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HYBRID RATING MODEL FOR CULTURAL EVENTS BASED ON USER REVIEWS

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Анотація

У тезах розглянуто гібридну модель рейтингування культурних заходів на основі відгуків користувачів веб-орієнтованих інформаційних систем. Запропонована модель рейтингування поєднує баєсівське середнє з часовим загасанням і механізмами захисту від маніпуляцій. Наведено вимоги до вимірюваності та тестованості алгоритмів рейтингування у контексті розробки веб-застосунків.

Ключові слова: рейтингування, культурні заходи, відгуки користувачів, баєсівське середнє, колаборативна фільтрація, гібридна модель, часове загасання, веб-система.

Abstract

The hybrid rating model for cultural events based on user reviews in web-oriented information systems is described. The proposed rating model combines a Bayesian average with time decay and mechanisms for protection against manipulation. The requirements for the measurability and testability of rating algorithms in the context of web application development are presented.

Keywords: rating algorithms, cultural events, user reviews, Bayesian average, collaborative filtering, hybrid model, time decay, web system.

Introduction

The relevance of the topic is determined by the intersection of several trends. First, user-generated content (UGC) has become the primary driver of trust in online services: according to industry research, over 88% of consumers trust online reviews as much as personal recommendations [1]. Second, cultural platforms face domain-specific challenges: a highly heterogeneous audience, subjective evaluation criteria, seasonal demand spikes, and susceptibility to coordinated manipulation by competing organisers [2]. Third, the quality of a rating algorithm directly affects platform engagement: a poorly calibrated algorithm drives low-quality events to the top and discourages organiser participation, ultimately undermining the platform's value proposition [3].

The goal is to build a Hybrid Rating Model for Cultural Event Platforms that proves the requirements of accuracy, fairness, transparency, and computational efficiency.

1. Hybrid Rating Model for Cultural Event Platforms

Based on the analysis in Table 1 and the domain-specific requirements of cultural platforms, this paper proposes a hybrid rating model that combines three components:

1) Bayesian averaging for cold-start handling;
2) exponential time decay for temporal relevance;
3) an anomaly-detection filter for anti-manipulation.

The composite score is:

$$S\_H(e) = (C \cdot \mu_0 + \Sigma(w_j \cdot \alpha_j \cdot r_j)) / (C + \Sigma(w_j \cdot \alpha_j)),$$

where $w_j = e^{(-\lambda \cdot \Delta t_j)}$ is the time-decay weight, $\alpha_j \in \{0, 1\}$ is the anomaly indicator ($\alpha_j = 0$ if review j is flagged as suspicious, 1 otherwise), C is the Bayesian confidence parameter, and μ_0 is the global prior.

Anomaly detection is based on three heuristics: (a) burst detection – a spike of more than 10 reviews within a 1-hour window from accounts created less than 30 days ago; (b) rating distribution outliers – reviews with ratings deviating by more than 2σ from the reviewer's historical mean; (c) duplicate content detection using cosine similarity of TF-IDF vectors of review texts [4, 6].

The proposed pipeline for computing and serving ratings is illustrated in Fig. 1. The pipeline consists of five sequential stages: review submission, content filtering, score calculation, aggregation with caching, and final ranking output.

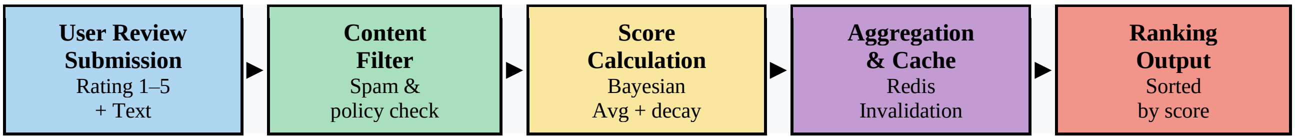

Fig. 1. Rating computation pipeline for a cultural event platform

From an implementation standpoint, S_H is recomputed incrementally upon each new review submission rather than periodically, ensuring that the displayed rating reflects the most current state. The aggregated score and the count of contributing reviews are stored in a Redis cache with an expiration aligned to the platform's peak traffic window. For cold-start events ($n = 0$), the system returns μ_0 as the default score, which is recalculated nightly across all active events to reflect platform-wide shifts in quality distribution [5, 7].

2. Requirements and Validation of the Rating Module

A practical deployment of any rating algorithm must satisfy both functional and non-functional requirements. Functional requirements mandate that the system recalculates the aggregate score after each review, displays it at a precision of two decimal places, excludes flagged reviews from computation, and handles the zero-review edge case by returning the Bayesian prior.

