Thus, venue area is used as the evaluation criterion for this factor. Given the assumption that the per capita area within venues remains constant, the venue area can be represented by **seating capacity**.

- **Gender Equity**

Equal participation opportunities can be reflected in a balanced gender ratio. The closer the gender ratio is to 1, meaning the proportion of male athletes approaches 0.5, the more balanced the participation opportunities are for different genders. To map the score to its highest value when the proportion is 0.5 and to constrain the score within the interval [0,1], the following treatment is applied:

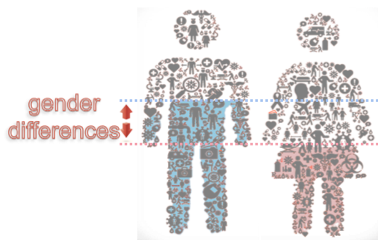


Figure 4

$$f_2(x) = -4(x-0.5)^2 + 1 \tag{2}$$

- **Sustainability**

Based on relevant literature[8] and the sustainability plan of the 2016 Rio Olympic Games, environmental sustainability can be evaluated through the following nine dimensions($a_i,\ i \in \{1,2,3,4,5,6,7,8,9\}$) water treatment and conservation, environmental awareness, the use and management of renewable energy, carbon emissions during the Olympic Games, air quality and neutralization of traffic emissions, soil and ecosystem protection, sustainability in venue design and construction, reforestation, biodiversity and cultural protection, eco-certified procurement, and solid waste management. Then, mathematical fuzzy methods are applied to defuzzify these dimensions, scoring the influence (h_i) of related projects or activities in each dimension:.

$$f_3(x) = \sum a_i \times x_i \tag{3}$$

The specific evaluation method for h_i is as follows: a positive influence is assigned a weight of add one, a negative influence is assigned a weight of minus one, and no influence or neutrality is assigned a weight of zero.

- **Diversity**

According to the problem analysis, seventy-five can be used as the threshold: if the number of participating countries from four continents is no less than seventy-five, this factor is assigned a score of 100; if the number is less than seventy-five, no processing is applied.

- **Inheritance and Innovation**

SDEs that attract young audiences will inevitably also attract the participation of young athletes. Additionally, the introduction of new technologies requires the involvement of young athletes to effectively utilize these technologies. Therefore, this factor can be represented by the proportion of young athletes.

- **Safety and Fair Play**

High anti-doping standards are reflected in the number of doping violation incidents. The more frequent such incidents, the stricter the standards can be considered. Therefore, the score for this factor can be equivalent to the number of doping violation incidents.

5 SDEs Eligibility Assessment Model

5.1 Analytical Hierarchy Process

➢ Construct a hierarchy diagram

According to the topic, the evaluation objectives, the number of programs, and the evaluation indicators are determined as follows:

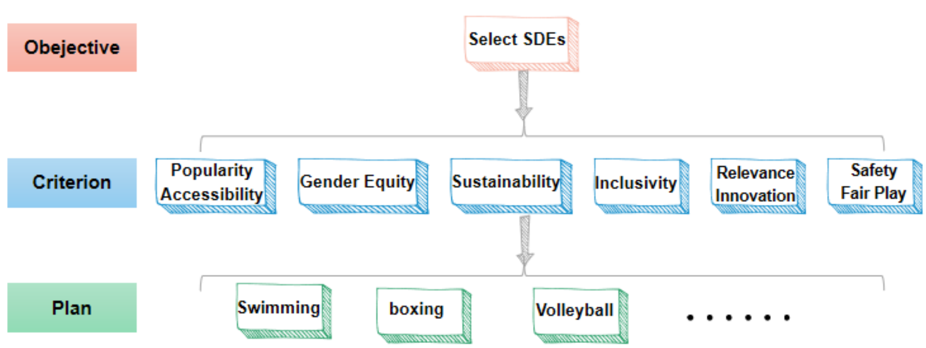


Figure 5

➢ Construct a judgment matrix

Due to the complexity of numerous factors, they were grouped and analyzed in pairs. Based on the literature review, the following judgment matrix was derived:

