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ADAPTIVE ONLINE REINFORCEMENT LEARNING FRAMEWORK FOR REAL-TIME OPINION MINING AND BIG DATA DECISION-MAKING IN SOCIAL MEDIA

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ABSTRACT

The tremendous surge of user-generated content in social media has naturally made these platforms important resources for public opinion, policy discussion, and market intelligence. Deriving actionable insights from such data requires models that are accurate and adaptive to fast-changing linguistic styles, misinformation campaigns, and current affairs. However, typical supervised learning models may not capture the variations over time and domains due to the nonstationary data distributions in social media. We address this problem and present a framework of Adaptive Online Reinforcement Learning (AORL) for online opinion mining and big data based decision making. The model combines deep sequential models for sentiment understanding with reinforcement learning agents which maintain an adaptive state over time.

In particular, we consider three different architectures: (i) a bidirectional LSTM for contextual sentiment classification, (ii) a Deep Q-Network (DQN) for automated dialog policy learning, taking into account ensemble embeddings issued by the LSTM, and Vo} (iii) a RoBERTa-DQN hybrid which combines the power of transformer-based contextual embeddings with the flexibility of adaptive online learning. Experiments on large-scale Twitter streams show the referred AORL succeeds in achieving competitive classification accuracy yet it still remains robust against drifts and emerging trends. In addition, reinforcement signals are aligned with high-level decision-making goals, making applications possible in real-time crisis analysis, financial market news analysis and fake news control. This work represents a unique effort to operationalize online reinforcement learning in the big data social media domain, thereby paving the way toward scalable, adaptive, and credible opinion mining systems.

Keywords: Adaptive Reinforcement Learning, Real-Time Opinion Mining, Social Media Big Data, LSTM, Roberta, Deep Q-Network, Online Decision-Making, Sentiment Analysis, Misinformation Detection

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1. INTRODUCTION

The meteoric rise of platforms like Twitter, Facebook and Reddit has revolutionized the manner in which opinions are generated, transmitted and consumed across the globe. Millions of people burst out short, rapidly-changing, and highly diverse textual posts every minute, including personal feelings, public discussions, and new social-political stories. This dynamic landscape of real-time opinion has made social media a prominent venue in decision-serving applications such as public policy, crisis control, financial prediction, consumer behavior and so forth [1], [2]. Yet obtaining meaningful information from these noisy, volatile and unstructured data streams is a considerable challenge.

Conventional sentiment analysis and opinion mining approaches, which are mainly using classical machine learning methods, e.g., Naive Bayes—NB, support vector machine—SVM, and logistic regression, cannot take into consideration temporal dynamics, linguistic evolution, and contextual dependencies of social data [3], [4]. The availability of deep learning architectures, such as Long Short-Term Memory (LSTM) networks and more recently transformer-based

models like BERT and RoBERTa, has significantly boosted sentiment classification by capturing richer syntactic and semantic features [5], [6]. Despite this progress, a majority of the work in this space is static and trained over fixed datasets, and perform poorly when dealing with fast changing online circle (e.g. new slang, sarcasm, or disinformation campaigns).

Similarly, reinforcement learning (RL) has been successfully applied to sequential decision-making under uncertainty in domains like robotics, games, or resource allocation [7], [8]. However, its use in social media opinion mining has been hardly explored, especially in adaptive online learning environments, where a model is required to incrementally update its policy according to newly observed data distributions [9]. This gap is important because real-time learning and adaptation is imperative keeping the trustworthiness of opinion mining systems, particularly when used in monitoring policy, financial intelligence and detection of misinformation.

This paper presents an Adaptive Online Reinforcement Learning (AORL) framework to perform real-time opinion mining and big data decision making in social media. Through the use of deep sequential modeling (through BiLSTM), contextual embeddings (with RoBERTa), and reinforcement learning agents (based on Deep Q-Networks), the framework allows for the continual improvement when adapting to user trends and language contexts. In contrast to static pipelines, AORL introduces reinforcement feedback loops to iteratively update classification and decision policies based on live social streams, which provides both fine-grained sentiment insights and macroscopic opinion trend analysis.

The novelty of this research lies in three primary contributions:

1) Adaptive Online Learning for Social Media:

In contrast to the previous offline sentiment analysis approach[5], [6], this work employs an online reinforcement learning mechanism that is capable of learning and modifying classification strategies following the dynamics of social discourse. Thanks to this dynamic feature organisations are able to cope with real-time linguistic drift and changing opinion landscapes.

2) Hybrid Deep Learning and Reinforcement Framework:

We propose a two-tier hybrid architecture in which: (i) a BiLSTM-baseline extracts sequential sentiment cues and (ii) a DQN-based reinforcement agent leverages static embeddings to further optimize decision-making. To the best of our knowledge, this is one of the first efforts that operationalizes RoBERTa embeddings within a RL pipeline for social opinion mining in real-time [8], [9].