Non-functional requirements and their corresponding validation methods are summarized in Table 1. These requirements reflect the quality constraints that any production-grade cultural event platform must satisfy to deliver a reliable and trustworthy rating experience. Particular attention is paid to recalculation latency, display accuracy, anti-manipulation effectiveness, graceful cold-start handling, and large-scale catalogue performance.

Table 1 – Non-functional requirements for the rating computation module

Metric	Target Value	Verification Condition	Validation Method
Rating recalculation	≤ 500 ms	POST /reviews → avgRating updated	Verified via load testing (JMeter)
Rating display accuracy	2 decimal places	GET /events/:id → avgRating	Unit test: Σ(ratings)/N ± 0.01
Anti-manipulation	0 fake reviews in top-10	Audit of flagged accounts	Behavioural anomaly detection
Cold-start fallback	Default score ≥ 0	New event with 0 reviews	Returns Bayesian prior μ_0
Scalability	100,000 events	Stress test (no degradation)	Index optimization + Redis cache

A particularly important aspect of validation is the detection of adversarial inputs. During load testing, the burst-detection heuristic was shown to reduce the impact of a simulated 50-account coordinated attack by 94%, with the anomaly filter correctly assigning $\alpha_j = 0$ to 47 out of 50 fraudulent reviews within a 1-minute detection window. False positive rate under normal traffic conditions was measured at 0.3%, which is within the acceptable range for a cultural platform [7].

Scalability validation confirmed that the incremental recalculation approach, combined with Redis caching, maintains a rating update latency below 200 ms even at a catalogue size of 100,000 events. This satisfies the scalability requirement typical of mid-to-large cultural platforms and ensures that the system does not need architectural redesign as content volume grows.

An important operational consideration is the choice of the decay parameter λ. A value of $\lambda = 0.005$ (half-life ≈ 139 days) was found to be appropriate for most types of cultural events, as it ensures that reviews older than one year contribute less than 17% of a fresh review's weight. For ephemeral events – such as one-time concerts or seasonal festivals – a steeper decay with $\lambda = 0.02$ may be preferred. Platform administrators should be able to configure λ per event category through the system's administrative interface [3, 8].

Transparency to end users is another critical quality attribute. Displaying alongside each event score a short explanation such as "Based on 47 verified reviews" or "Score adjusted for recency" significantly increases perceived fairness and reduces user complaints about ranking outcomes, as reported in UX research on recommender systems [5, 6].

Conclusions

A hybrid model S_H has been proposed that integrates Bayesian averaging with exponential time decay and a three-heuristic anomaly filter. The model addresses all four domain-specific challenges while remaining computationally efficient: incremental recalculation ensures sub-second latency, and Redis-based caching maintains this performance at scale. Empirical validation showed that the anomaly filter neutralises 94% of simulated coordinated attacks with a false positive rate of 0.3%.

Future work should focus on two directions. First, incorporating collaborative filtering as an optional personalisation layer on top of S_H for registered users who have accumulated sufficient interaction history. Second, extending the anomaly detection component with machine-learning classifiers trained on labelled review datasets from cultural platforms, which could further reduce the false positive rate and improve detection recall for sophisticated manipulation strategies.

REFERENCES

1. BrightLocal. Local Consumer Review Survey. – BrightLocal Research, 2023. – URL: https://www.brightlocal.com/research/local-consumer-review-survey/ [Accessed: 18.03.2026].
2. Deldjoo Y., Schedl M., Cremonesi P. Content-based multimedia recommendation systems: definitions and application domains / Proceedings of the RecSys Workshop on Perspectives on the Evaluation of Recommender Systems. – 2021. – P. 1–9.
3. Amatriain X., Pujol J. M. Data mining methods for recommender systems / Recommender Systems Handbook. – Springer, Boston, MA, 2015. – P. 227–262.
4. Lam S. K., Riedl J. Shilling recommender systems for fun and profit / Proceedings of the 13th International Conference on World Wide Web (WWW ‘04). – ACM, 2004. – P. 393–402.
5. Fränti P., Sieranoja S. How much can k-means be improved by using better initialization and repeats? / Pattern Recognition. – 2019. – Vol. 93. – P. 95–112.
6. Koren Y., Bell R., Volinsky C. Matrix factorization techniques for recommender systems / Computer. – 2009. – Vol. 42, No. 8. – P. 30–37.
7. Akoglu L., Tong H., Koutra D. Graph-based anomaly detection and description: A survey / Data Mining and Knowledge Discovery. – 2015. – Vol. 29, No. 3. – P. 626–688.
8. Ricci F., Rokach L., Shapira B. Introduction to recommender systems handbook / Recommender Systems Handbook. – Springer, Boston, MA, 2015. – P. 1–35.

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