Table 2

index	Popularity and Accessibility	Gender Equity	Sustainability	Inclusivity	Relevance and Innovation	Safety and Fair Play
Popularity and Accessibility	1	5	9	4	6	7
Gender Equity	0.2	1	6	0.333	2	4
Sustainability	0.111	0.167	1	0.143	0.2	0.333
Inclusivity	0.25	3	7	1	4	5
Relevance and Innovation	0.167	0.5	5	0.25	1	2
Safety and Fair Play	0.143	0.25	3	0.2	0.5	1

➢ **Check consistency matrix**

Based on subjective judgment and expert experience, the relationships between factors were evaluated. To ensure consistency, the CR test was applied for correction, using the following formula:

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}}$$

Among them,RI represents the average random consistency index, which can be obtained from the lookup table based on the specific order. CI denotes the consistency index and is calculated using the following formula:

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n - 1}$$

Here, λ represents the eigenvalue, and n denotes the matrix order.

Table 3

Item	Eigenvectors	Weight(%)	Maximum Feature Root	CI Value
Popularity and Accessibility	2.804	46.735		
Gender Equity	0.81	13.507		
Sustainability	0.164	2.74	6.399	0.08
Inclusivity	1.381	23.022		
Relevance and Innovation	0.519	8.657		
Safety and Fair Play	0.32	5.339		

The calculated CR value was less than 0.1, indicating that it fell within the acceptable consistency range.

➢ **Determine the Weights**

After identifying the eigenvector corresponding to the maximum eigenvalue, it is normalized to determine the relative weight of each element.

5.2 Binary Classification Based on PCA Combined with SVM

Using the analytic hierarchy process (AHP), it was determined that sustainability-related factors are overly subjective and not conducive to model evaluation. Consequently, these factors were excluded from subsequent data processing.

5.2.1 PCA for dimensionality reduction

Principal Component Analysis (PCA) is a dimensionality reduction technique that projects data into a new coordinate system via linear transformation, maximizing variance along the new axes. This method is suitable for selecting and processing Olympic events within the ontology, thereby accelerating model training.

5.2.2 SVM

Support Vector Machine (SVM) is a supervised learning method widely used for classification and regression tasks. The core idea of SVM is to separate the dataset into different classes by finding an optimal hyperplane. The goal is to maximize the margin between categories, defined as the distance from the support vectors to the hyperplane, thereby enhancing the model's generalization ability.

➢ **Define kernel functions:**

Since the data in this problem are nonlinear and not linearly separable, we use the Radial Basis Function (RBF) kernel to construct the dual optimization problem for SVM.

The general form of RBF nucleus is:

$$K(x_i, x_j) = \exp\left(-\gamma \|x_i - x_j\|^2\right)$$

Where γ is a parameter of the kernel function that controls the "width" of the RBF kernel. A large value of γ causes the kernel function to concentrate near the data points, leading the model to memorize the training samples (high variance). Conversely, a smaller value of γ causes the kernel function to cover a wider area, resulting in higher bias.

➢ **Construct a dual optimization problem:** Objective Function:

$$\max_{\alpha} \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j)$$

$$s.t. \quad \sum_{i=1}^{n} \alpha_i y_i = 0, \quad 0 \leq \alpha_i \leq C, \quad \forall i$$

Among them:

- α_i is a Lagrange multiplier and is related to each sample x_i 。

- y_i is the label of the sample x_i , $y_i \in \{0, 1\}$.

- $K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2)$ is the RBF kernel function that calculates the kernel values of samples x_i andx_j .

- C is the penalty parameter of the SVM and is used to control the size of the interval and the trade-off of classification errors.

➢ **Solve optimization problems:**

The dual optimization problem is a convex quadratic programming problem, and commonly used solution algorithms include the Sequential Minimal Optimization (SMO) algorithm. By solving this problem, we obtain the values of the Lagrange multipliers α_i, from which we can identify the support vectors, i.e., the training samples for which $\alpha_i > 0$.The final decision function is:

$$f(x) = \text{sign}\left(\sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b\right)$$

Among them, b is the bias term, which is calculated by selecting the support vector. The specific formula is:

$$b = y_k - \sum_{i=1}^{n} \alpha_i y_i K(x_i, x_k)$$

where x_k is a support vector and $0 < \alpha_k < C$.