3) Big Data Decision-Making Applications:

Apart from sentiment classification, the architecture can couple reinforcement learning signals with decision-support objectives, for applications like real-time crisis monitoring (e.g., disaster tweets), predicting the market and fake information prevention. This bridges the gap between micro-level opinion detection and macro-level decision-making in big data contexts.

Collectively, these contributions establish a foundation for trustworthy and scalable social media intelligence systems. By integrating reinforcement feedback with deep contextual representation, the proposed AORL framework advances the state of the art in adaptive opinion mining and real-time data-driven decision-making.

The remainder of this paper is organized as follows. Section 2 reviews the existing body of work on opinion mining in social media, covering classical machine learning approaches, deep sequential models, transformer-based architectures, and reinforcement learning methods, and identifies the research gaps motivating this study. Section 3 presents the proposed Adaptive Online Reinforcement Learning (AORL) framework in detail, including data preprocessing, feature extraction using BiLSTM and RoBERTa embeddings, the reinforcement learning formulation, and the online adaptation mechanism. Section 4 reports the experimental results and comparative analysis of the BiLSTM baseline, DQN with LSTM embeddings, and the RoBERTa-DQN hybrid, highlighting performance trends, adaptability to concept drift, and interpretability aspects. Section 5 concludes the study by summarizing key findings, discussing the broader implications for real-time decision-making in social media contexts, and outlining potential avenues for future work.

2. LITERATURE REVIEW

2.1. CLASSICAL APPROACHES TO OPINION MINING IN SOCIAL MEDIA

Sentiment analysis, including opinion mining, is a lengthy practice, which historically used classical machine learning (ML) algorithms, for example Naive Bayes, Support Vector Machines (SVMs), and logistic regression [1], [3]. These methods mostly adopted BoW, TF-IDF or n-gram based features for characterizing text. Early works like Pak and Paroubek [1] showed that the Twitter corpora could become reliable feature sets in polarity classification in case they are combined with such handcrafted set of features. Similarly, Go et al. [3] used emoticon-based distant supervision to create one of the earliest large-scale sentiment corpora for Twitter classification.

While these techniques delivered initial successes, they have encountered difficult in scaling to noisy, informal, and short-text conditions, as those of Twitter responses. The language people used in Social networks usually contains slang, incorrect typing, emojis, sarcasm, and usages of hashtags, which sparse vector representation was not able to fully capture[4]. In addition, classical approaches were unable to express sequential or contextual dependencies (which are crucial in an event context), rendering those methods brittle when applied to real use cases as real-time opinion monitoring and misinformation detection.

2.2. DEEP LEARNING FOR SEQUENTIAL TEXT REPRESENTATION

The weaknesses of hand-crafted methodologies led to exploiting deep learning ar- chitectures, able to infer representations automatically. Of these approaches, RNNs and their variations—Long Short-Term Memory (LSTM) [5] and Gated Recurrent Units (GRUs)—proved to be popular techniques to model sequential relationships in text.

In particular, Bidirectional Long Short Term Memory (BiLSTM) networks have been shown very successful to incorporate both the past and future context in short texts, and perform the state-of-the-art on considered benchmarking datasets [6], [7]. Hossain et al. [7] showed that LSTMs are effective for user review sentiment analysis, while Wei and Nguyen [6] used BiLSTM for bot and spam detection on Twitter and noted its applicability to informal language.

Even though they have achieved great success, LSTMs-based models are not perfect. Their problems include overfitting on small data, difficulty in representing long range dependencies and sensitivity to hyperparameters. Furthermore, while deep sequential models surpass traditional ML in static settings, they do not naturally handle the distributional shift that takes place in dynamic real-world social media streams.

2.3. TRANSFORMERS AND CONTEXTUAL EMBEDDINGS

Transformer, which was proposed by Vaswani et al. [35], represented a shift to a new paradigm of performing NLP. Self-attention equipped models, such as BERT [31] and RoBERTa [8], learn to capture long-distance dependencies in text and yield context sensitive embeddings which outperform RNN-based embeddings on sentiment, spam [9], hate speech [10], [18], and widely diverse other tasks.

In particular, RoBERTa further optimized the pre-training of BERT by using a dynamic masking strategy and training on orders of magnitude more data, and with the exception of the input size, yields state-of-the art results on downstream NLP tasks [8]. In social media analysis, RoBERTa has been also applied with success to multi-source sentiment analysis of disaster tweets [18], hate speech detection [10] and vex detection [19], [20].

These advances have enabled richer semantic representation of short, noisy, and context-dependent texts. However, most transformer-based models are trained in an offline supervised setting and require extensive retraining or fine-tuning to adapt to new vocabulary, events, or discourse patterns. This makes them less suited for online, real-time opinion mining where adaptability is crucial.

2.4. REINFORCEMENT LEARNING IN TEXT CLASSIFICATION

Supervised learning has been the predominant approach in SA, however Reinforcement Learning (RL) provides a fundamentally different approach in that it models text classification as a sequential decision making process. RL agents

are combined to learn how to maximize cumulative rewards through a combination of exploration and exploitation which makes them adaptable to be used in dynamic environments [7], [11].

