UDC [004.774:7](043.2)

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METHODS FOR RATING CULTURAL EVENTS BASED ON USER REVIEWS

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Анотація
У тезах розглянуто методи рейтингування культурних заходів на основі відгуків користувачів веб-орієнтованих інформаційних систем. Проаналізовано основні підходи до агрегування оцінок. Описано переваги та обмеження підходів з урахуванням специфіки культурних платформ.
Ключові слова: рейтингування, культурні заходи, відгуки користувачів, баєсівське середнє, колаборативна фільтрація, гібридна модель, часове загасання, веб-система.

Abstract
Methods for rating cultural events based on user reviews on the internet are described. The main approaches for rating were analysed. Advantages and limitations of each approach are described with respect to the specifics of cultural platforms.
Keywords: rating algorithms, cultural events, user reviews, Bayesian average, collaborative filtering, hybrid model, time decay, web system.

Introduction

Modern cultural life is based on specialized web platforms that collect information about concerts, exhibitions, theatre performances, festivals, and other events. A key feature distinguishing such platforms from simple event calendars is the ability for users to rate and review events, thereby forming a public reputation signal that guides other potential visitors in their decisions.

The objective of this paper is methods for rating cultural events based on user reviews, to analyse their strengths and limitations, and to propose a hybrid model that satisfies the requirements of accuracy, fairness, transparency and computational efficiency.

1. Fundamentals of Rating Systems for Cultural Platforms

A rating system for a cultural event platform is a computational mechanism that transforms a collection of discrete user scores into a single aggregate value suitable for comparative rating. Formally, let $E = \{e_1, e_2, ..., e_n\}$ be the set of events, and $R(e_i) = \{r_1, r_2, ..., r_k\}$ be the multiset of individual ratings assigned to event e_i, where each $r_j \in \{1, 2, 3, 4, 5\}$. A rating algorithm $f : R(e_i) \to \mathbb{R}$ maps this multiset to a real-valued score used for rating [1].

The cultural domain introduces several requirements that complicate the design of f. First, cold-start fairness: newly published events have zero or few reviews and must not be disadvantaged relative to well-reviewed events in initial ratings. Second, temporal relevance: a concert reviewed positively two years ago may no longer reflect the current quality of the organiser. Third, anti-manipulation robustness: organisers may solicit fraudulent positive reviews or competitors may post coordinated negative ones. Fourth, interpretability: both users and organisers must understand why an event received its rating [2].

2. Overview of Rating Algorithms

The simplest algorithm, the arithmetic mean (Simple Average), computes the average score as the sum of all ratings divided by their count. Although maximally transparent, it suffers from a well-known sampling bias: an event with two five-star reviews will outrank one with 500 reviews averaging 4.8 stars. For cultural platforms with large numbers of newly published events, this bias is particularly harmful [1].

The Bayesian Average addresses the cold-start problem by shrinking the estimate towards a global prior μ_0 when the number of reviews is small. The formula is:

$$S\_B(e) = (C \cdot \mu_0 + \Sigma r_j) / (C + n),$$

where n is the number of reviews, Σr_j is their sum, μ_0 is the global mean score across all events, and C is a confidence parameter (typically set to the median number of reviews per event). As $n \to \infty$, S_B(e) converges to the simple average; for small n, it converges to μ_0. This approach is widely employed in recommender systems, including the IMDb weighted rating formula [1, 3].

The Wilson Score Interval, originally developed for binary rating systems (like/dislike), computes the lower bound of a confidence interval for the true positive proportion. It is defined as:

$$W(\hat{p}, n) = (\hat{p} + z^2/2n - z\cdot\sqrt{(\hat{p}(1-\hat{p})/n + z^2/4n^2)}) / (1 + z^2/n),$$

where $\hat{p}$ is the observed proportion of positive ratings and z is the z-score corresponding to the desired confidence level (commonly $z = 1.96$ for 95%). For five-star scales, positive ratings are typically defined as those ≥ 4 [4].

Time-Decay Weighting assigns a decreasing weight to older reviews, reflecting the assumption that recent user experience is more indicative of current quality. A common exponential decay model is:

$$S\_T(e) = \Sigma(w_j \cdot r_j) / \Sigma w_j, \text{ where } w_j = e\hat{}(-\lambda \cdot \Delta t_j),$$

where Δt_j is the age of review j in days and λ is the decay rate (e.g., $\lambda = 0.005$ for a half-life of approximately 139 days). This model is particularly relevant for cultural events that may change artistic direction, venue or team over time [5].

Collaborative Filtering (CF) departs from aggregation-based approaches and instead models the latent preferences of individual users and events. In matrix factorization CF, user–event interactions are represented as a sparse matrix A, which is decomposed as $A \approx U\cdot V$^T where U and V are low-dimensional latent factor matrices. The predicted rating for user u and event e is $\hat{r}_{ue} = u_u \cdot v_e$^T. CF produces highly personalized ratings but requires a sufficiently dense interaction matrix and substantial computational resources, making it practical primarily for large platforms [6].

Table 1 – The algorithms for cultural event platforms

Algorithm	Complexity	Transparency	Speed	Key Characteristics
Simple Average	Low	High	Fast	Does not account for review count; biased with few reviews
Bayesian Average	Medium	High	Fast	Balances low-count items; requires global prior calibration
Wilson Score	Medium	High	Fast	Ideal for binary ratings; less suitable for 5-star scales
Time-Decay Weighted	Medium	Medium	Fast	Emphasizes recent reviews; risk of losisng historical context
Collaborative Filtering	High	Medium	Slow	Personalized; requires large user-event interaction matrix
Hybrid (CF + Bayesian)	High	Medium	Medium	Best accuracy; highest implementation complexity

Conclusions

This paper has systematised five principal rating algorithms applicable to cultural event platforms – simple average, Bayesian average, Wilson score, time-decay weighting, and collaborative filtering – and analysed their suitability according to the criteria of cold-start fairness, temporal relevance, anti-manipulation robustness, interpretability and computational efficiency.

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