► In summary, the data after PCA dimensionality reduction is used as the input of SVM to train the SVM model. We can get the Accuracy Score as 0.751724.

The resulting SVM training graph is:

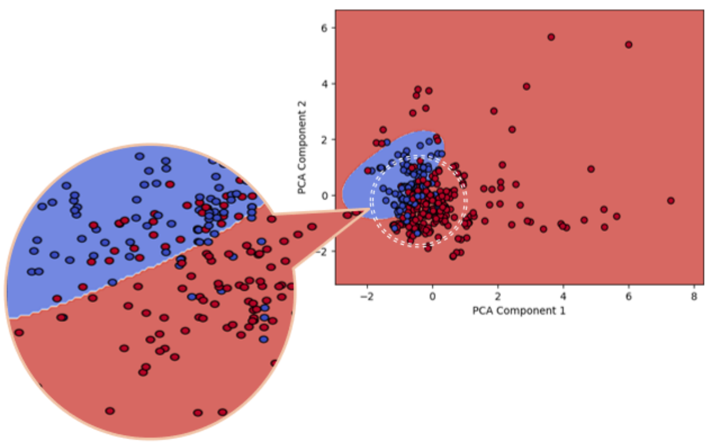


Figure 6

5.3 Weighted SVM based on Bayesian Optimization

5.3.1 Feature-Weighted SVM

Since the accuracy of the above model is not as expected, the main problem is that we did not set the weight of each factor during model training. Therefore, we tried to use the feature-weighted SVM model to improve the accuracy of the model. Assume that the feature vector $\mathbf{x}_i = [x_{i1}, x_{i2}, \ldots, x_{id}]$ is the original feature vector, and the feature weight vector $\mathbf{w}_{\text{weights}} = [w_1, w_2, \ldots, w_d]$ controls the impact of each feature on the classification decision. [9]The weighted feature vector becomes:

$$\tilde{\mathbf{x}}_i = \mathbf{w}_{\text{weights}} \circ \mathbf{x}_i = [w_1 x_{i1}, w_2 x_{i2}, \ldots, w_d x_{id}]$$

Here, $\circ$ represents element-wise multiplication (Hadamard product).

Then, the optimization goal of weighted SVM becomes the standard SVM problem based on weighted features, and the optimization goal is:

$$\min_{\mathbf{w},b,\xi,\mathbf{w}_{\text{weights}}} \left(\frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n}\xi_i \right)$$

The constraints are:

$$y_i\left(\mathbf{w}^T\tilde{\mathbf{x}}_i + b\right) \geq 1 - \xi_i, \quad \xi_i \geq 0, \quad \forall i = 1, 2, \ldots, n$$

Further expansion:

$$y_i\left(\mathbf{w}^T(\mathbf{w}_{\text{weights}} \circ \mathbf{x}_i) + b\right) \geq 1 - \xi_i$$

Therefore, in the objective function of weighted SVM, $\mathbf{x}_i$ is adjusted by the feature weight $\mathbf{w}_{\text{weights}}$, resulting in the optimization process not only needing to optimize $\mathbf{w}$ and b, but also needing to optimize the weight vector $\mathbf{w}_{\text{weights}}$ in order to find the optimal feature importance during training.

5.3.2 Bayesian optimization basic process

After trying traditional optimization methods such as grid search and random search, we found that the effect was not ideal. Therefore, we used the Bayesian optimization algorithm, which performs well in optimization problems with high-dimensional and noisy data.Figure 7 illustrates the change in loss during the Bayesian optimization process.