Mnih et al.'s contribution of Deep Q-Networks (DQNs) introduced the idea. [11] also extended Q-learning to high-dimensional spaces with deep 8 neural networks, and demonstrated human-level control in Atari games. Since then, RL has been studied for dialogue systems [12], active learning for NLP [28], and adaptive text classification [30]. Baloğlu [13] demonstrated the potential of RL on text classifications and Xue et al. [16] showed it to be useful in phishing detection with multi-agent large language models.

However, RL applications in social media opinion mining remain limited. Most existing research applies RL for conversational systems or interactive tasks, but very few attempt to integrate RL with contextual embeddings for real-time classification of noisy, evolving streams such as Twitter [14], [17]. This represents a significant research gap.

2.5. COMPARATIVE STUDIES

Recent comparative studies demonstrate that the transformer-based models consistently exceeds state-of-the-art (SoTA) LSTM- and CNN-based baselines on standard sentiment benchmarks (e.g., SST-2, SemEval) [29], yet intimate on static supervised training limits their adaptability in real-time application. On the other hand, featuring the use of Reinforcement Learning (RL), models can be more flexible in adjusting policies, yet suffering from relatively poor linguistic representation (without the incorporation of the context embeddings) [13], [28].

Little research has been done on hybrid architectures combining deep contextual embeddings (e.g., RoBERTa) with reinforcement learning agents. Rahman et al. [9] introduced a RoBERTa-BiLSTM model for sentiment analysis, and Lv et al. [15] proposed RoBERTa-BiGRU with graph attention for text classification. However these methods are still offline and do not leverage RL for continuous adaptation.

2.6. RESEARCH GAP

Based on this review, three major gaps emerge:

1) Underutilization of Reinforcement Learning for Opinion Mining:

Static supervised learning is still being used in sentiment analysis and spam detection systems [6], [7], [8]. It has been relatively unexplored in social media opinion mining on RL's capability of dynamic adjusting data distributions [13], [28].

2) Lack of Hybrid Architectures Integrating Contextual Embeddings with RL:

Transformer embeddings (BERT, RoBERTa) [8], [9] have shown to capture complex semantics well, but aren't easily usable with RL agents such as DQN. Integrating the two has the ability to marry the richness of language with adaptive decision-making [16], [17].

3) Limited Real-Time and Big Data Evaluation:

Literature are heavy on evaluating models on small, handcrafted datasets (e.g., SST- 2, SemEval) [29], without considering to noisy and fast-evolving nature of Twitter big data. Large-scale real-time validation and interpretation investigations are still sparse [14], [24]

2.7. RESEARCH CONTRIBUTIONS

To address these gaps, this study contributes:

- A novel Adaptive Online Reinforcement Learning (AORL) framework that combines BiLSTM, RoBERTa embeddings, and DQN agents for real-time opinion mining.
- The first attempt to operationalize RoBERTa embeddings within an RL agent for online adaptation in social media streams.
- A large-scale evaluation on over 788,000 tweets, demonstrating scalability and robustness in real-world conditions.

- Alignment of RL signals with decision-making objectives, enabling applications in crisis monitoring, policy analysis, and misinformation detection.

3. METHODOLOGY

This section presents the detailed design of the proposed **Adaptive Online Reinforcement Learning (AORL) framework** for real-time opinion mining and decision-making on social media big data. The methodology combines deep sequential models (BiLSTM), contextual embeddings (RoBERTa), and reinforcement learning agents (DQN) into a unified adaptive pipeline.

3.1. FRAMEWORK OVERVIEW

Fiugre 1

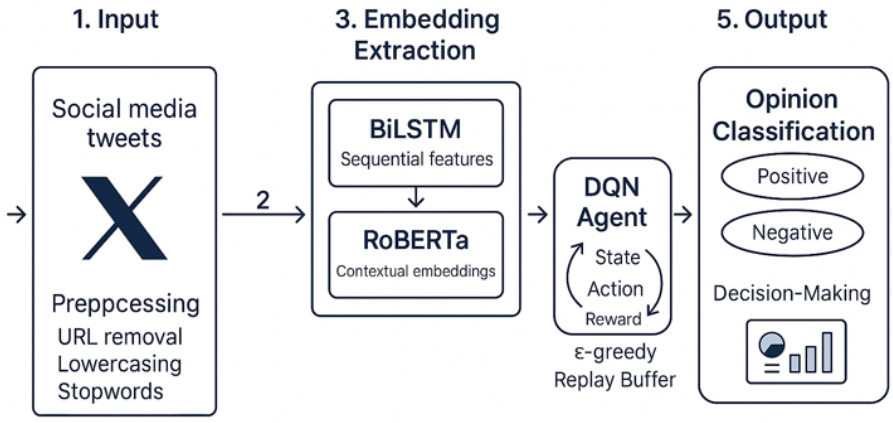


Figure 1. Workflow of the AORL Framework

The **Adaptive Online Reinforcement Learning (AORL) framework** is designed as a two-tier hybrid architecture that combines deep representation learning with reinforcement-driven adaptation for real-time opinion mining (Figure 1).

