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SENTIMENT ANALYSIS OF E-COMMERCE REVIEWS USING BGE EMBEDDINGS AND RAINBOW DEEP REINFORCEMENT LEARNING

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ABSTRACT
Sentiment analysis of large-scale e-commerce review data presents significant challenges, particularly due to imbalanced class distributions and the need for deep semantic understanding. In this work, we propose a robust hybrid pipeline that integrates BGE (BAAI General Embedding) sentence embeddings with a Rainbow Deep Q-Network (DQN) reinforcement learning framework for binary sentiment classification. The system frames sentiment prediction as a reward-driven decision problem, where the agent learns to classify reviews as Positive or Negative by receiving class-weighted rewards. The pipeline preprocesses Flipkart customer reviews, generates normalized BGE-small-en embeddings, and trains a Rainbow DQN with dueling architecture, Adam optimizer, and Huber loss. Experiments on a subset of 50,000 reviews demonstrate that the proposed method achieves an overall accuracy of 96.19%, with per-class F1-scores of 0.98 (Positive) and 0.88 (Negative), outperforming traditional ML and deep learning baselines. The study highlights the effectiveness of combining semantic embeddings with adaptive reinforcement learning for scalable, imbalance-aware sentiment classification.

KEYWORDS: *Sentiment Analysis, BGE Embeddings, Rainbow Deep Q-Network (DQN), Reinforcement Learning, Imbalanced Data, E-Commerce Reviews*

1. INTRODUCTION

In today's digital era, online shopping platforms generate a massive volume of customer reviews daily. These reviews contain valuable insights about product quality, customer satisfaction, and user experience. Analyzing them manually is time-consuming and impractical, necessitating intelligent automated systems for sentiment classification.

Sentiment analysis, or opinion mining, is a technique used to determine whether a piece of text conveys positive, negative, or neutral emotion. It plays a crucial role in e-commerce decision-making, brand monitoring, and product feedback evaluation.

Traditional machine learning approaches such as Naïve Bayes, SVM, and Logistic Regression struggle to capture deep contextual relationships in text and are particularly sensitive to class imbalance, leading to degraded performance on minority sentiment classes.

Recent advances in transformer-based embeddings, such as BGE (BAAI General Embedding), offer rich contextual representations that encode semantic nuances effectively. However, even with high-quality embeddings, conventional classifiers may not optimally align with real-world objectives, particularly when minority-class recognition is critical.To address these challenges, this work integrates BGE sentence embeddings with a Rainbow Deep Q-Network (DQN) reinforcement learning framework. We introduce a reward-driven classification approach with class-specific weighting to handle imbalanced data, combined with a dueling architecture for improved learning stability.

The proposed approach enables the model to prioritize minority-class recognition without sacrificing majority-class accuracy, providing a practical and scalable solution for large-scale sentiment analysis tasks. This design also emphasizes reproducibility and computational efficiency, making it suitable for real-world deployment.

2. OBJECTIVE

The primary objectives of this study are:

1. Develop a reproducible pipeline integrating BGE embeddings with Rainbow DQN for binary sentiment classification of e-commerce reviews (Negative, Positive).
2. Mitigate class imbalance effects through reward shaping and class-aware optimization strategies within the reinforcement learning framework.
3. Assess model performance using accuracy, precision, recall, and per-class F1-scores to ensure effective minority-class recognition.
4. Establish a flexible methodology that can be extended to multi-class, multi-domain, and real-time sentiment classification tasks.

3. PROBLEM STATEMENT

Real-world e-commerce review datasets suffer from a strong class imbalance, where positive reviews significantly outnumber negative ones. Traditional supervised models tend to overfit the majority class, resulting in poor recognition of minority sentiments such as negative reviews.

Additionally, customer review text is inherently unstructured, containing noise, typos, slang, and varied writing styles. Standard preprocessing pipelines often fail to clean and normalize this data adequately for accurate downstream classification.

Existing approaches also fail to adapt to dynamic data patterns; they treat classification as a static supervised problem and do not leverage feedback mechanisms that enable iterative improvement. This limits their utility in rapidly evolving e-commerce environments.

This research addresses the imbalance and adaptability challenges by integrating BGE embeddings for semantic understanding with a Rainbow Deep Q-Network (DQN) that employs reward-driven learning. The agent learns class-aware strategies that promote balanced performance, improving sentiment prediction across all classes in large-scale review data.

4. METHODOLOGY

4.1 Data Collection and Preprocessing

We used a dataset of Flipkart product reviews, sampling 50,000 reviews containing text summaries and corresponding star ratings. Ratings were mapped to binary sentiment classes: Negative (≤ 2) and Positive (≥ 4). Neutral reviews were removed to focus on binary classification. The train/test split was 80%/20%.

Text preprocessing steps included: lowercasing all text; removing HTML tags, URLs, emojis, and punctuation; stripping extra whitespace; and applying stopword removal using NLTK while retaining negation words (not, no, never) to preserve sentiment-relevant signals.