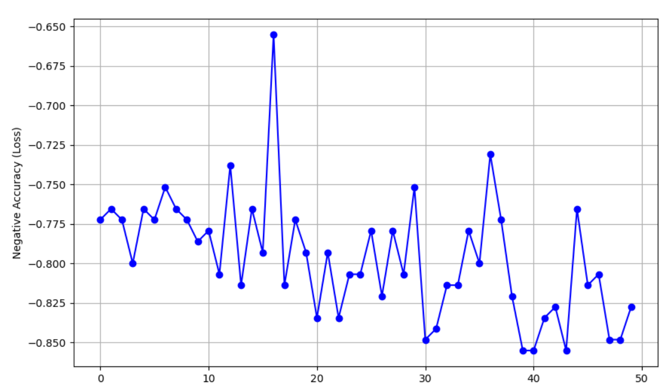


Figure 7

Bayesian optimization is a global optimization method based on Bayesian statistical theory, which is particularly effective for optimizing functions with high computational cost and cannot use gradient information for optimization. It is often used in hyperparameter tuning and experimental design of machine learning models. The core idea is to iteratively update the probability model of the objective function through previous evaluation results, and then select the next evaluation point based on the model to efficiently find the optimal solution[10].

➤ **Choosing the objective function:**

The goal of Bayesian optimization is to optimize a black box function $f(x)$, where x is a set of hyperparameters and $f(x)$ is the performance of the model (such as accuracy, loss function, etc.). For this problem, we use the inverse of accuracy as the black box function, which can be described as:

$$F(x) = -\frac{1}{N}\sum_{i=1}^{N}\delta\left(\hat{y}_i, y_i\right)$$

Among them:

- N is the number of samples in the test set,
- $\hat{y}_i$ is the predicted label of the ith sample,
- y_i is the actual label of the ith sample,
- $\delta(\hat{y}_i, y_i)$ is the Kronecker delta function, which is 1 if $\hat{y}_i = y_i$ and 0 otherwise.

➤ **Building a proxy model:**

The proxy model we constructed for this problem is Gaussian Process Regression, which is used to approximate the target function $f(x)$.

Gaussian process regression is the fundamental model in Bayesian optimization. It assumes that the objective function follows a Gaussian process, and infers the distribution of unknown points based on the relationships between existing data points. The advantage of Gaussian process regression is its ability to provide uncertainty estimates for predictions, enabling Bayesian optimization to make more informed decisions based on this information.

The core formula of Gaussian process is:

$$f(x) \sim \mathcal{GP}(m(x), k(x, x'))$$

Among them, $m(x)$ is the mean function, which is usually assumed to be zero; $k(x, x')$ is the covariance function (kernel function), which describes the correlation between sample points.

The advantage of the Gaussian process lies in its flexibility and powerful uncertainty quantification ability, which enables it to fully consider the "unknown" of the model during the optimization process. The surrogate model learns the distribution of the target function through the existing evaluation data $D = \{(x_1, f(x_1)), (x_2, f(x_2)), \ldots, (x_n, f(x_n))\}$, so that it can predict the function value of the unknown point.

➢ **Selecting a sampling strategy:**

Based on the agent model, define an acquisition function to select the next hyperparameter sampling point. The acquisition function can measure the "benefits" of the current sampling point by balancing "exploration" and "exploitation", that is, based on the Gaussian process regression model, determine which unexplored areas may give better objective function values.

Specifically, we use the expected improvement (EI) function, whose goal is to select the point that maximizes the expected improvement of the current optimal point. The formula for calculating the expected improvement is as follows:

$$\mathrm{EI}(x) = \mathbb{E}[\max(f(x) - f(x_{\text{best}}), 0)]$$

Where $f(x)$ represents the objective function, $f(x_{\text{best}})$ is the currently known optimal value, and $\mathbb{E}$ represents the expected value. The expected improvement function calculates the expected improvement of a new candidate point relative to the current optimal point and selects the point that maximizes the expected improvement.

➢ **Evaluating the objective function:**

The objective function is evaluated at the points selected by the acquisition function, and the evaluation results are fed back into the surrogate model. This step generates new sample data to update the surrogate model.

➢ **Update the proxy model:**

The surrogate model is updated with new evaluation results to more accurately predict the unknown regions of the objective function. This update improves the accuracy of the next step in the selection process.