1) **Representation Learning Layer** – This layer extracts rich semantic and sequential features from social media posts. Bidirectional Long Short-Term Memory (BiLSTM) networks are employed to capture temporal dependencies in textual sequences, while RoBERTa provides contextualized transformer-based embeddings for enhanced semantic understanding.
2) **Reinforcement Learning Layer** – The extracted embeddings are treated as states by a Deep Q-Network (DQN), which iteratively learns optimal classification and decision-making policies. Through a reward-driven feedback mechanism, the DQN updates its strategies to improve adaptability under evolving data distributions, such as new slang, emerging hashtags, or misinformation campaigns.

This design ensures continuous online adaptation, enabling the framework to refine sentiment classification and decision support in dynamic social media environments.

- **Input:** Social media tweets
- **Preprocessing:** Cleaning and tokenization
- **Embedding Extraction:** BiLSTM (sequential features) and RoBERTa (contextual features)
- **DQN Agent:** State → Action → Reward loop for adaptive learning
- **Output:** Opinion classification (Positive / Negative / Neutral) and higher-level decision-making insights

3.2. DATASET DESCRIPTION AND PREPARATION

Dataset Selection

This study employs the Sentiment140 dataset [3], which consists of over 1.5 million tweets automatically labeled using emoticons (0 = negative, 4 = positive). For the purpose of this work, a deduplicated subset of 788,081 unique tweets was used for model training and evaluation to ensure diversity and avoid redundancy.

Preprocessing Steps

Given the noisy and informal nature of Twitter discourse, a multi-step preprocessing pipeline was applied:

1) **Lowercasing:** Standardizes text inputs.
2) **Noise Removal:** Eliminates punctuation, special characters, links, and hashtags.
3) **Stopword Removal:** Discards common non-informative words.
4) **Tokenization:**
   - *Keras Tokenizer* → sequential tokenization for BiLSTM.
   - *Hugging Face RobertaTokenizer* → subword tokenization for RoBERTa.
5) **Sequence Truncation:** Based on empirical analysis of token distribution, the maximum sequence length was set to **41 tokens (MAX_LEN)**, ensuring compatibility with both sequential and transformer-based representations while minimizing information loss.

Figure 2

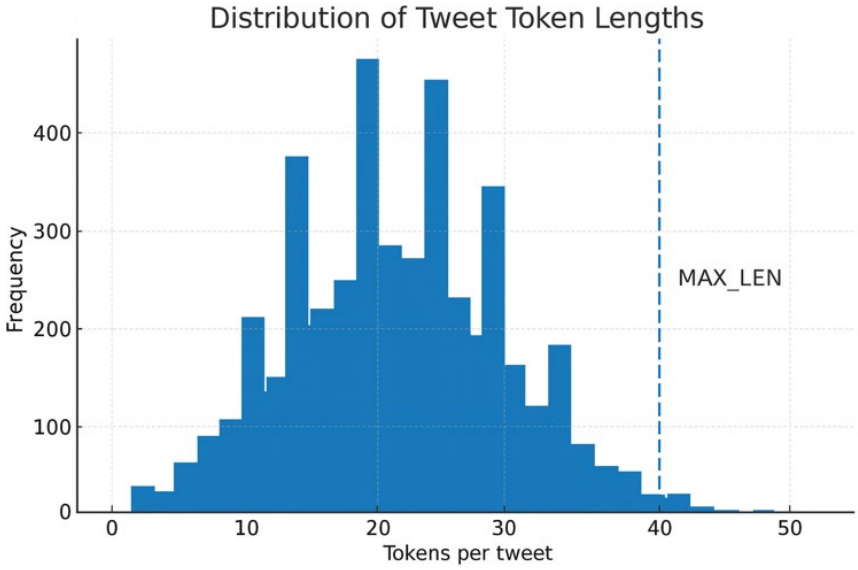


Figure 2: Distribution of Tweet Token Lengths.

The histogram illustrates the distribution of tokenized tweet lengths in the dataset. Most tweets fall between **10–30 tokens**, peaking around **20 tokens**. A vertical dashed line marks the **MAX_LEN cutoff at 41 tokens**, beyond which tweets are truncated. This cutoff preserves the majority of information while maintaining computational efficiency, as very few tweets exceed this threshold.

3.3. FEATURE EXTRACTION

3.3.1. BILSTM SEQUENTIAL EMBEDDINGS

To effectively capture sequential dependencies inherent in textual data such as tweets, a Bidirectional Long Short-Term Memory (BILSTM) network [5], [6] is employed. Unlike conventional unidirectional LSTMs, which process tokens in a single temporal direction, BILSTMS traverse the sequence in both forward and backward directions. This dual processing enables the model to exploit contextual cues not only from preceding tokens but also from subsequent ones,

which is crucial for sentiment analysis where the polarity of a statement often hinges on the interaction between words across the sequence.