4.2 Feature Extraction

We employed BGE-small-en (BAAI General Embedding) to compute sentence embeddings for each review. These embeddings capture rich contextual information and semantic meaning by encoding relationships between words and phrases in a high-dimensional vector space. All embeddings were precomputed and normalized to unit length to improve model stability, and stored to reduce redundant computations during reinforcement learning training.

4.3 Reinforcement Learning (RL) Formulation

Sentiment classification is framed as a reinforcement learning task, where:

- Observation Space: Sentence embeddings of each review (BGE-small-en vector)
- Action Space: Predict one of two sentiment classes — Negative (0) or Positive (1)
- Reward System: Correct predictions receive class-weighted positive rewards; incorrect predictions receive penalties, with stronger penalties for minority-class errors to handle imbalance
- Environment Dynamics: Random sampling of observations per step to prevent overfitting

The agent is trained using a Rainbow Deep Q-Network with a dueling architecture. Gradients are clipped during training to maintain numerical stability.

4.4 Rainbow DQN Architecture

The Rainbow DQN model incorporates the following components:

- Feature Layers: Fully connected layers with ReLU activation and dropout regularization
- Dueling Architecture: Separate value and advantage estimation streams that are merged to produce final Q-values
- Output: Q-values for each sentiment class, guiding action selection during training and inference

Optimizer: Adam | **Loss:** Smooth L1 (Huber) | **Batch Size:** 64 | **Epochs: 10** (scalable)

5. MODEL EVALUATION AND PERFORMANCE

The proposed sentiment classification framework — combining BGE embeddings with a Rainbow DQN reinforcement learning model — was evaluated using accuracy, precision, recall, per-class F1-scores, and graphical analysis including training loss curves, confusion matrices, and classification reports.

The model achieved an overall accuracy of 96.19% on the test set. Per-class results show strong performance for both Positive and Negative classes, with F1-scores of 0.98 and 0.88 respectively — confirming that the reward shaping strategy effectively addresses the class imbalance problem.

Metric	Positive Class	Negative Class	Overall
Accuracy	—	—	96.19%
Precision	0.98	0.92	—
Recall	0.99	0.88	—
F1-Score	0.98	0.90	—

Table 1: Per-Class Evaluation Metrics of the proposed Rainbow DQN + BGE model.

5.1 Analysis

The proposed model is benchmarked against standard baselines to confirm its superiority:

Model / Method	Approach	Accuracy	F1-Score
Proposed: Rainbow DQN + BGE	RL + Adaptive rewards	97.25	0.97
DRL Actor-Critic+SBERT	Class-weighted rewards	0.78	0.74
DQN + SBERT	Standard rewards	0.75	0.72
Q-Learning + SBERT	Basic reward scheme	0.73	0.70
REINFORCE + SBERT	Monte Carlo rewards	0.70	0.67

Table 2: Performance comparison across methods on Flipkart review dataset.

6. RESULT ANALYSIS

The Rainbow DQN-based sentiment classifier with BGE-small-en embeddings achieved an overall accuracy of 96.19%, performing strongly on both Positive and Negative sentiment classes. The Positive class F1-score of 0.98 reflects excellent majority-class performance, while the Negative class F1-score of 0.88 demonstrates meaningful minority-class recognition — a significant improvement over baselines.

Monte Carlo-style sampling during environment interaction reduced variance in the reward signal, and the dueling architecture enabled stable convergence of Q-value estimates across episodes. The training loss curve (Figure 1) shows consistent decrease over episodes, confirming effective learning and model convergence.The class-weighted reward mechanism guided the policy to better distinguish Negative reviews, directly addressing the inherent imbalance in the Flipkart dataset where positive sentiment reviews constitute the majority. Confusion matrix analysis (Figure 3) reveals that most misclassifications occur at the Positive-Negative boundary, consistent with the semantic similarity between mildly negative and neutral-toned reviews.

Precomputed BGE embeddings significantly reduced training time by eliminating redundant forward passes through the transformer model during RL training episodes. Graphical analysis of the error distribution (Figure 4) confirms that prediction errors are concentrated near zero, indicating high reliability of the proposed system.

7. CONCLUSION

This study presents a robust and efficient framework for binary sentiment analysis by integrating BGE sentence embeddings with a Rainbow Deep Q-Network (DQN) Actor-Critic reinforcement learning model. The reward-shaped, class-aware training strategy directly addresses the class imbalance problem prevalent in real-world e-commerce datasets, enabling more reliable detection of negative sentiments without sacrificing positive-class accuracy.

Experimental results on 50,000 Flipkart customer reviews demonstrate that the proposed method achieves 96.19% accuracy with per-class F1-scores of 0.98 (Positive) and 0.88 (Negative), outperforming both traditional machine learning baselines (~75%) and standard deep learning models (~90%). The findings confirm the effectiveness of combining pre-trained contextual embeddings with adaptive reinforcement learning for scalable, real-world sentiment classification.

Future work may explore integrating more advanced embedding models such as BGE-large or domain-specific BERT variants, extending to multi-class sentiment classification (including neutral), implementing dynamic reward shaping, and scaling to multilingual or multi-domain datasets for broader applicability.

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