➤ **Repeat Iteration:**

Repeat the above steps until the termination condition is met, such as reaching the maximum number of evaluations, or the objective function value converges to a stable value. Therefore, the Accuracy Score of the SVM model after Bayesian weight optimization is 0.855238, with the sample predictions compared to the actual values shown in Figure 8, and the weights of each factor displayed in Figure 9.

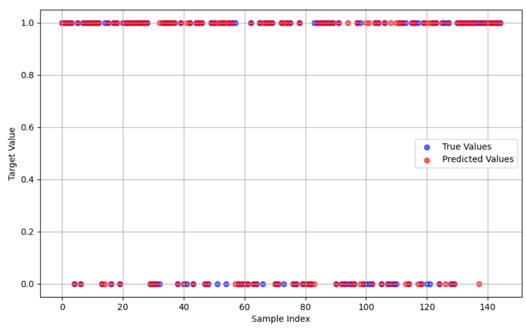


Figure 8

Aligns	Weigh
Popularity	30.0000
Accessibility	30.0000
Gender Equity	16.0285
Inclusivity	13.1006
Relevance and Innovation	1.0000
Safety and Fair Play	1.0000

Figure 9

Then, the weighted data is brought into the model for training to obtain the scores of each SDEs in all years. The average of the scores of each SDEs in different years is the final score of the project under the IOC standard. The ten projects that best meet the Olympic standards after sorting are shown in Table 4:

Table 4

SDE(s)	Score	Rank	SDE(s)	Score	Rank
Weightlifting	0.9783	1	Taekwondo	0.9696	6
Rowing	0.9780	2	Shooting	0.9696	7
Judo	0.9722	3	Wrestling Freestyle	0.9662	8
Wrestling Greco-Roman	0.9719	4	Boxing	0.9607	9
Aquatics Swimming	0.9707	5	Gymnastics Artistic	0.9468	10

6 Test Conduction

Among the events that have changed recently, we selected 3v3 basketball, karate, and softball. In the final test results, only 3v3 basketball did not match the actual results, while karate and softball were consistent with the actual results. The reasons for the analysis are as follows:

In our model test results, 3V3 basketball failed to be included in the final selection. Considering the weights of various factors in the training model, it may be because the inclusiveness is too low. The Olympic basketball event focuses too much on competitiveness and viewing, resulting in many countries that practice this sport being excluded from the Olympics. Countries need to obtain a small number of qualifying places through world or regional qualifying competitions, which ultimately leads to too few participating countries.

Among the Olympic events that have always existed, we selected weightlifting with the highest score, cycling track with the lowest score, and track and field with a middle score according to the weighted SVM model. The final test results are consistent with the actual results. The reasons are as follows:

The three SDEs tested by the model, which have existed since 1988 or earlier, boast a vast global fan base and require relatively simple venues and equipment, minimizing costs and logistical challenges during promotion. They also demonstrate broad international reach, gender inclusivity, and widespread participation across multiple continents. These events not only align with the International Olympic Committee's six evaluation criteria but have also maintained their core Olympic status through continuous innovation and adaptation to modern audiences.

To sum up, it can be seen that the accuracy of the model is relatively high.

Table 5

SDE(s)	introduction to SED	Compliance
3v3	Joined in 2020	no
karate	Joined in 2020 Removed in 2024	yes
softball	Joined in 2020	yes
Weightlifting	Has been around since 1920	yes
Athletics	Has been around since 1896	yes
Cycle	Has been around since 1896	yes

7 Prediction

For the SDEs that may be introduced in 2036, we need to evaluate them through data from 2024 and before. Therefore, in this question, we use the ARIMA time series to predict the data in 2032 and apply the autocorrelation function ACF test.

The ARIMA model is a widely used statistical method for time series forecasting. In this case, we use the ARIMA (p, d, q) model to predict required data for 2032. Here:

- **AR (Autoregressive)**: Models the relationship between current and past values, using historical data to predict future values. The formula for a p-order autoregressive process is:

$$y_t = \mu + \sum_{i=1}^{p} \gamma_i y_{t-i} + \epsilon$$

  where y_t is the current value, μ is a constant, p is the order, γ_i represents autocorrelation coefficients, and ϵ is the error.