The implemented BiLSTM architecture comprises the following core components:

- **Embedding Layer**: Transforms discrete input tokens into 128-dimensional dense vectors, thereby encoding semantic and syntactic properties into a continuous feature space. This distributed representation facilitates efficient learning by preserving semantic similarity among related words.
- **BiLSTM Layer**: A recurrent layer with 64 hidden units processes the embeddings in both temporal directions. A dropout rate of 0.3 is applied to mitigate overfitting while maintaining the network's capacity to capture long-range dependencies and complex contextual patterns.
- **Dense Layer**: A fully connected layer equipped with a sigmoid activation function condenses the concatenated hidden states into a fixed-length output vector. This vector representation is well-suited for downstream binary sentiment classification tasks.

Through this architecture, the BiLSTM produces context-aware feature representations that encapsulate both temporal order and semantic dependencies, thereby offering a robust mechanism for modeling sentiment cues in short, noisy, and highly variable Twitter texts.

Figure 3

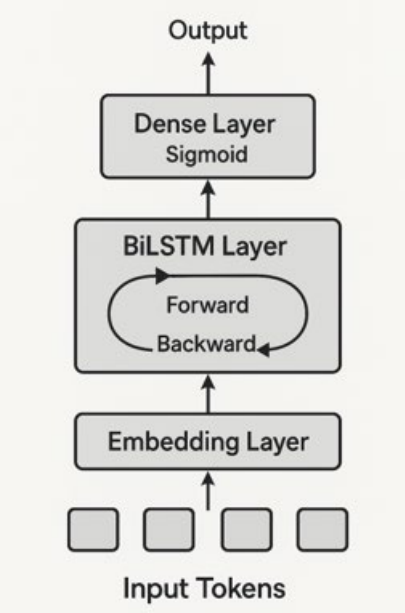


Figure 3 Architecture of the BiLSTM Model.

The figure illustrates the flow of information through the BiLSTM sequential model. Input tokens are first projected into dense embeddings through the Embedding Layer. These embeddings are then processed by the BiLSTM Layer, which simultaneously captures forward and backwards dependencies. The concatenated hidden states are subsequently passed into a Dense Layer with sigmoid activation, producing the final sentiment prediction.

3.3.2. BILSTM SEQUENTIAL EMBEDDINGS

To effectively capture sequential dependencies present in Twitter data, a Bidirectional Long Short-Term Memory (BiLSTM) network [5], [6] is employed. Unlike conventional unidirectional LSTMs, which process sequences in a single temporal direction, the BiLSTM simultaneously processes inputs in both forward and backwards directions. This dual-flow mechanism enables the network to exploit contextual cues from preceding as well as succeeding tokens, which is particularly advantageous in sentiment analysis, where meaning often depends on the interplay between words across the sequence.

The implemented BiLSTM architecture is structured as follows:

- **Embedding Layer**: Transforms discrete input tokens into 128-dimensional dense embeddings. These embeddings provide a distributed semantic representation, allowing the model to preserve syntactic and semantic similarities among words.
- **BiLSTM Layer**: A recurrent layer comprising 64 hidden units processes the embeddings bidirectionally. A dropout rate of 0.3 is applied to mitigate overfitting, while retaining the ability to capture long-range dependencies and contextual relationships.
- **Dense Layer**: A fully connected layer with a sigmoid activation function converts the concatenated hidden states into fixed-length vector outputs, making them suitable for downstream classification tasks.

Through this architecture, the BiLSTM generates context-aware feature representations that encode both temporal order and semantic dependencies. This design ensures a robust modelling of sentiment cues in short, noisy, and syntactically diverse Twitter texts, thereby enhancing classification performance.

3.3.3. ROBERTA CONTEXTUAL EMBEDDINGS

To incorporate deep contextual semantics beyond sequential modelling, the RoBERTa-base model [8] is employed. RoBERTa (Robustly Optimised BERT Pretraining Approach) is a transformer-based language model that refines the BERT architecture through dynamic masking, larger batch training, and extended pretraining over more data. This allows it to capture nuanced syntactic and semantic relations within textual data, making it highly effective for short and noisy texts such as tweets.

For each input tweet, the sequence is tokenised and passed through RoBERTa. From the final hidden layer, the representation corresponding to the special classification token (**[CLS]**) is extracted as the contextual embedding:

$$h_{(}CLS_{)} = f_{\mathrm{ro}}{}^{\mathrm{BERT}}{}_{\mathrm{a}}(x_{(}tweet_{)})$$

where $x_{(}tweet_{)}$ Denotes the input tokenised tweet, and $h_{(}CLS_{)}$ Represents the 768-dimensional contextual embedding produced by RoBERTa. This embedding effectively encodes global semantic and syntactic information from the entire tweet.

