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Adaptive Sentiment Evaluation in Social Media Analysis

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Abstract

Social media platforms constitute complex socio-emotional environments in which linguistic expression, emotional intensity, and collective behavior interact dynamically. Recent benchmark-driven studies demonstrate that transformer-based sentiment models consistently outperform traditional lexicon-based approaches on large-scale social media datasets [4, 7]. However, sentiment scores cannot be interpreted as absolute ground-truth quantities, and conventional pipelines relying on static aggregation inadequately reflect contextual variability and inter-model disagreement, particularly in heterogeneous social media discourse [3, 6, 7].

This study presents a large-scale sentiment and behavioral analysis of Reddit discussions using an adaptive sentiment evaluation framework. The proposed Adaptive Dynamic Reliability-Triggered Weighting (ADRTW) mechanism dynamically adjusts the contribution of multiple sentiment models based on text-specific characteristics. The framework integrates lexicon-based sentiment analyzers, including VADER and TextBlob, with a transformer-based contextual language model (BERT) [1, 2], motivated by the observation that different linguistic structures favor different sentiment modeling paradigms.

The ADRTW evaluation layer combines surface-level textual features with inter-model consistency measures to estimate context-dependent reliability weights, enabling conflict-aware sentiment fusion. Consequently, sentiment scores are interpreted as relative, context-aware estimations rather than fixed numerical labels.

The analysis is conducted on approximately 1,000 Reddit posts and over 300,000 English-language comments collected between 2017 and 2025 via the Reddit API. Toxicity indicators are analyzed alongside adaptive sentiment trajectories to decouple negative affect from harmful discourse behavior [5]. Temporal and clustering analyses further reveal recurring participation archetypes and topic-dependent emotional rhythms [7]. Overall, the proposed framework provides a flexible and interpretable basis for analyzing emotional dynamics in large-scale social media discourse. Compared to static averaging baselines, ADRTW significantly reduces sentiment variance and improves temporal consistency across Reddit discussion clusters.

Problem 1 (Adaptive Sentiment Assessment)**.** *Designing a sentiment analysis system that reliably captures emotional and behavioral patterns in large-scale social media discourse presents a significant challenge. Traditional sentiment pipelines based on static model aggregation fail to adapt to contextual variability, inter-model disagreement, and heterogeneous linguistic structures. How can an adaptive reliability-aware fusion mechanism provide more stable and interpretable sentiment estimates across diverse discussion contexts?*

Remark 2 (Contribution Summary)**.** This work contributes a context-sensitive framework that reframes sentiment aggregation as a reliability-weighted interpretation problem.

Definition 3 (Sentiment Signal)**.** For a given social media text x, a sentiment model i produces a real-valued sentiment signal $s_i(x)$, representing the estimated emotional polarity or intensity expressed in the text.

Definition 4 (Adaptive Dynamic Reliability-Triggered Weighting)**.** Adaptive Dynamic Reliability-Triggered Weighting (ADRTW) is a reliability-aware sentiment fusion framework in which multiple sentiment signals are combined using dynamically estimated context-dependent weights. The aggregated sentiment is defined as

$$S_{\mathrm{ADRTW}}(x) = \sum_{i=1}^{N} w_i(x)\, s_i(x),$$

where $s_i(x)$ is the sentiment output of model i and $w_i(x)$ is its normalized reliability weight.

Remark 5. The reliability score $R_i(x)$ is computed as a composite indicator derived from (i) inter-model polarity dispersion, (ii) surface-level textual feature consistency (e.g., length and lexical density), and (iii) short-term historical stability across similar discourse contexts.

Proposition 6 (Reliability-Weighted Sentiment Fusion Property)**.** *Let $R_i(x)$ denote the estimated reliability of sentiment model i for input text x. If the fusion weights are defined as*

$$w_i(x) = \frac{R_i(x)}{\sum_{j=1}^{N} R_j(x)},$$

then the ADRTW estimator $S_{ADRTW}(x)$ reduces the influence of unreliable or conflicting sentiment predictions while preserving consistent emotional signals.

Empirical Implication 7. *When sentiment models with higher contextual reliability receive larger weights, the ADRTW estimator exhibits increased stability and reduced sensitivity to inter-model disagreement.*

Example 8. If a Reddit post contains sarcasm and slang, lexicon-based models may disagree with BERT. ADRTW assigns lower weights to inconsistent models and emphasizes context-aware predictions, producing a more reliable sentiment score.

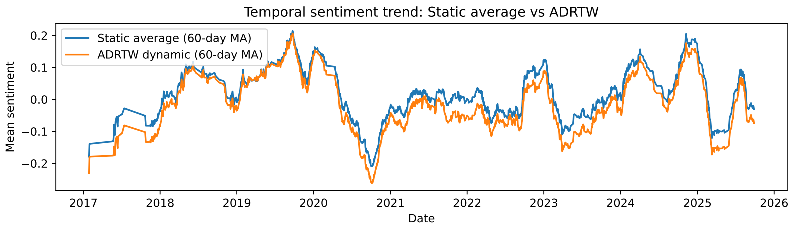

Figure 1. Temporal comparison of static averaging and ADRTW-based sentiment over Reddit discussions.

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