- **MA (Moving Average)**: Focuses on error accumulation. The formula for a q-order process is:

$$y_t = \mu + \epsilon_t + \sum_{i=1}^{q} \theta_i \epsilon_{t-i}$$

- **Full ARIMA Model**: Combines these components, accounting for d, the number of differencing steps to achieve stationarity:

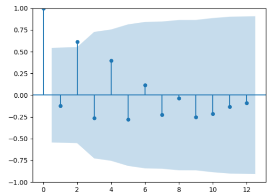
$$y_t = \mu + \sum_{i=1}^{p} \gamma_i y_{t-i} + \epsilon + \sum_{i=1}^{q} \theta_i \epsilon_{t-i}$$

For this problem, $p = q = d = 1$.

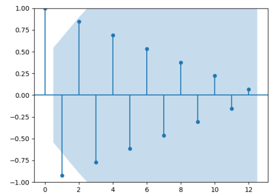
Based on the data from 2000 to 2024, we predict the data of various factors in 2032 and the results are shown in Table 6:

Table 6

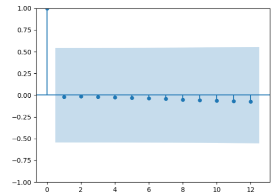
	Croquet	Polo	breaking	Basque Pelota	Cricket	Electronic Sports
Popularity	50.6014	118.3817	258.7765	32.3397	120.4588	332.3413
Accessibility	3500	60000	4700	5000	25000	35000
Gender Equity	0.5160	0.6465	0.4848	0.7727	0.7554	0.6708
Inclusivity	28.0723	21.0384	16.0	33.3572	32.5141	129.9928
Relevance and Innovation	0.5011	0.6577	0.3939	0.2033	0.4082	0.8765



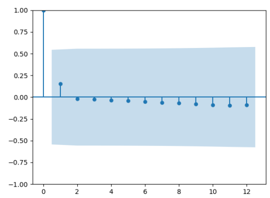
(a) Popularity



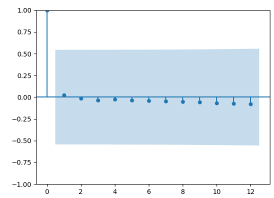
(b) Accessibility



(c) Gender Equity



(d) Inclusivity



(e) Relevance and Innovation

Figure 10: Overall Caption for All Images

The ACF plot above shows the correlation between different lags in the residual series (the difference between the actual value and the predicted value). The model fits well, and the autocorrelation of the residuals is close to zero at all lags; there is no significant linear dependence between the residuals.

Bringing the above data back to the weighted SVM model, we can get the Predicted Probabilities of each item:

Table 7

aligns	Predicted Probabilities	aligns	Predicted Probabilities
Croquet	0.5000	Basque Pelota	0.3341
Polo	0.5871	Cricket	0.7214
breaking	0.8903	Electronic Sports	0.8504

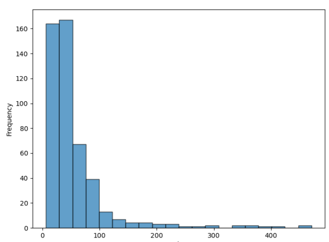
Therefore, we can get the top three SDEs recommended for the 2032 Brisbane Olympics: first: breaking; second: Electronic Sports; third: Cricket. Among them, breaking ranks the highest and has the highest probability of being included in the 2036 Olympics, while Croquet has a Predicted Probabilities of 0.5 in 2032 and was not selected for the Olympics. Observing the data, we can see that its Popularity and Inclusivity scores are both on an upward trend, so it has the potential to be selected as an Olympic event in 2036.

8 Model Analysis

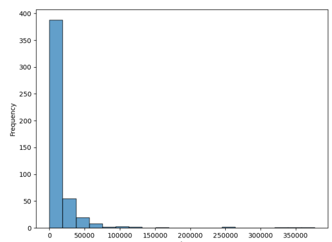
8.1 Sensitivity Analysis

8.1.1 Project Histogram

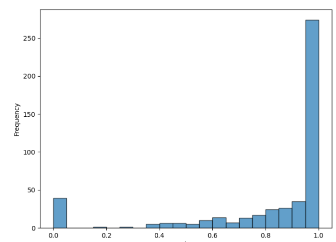
In SVM model stability analysis, the Project Histogram is a visualization tool used to display the distribution of model output or prediction results. It usually displays the frequency distribution of the model's output results or prediction values in different experiments or data set partitions. By observing the histogram, the model's output consistency, stability, and whether there is a deviation can be evaluated.