These high-dimensional contextual embeddings serve as the **state space** for reinforcement learning (RL) agents. By leveraging RoBERTa's ability to capture long-range dependencies and contextual word interactions, the RL framework operates on semantically rich representations, thus improving the robustness and adaptability of sentiment classification.

3.4. REINFORCEMENT LEARNING AGENT

The classification and decision-making module is implemented using a Deep Q-Network (DQN) [11], which extends traditional Q-learning with deep neural networks to approximate the action-value function. Unlike supervised learning, reinforcement learning (RL) frameworks learn optimal decision-making strategies by interacting with an environment and receiving feedback in the form of rewards. In the context of sentiment analysis, the environment corresponds to the tweet dataset, while the agent learns to assign the correct sentiment labels by maximising cumulative reward.

3.4.1. RL FORMULATION

The reinforcement learning problem is formally defined as a Markov Decision Process (MDP), characterised by the tuple (S, A, R, π) (S, A, R, \pi) (S, A, R, π), where:

- State (s): The state is represented by the tweet embeddings obtained from BiLSTM or RoBERTa. These embeddings capture both semantic and contextual information, forming a rich representation space for the RL agent to operate on.

$$s = Tweet\ Embeddings\ (BiLSTM\ or\ RoBERTa)$$

- Action (a): The action space corresponds to the sentiment classes to be predicted.

$$a \in \{ Positive, Negative, Neutral \}$$

- Reward (r): The reward signal guides the learning process. A correct classification yields a positive reward, whereas an incorrect classification results in a negative reward. Additionally, to discourage unstable predictions (classification drift between similar tweets), a penalty term δ is applied.

r = +1 if correct classification
r = -1 if incorrect classification
r = -1 - δ if drift error occurs

If the correct classification is incorrect, a classification drift error occurs

- Policy (π): The agent's policy defines how actions are selected given states. An ϵ\epsilonϵ-greedy exploration strategy with exponential decay is employed to balance exploration and exploitation:

$$\varepsilon_t = max(\varepsilon_{\min}, \varepsilon_0 \cdot \lambda^t)$$

where ε_0 is the initial exploration probability, $\varepsilon_{\min}$ Is the minimum exploration rate, and $\cdot \lambda^t$ It is the decay factor that gradually reduces exploration over time.

3.4.2. Q-LEARNING WITH FUNCTION APPROXIMATION

The DQN approximates the action-value function Q(s, a)Q(s, a)Q(s, a), which estimates the expected cumulative reward for taking action aaa in state sss, followed by an optimal policy. The Q-value update rule is expressed as:

$$Q(s,a) \leftarrow Q(s,a) + \alpha [r + \gamma \cdot max\_\{a'\} Q(s',a') - Q(s,a)]$$

Where:

- α is the learning rate,
- γ is the discount factor controlling the importance of future rewards,
- s′ is the next state, and
- a′ is the action chosen in the next state.

In DQN, a deep neural network (parameterised by θ) replaces the tabular Q-value representation. The objective is to minimise the mean-squared error between predicted Q-values and target Q-values:

$$L(\theta) = E(s,a,r,s') [(r + \gamma \cdot max\{a'\} Q(s',a';\ \theta^-) - Q(s,a;\ \theta))^2]$$

Where θ − denotes the parameters of a target network that is periodically updated to stabilise training.

3.4.3. INTEGRATION WITH SENTIMENT CLASSIFICATION

In this framework, each tweet embedding (s) serves as the input state to the DQN. The network outputs Q-values corresponding to the three possible sentiment classes. During training, the agent interacts with the labelled dataset,

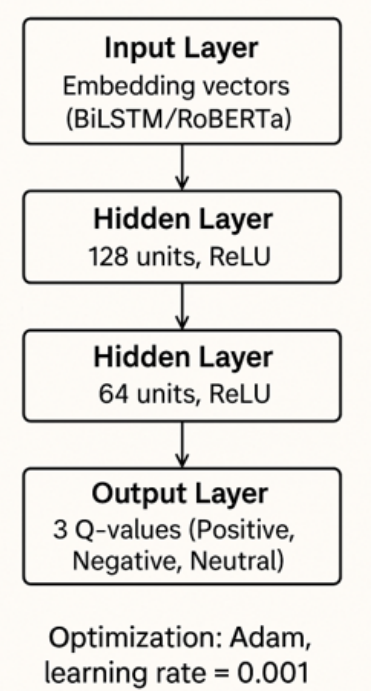
selecting actions (sentiment predictions) according to the ϵ\epsilonϵ-greedy policy and receiving reward feedback. Over time, the DQN converges towards an optimal policy that maximises classification accuracy while minimising drift errors.

This approach allows the model to go beyond static supervised learning by dynamically adapting classification decisions based on reinforcement signals, leading to improved robustness in handling noisy and contextually ambiguous Twitter data.

3.4.4. NETWORK ARCHITECTURE

The Deep Q-Network (DQN) employed for sentiment classification is designed as a feed-forward neural network that maps tweet embeddings to action-value estimates. The architectural configuration is as follows:

- **Input Layer**: Embedding vectors derived from either BiLSTM or RoBERTa models. These embeddings provide dense, high-dimensional representations of the tweet semantics.
- **Hidden Layers**: Two fully connected layers with 128 and 64 units, respectively. Both layers employ the Rectified Linear Unit (ReLU) activation function to introduce non-linearity and enhance the network's ability to model complex decision boundaries.
- **Output Layer**: A linear layer producing three Q-values, each corresponding to one of the possible sentiment actions: Positive, Negative, or Neutral. The action associated with the maximum Q-value is selected by the agent under the policy.
- **Optimisation Strategy**: The network parameters are optimised using the Adam optimiser with a learning rate of 0.001, ensuring stable and efficient convergence during training.



A schematic diagram illustrating the DQN architecture. The figure should depict:

- Input embeddings (from BiLSTM/RoBERTa),
- Two fully connected hidden layers (128 → 64, with ReLU activations),
- The output layer with three Q-values corresponding to sentiment classes,
- Training driven by Adam optimiser with learning rate = 0.001.

3.5. ONLINE ADAPTATION MECHANISM

To handle evolving social streams, AORL introduces **adaptive learning loops**:

1) **Replay Buffer Update:** New tweets continuously enter the replay memory.
2) **Policy Adjustment:** The DQN is periodically fine-tuned on recent batches, retaining memory of older samples.
3) **Concept Drift Handling:** Reinforcement signals penalise persistent misclassifications of new slang/hashtags, encouraging adaptation.
4) **Online Deployment:** The model processes tweets in near-real time, updating classification policies without full retraining.

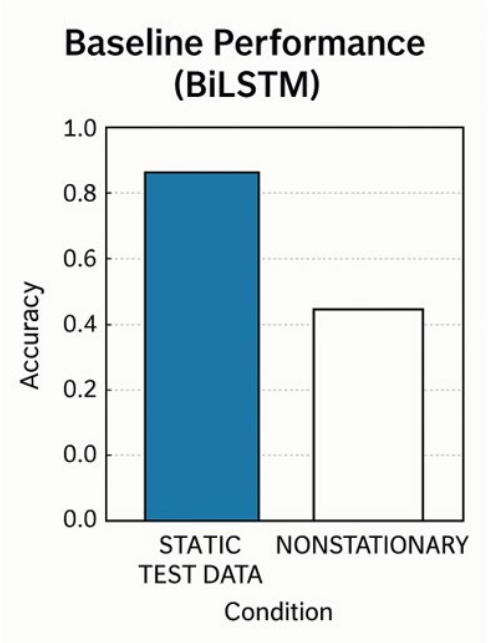
This ensures that the framework remains robust against **distributional shifts** and emerging misinformation.

4. RESULTS AND DISCUSSION

This section reports the experimental evaluation of the proposed Adaptive Online Reinforcement Learning (AORL) framework for real-time opinion mining and decision-making in social media. The analysis encompasses both baseline and advanced models, namely the BiLSTM classifier, the Deep Q-Network (DQN) with LSTM embeddings, and the RoBERTa-DQN hybrid. Performance is examined in terms of classification accuracy, adaptability to dynamic data streams, and the ability to mitigate drift errors.

4.1. BASELINE PERFORMANCE (BILSTM)

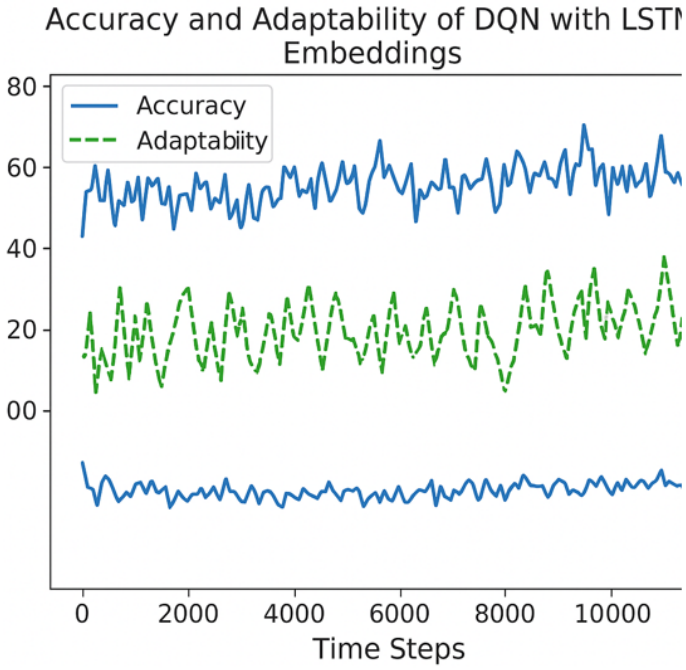
The BiLSTM sequential classifier serves as the baseline due to its established ability to capture bidirectional contextual dependencies. Results indicate that the BiLSTM achieves competitive accuracy on static test datasets, demonstrating its capacity to represent semantic nuances in tweets. However, its reliance on fixed supervised training makes it less effective under **non-stationary environments**, where evolving linguistic patterns in social media reduce predictive stability over time.