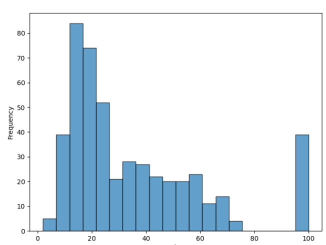
(a) Popularity



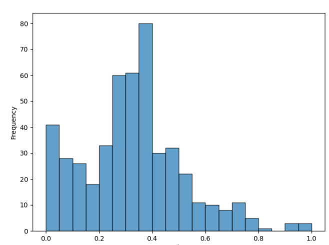
(b) Accessibility



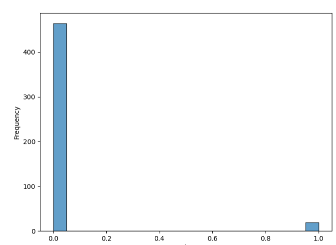
(c) Gender Equity



(d) Inclusivity



(e) Relevance and Innovation

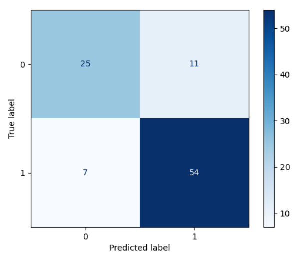


(f) Safety and Fair Play

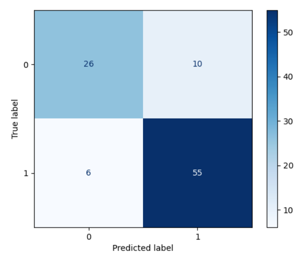
As shown in the Figure , the shape of the project histogram remains consistent in different experiments, and the prediction results are concentrated in a specific range, which shows that the model is stable under different data partitions.Additionally， the shape of the histogram has not changed significantly, indicating that the model still has stable behavior under different data partitions.

8.1.2 Cross-Validation and Confusion Matrix

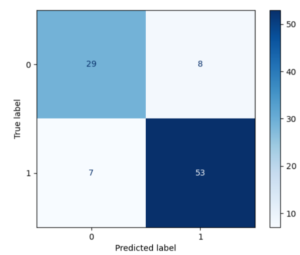
Cross-validation and confusion matrices are essential tools for evaluating the performance and reliability of machine learning models. Cross-validation assesses the model's stability and generalization across different data partitions, while the confusion matrix provides a detailed breakdown of classification results, highlighting true positives, false positives, true negatives, and false negatives. Figure 12 presents the confusion matrix of the model.



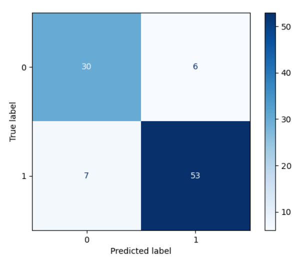
(a) Image 1



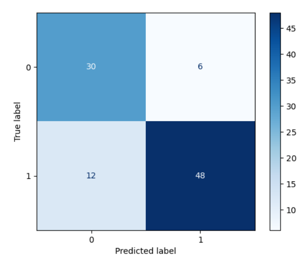
(b) Image 2



(c) Image 3



(d) Image 4



(e) Image 5

Figure 12: Confusion Matrix

In this question, five-fold cross-validation is used to evaluate the performance of the weighted SVM model. Additionally, a confusion matrix is constructed to provide further insights into the model's classification performance.

- **Cross-validation accuracy:** [0.8144, 0.8041, 0.8454, 0.8229, 0.7917]
- **Average cross-validation accuracy:** 0.8157
- **Cross-validation accuracy standard deviation:** 0.0181

Volatility and standard deviation of accuracy: From the cross-validation accuracy array, the performance of the model on different validation sets fluctuates, specifically: 0.8144, 0.8041, 0.8454, 0.8229 and 0.7917. Overall, the performance of the model is relatively stable, and the accuracy fluctuates between about 0.79 and 0.85.

Model stability: The standard deviation is 0.0181, indicating that the performance of the model in the five-fold cross validation fluctuates little, indicating that the model has good robustness. This shows that under different data partitions, the accuracy of the model remains relatively consistent and fluctuates little.

8.2 Factors Analysis

Since these three factors have a significant impact on the model, the three factors with the highest weights are selected for the following analysis

8.2.1 Popularity and Accessibility

- **Advantage:** Increases spectators and participants, ensuring sustainable event growth.
- **Shortcoming:** Overemphasis on popular sports may neglect niche or emerging ones, reducing event diversity.

8.2.2 Gender Equality

- **Advantage:** Enhances social value and global recognition, attracting more female participants.
- **Shortcoming:** Some traditional sports (e.g., wrestling, cricket) require long-term efforts for gender equality, limiting short-term growth.

8.2.3 Inclusiveness

- **Advantage:** Expands global participation, increasing the event's appeal.
- **Shortcoming:** High inclusivity demands may hinder the inclusion of emerging sports, especially less popular ones like e-sports.

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Proposal for the Inclusion and Exclusion of Olympics Sports

Dear Members of the International Olympic Committee (IOC),

We are honored to have contributed to the evaluation of potential new and removed sports for the upcoming 2032 Brisbane Summer Olympics. Based on advanced mathematical modeling techniques, our team has developed a comprehensive evaluation tool to assist in making informed, data-driven decisions. Below is a summary of our research and recommendations.

To evaluate the suitability of Olympic Sports and Events (SDEs), we constructed a mixed model based on Principal Component Analysis (PCA) and Support Vector Machine (SVM) classification. PCA was used to reduce dimensionality and extract key factors influencing the evaluation of SDEs, while SVM classified these sports based on their alignment with IOC standards. The model considered six critical criteria: *popularity and accessibility, gender equality, sustainability, inclusivity, relevance and innovation, and safety and fair competition*.

These criteria align with the Olympic spirit and reflect the current needs of the Games, including diversity, global participation, and commercial potential. By analyzing historical data and incorporating these factors, we created a model that offers IOC scientifically-backed decision support.

After evaluating SDEs added or removed from the Olympics in 2020, 2024, and 2028, as well as considering current trends, we propose the following recommendations:

- **Esports**: Esports ranks highly in *relevance and innovation* and *popularity*, attracting a young global audience. Although gender equality and safety standards are still being developed, its potential is undeniable.
- **Ultimate Frisbee**: With widespread global participation, especially in North America, Europe, and Asia, Ultimate Frisbee excels in *inclusivity* and *popularity*, and its low cost and environmental impact make it suitable for *sustainability*.
- **Field Hockey**: This traditional sport scores high on *gender equality* and *inclusivity*, and it remains a strong candidate for the Olympics due to its ability to attract both established and younger audiences.
- **Golf**: While popular, golf's high infrastructure demands and regional participation limits its alignment with accessibility and *sustainability*.

- **Wrestling**: Despite its long Olympic history, wrestling faces challenges in gender equality and modern audience appeal, which make it less suitable for the evolving nature of the Olympics.

The model demonstrated strong performance through cross-validation and sensitivity analysis, ensuring its robustness. The evaluation results, based on historical data and the key criteria, support our recommendations for new or removed sports. This scientific evaluation enables IOC to make decisions that reflect both the modern Olympic spirit and the preferences of global audiences.

Conclusion: Based on the model's evaluations, we recommend adding Esports, Ultimate Frisbee, and Field Hockey to the 2032 Games while reconsidering the inclusion of Golf and Wrestling. We believe this data-driven approach will aid the IOC in making decisions that resonate with contemporary values and future Olympic trends.

Thank you for the opportunity to contribute to this important process. Should you require further analysis or clarification, please do not hesitate to contact us.

Best wishes!

Yours Sincerely,

Team 15885