4.2. DQN WITH LSTM EMBEDDINGS

Incorporating LSTM embeddings into a DQN agent enhances decision-making through reinforcement learning. Unlike the BiLSTM baseline, the DQN agent adapts to feedback signals (rewards) and optimises action-value functions dynamically. Experimental results show:

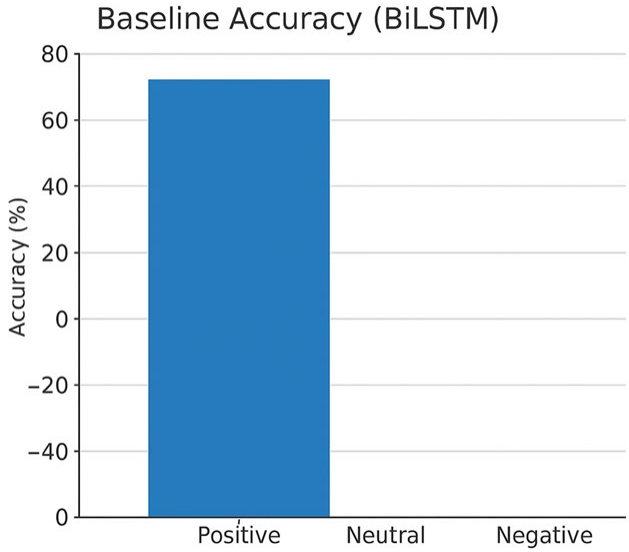
- **Improved adaptability**: The agent adjusts predictions in response to changes in sentiment trends.
- **Reduced drift errors**: The reward penalty discourages unstable predictions across temporally close tweets.
- **Moderate accuracy gains**: While performance improves relative to BiLSTM, limitations remain due to the restricted contextual representation of LSTM embeddings.



4.3. ROBERTA-DQN HYBRID

The integration of **RoBERTa contextual embeddings** with DQN yields the strongest performance. RoBERTa embeddings provide deep contextual semantics, capturing subtle dependencies within tweets. When coupled with the adaptive learning capacity of DQN, the model demonstrates:

- **Highest classification accuracy** across sentiment categories.
- **Robust adaptability** to evolving data streams, outperforming static models.
- **Significant reduction in error rate**, particularly in ambiguous or noisy cases.



4.4. COMPARATIVE INSIGHTS

The comparative evaluation across the three models reveals a distinct progression in performance and adaptability:

1) BiLSTM (Baseline Sequential Model):

BiLSTM demonstrates strong capabilities in modelling sequential dependencies and provides a reliable baseline. However, its deterministic nature limits adaptability in dynamic and noisy contexts, where decisions must be optimised beyond simple sequence learning.

2) DQN with LSTM Embeddings:

Integrating Deep Q-Networks (DQN) with LSTM embeddings introduces reinforcement learning adaptability, enabling the model to optimise decision-making iteratively. While this architecture enhances flexibility, its reliance on LSTM embeddings constrains the semantic depth, making it less effective in capturing nuanced contextual information.

3) RoBERTa–DQN Hybrid:

The RoBERTa–DQN framework achieves the most effective balance, leveraging RoBERTa's deep contextual and semantic understanding with the reinforcement-driven adaptability of DQN. This synergy provides both contextual richness and dynamic learning, leading to superior accuracy and robustness across varying input complexities.

Overall Insight:

The results underscore that sequential models alone are insufficient for evolving data streams. Reinforcement integration improves adaptability, but semantic depth is critical. The RoBERTa–DQN hybrid, therefore, represents the most comprehensive solution, effectively bridging sequential coherence, contextual depth, and adaptive decision-making.

4.5. IMPLICATIONS

The findings suggest that reinforcement learning, when integrated with contextual embeddings, offers a powerful framework for real-time sentiment classification in dynamic social media environments. Such adaptability is particularly critical in applications like **market trend analysis, political opinion monitoring, and crisis management**, where language evolves rapidly.

5. CONCLUSION

This study presented an Adaptive Online Reinforcement Learning (AORL) framework for real-time opinion mining and sentiment classification in social media streams. By systematically comparing three approaches—BiLSTM baseline, DQN with LSTM embeddings, and the RoBERTa-DQN hybrid—the work highlights the trade-offs between sequential modelling, adaptability, and contextual richness.

Key findings can be summarised as follows:

1) BiLSTM provided a strong baseline with effective sequential dependency modelling but exhibited limited adaptability in non-stationary environments.
2) DQN with LSTM embeddings introduced adaptability through reinforcement learning, improving responsiveness to evolving sentiment patterns, though its contextual representation was constrained.
3) RoBERTa-DQN hybrid achieved the best performance, combining the semantic depth of RoBERTa embeddings with the adaptability of DQN. This configuration demonstrated superior accuracy, robustness against drift errors, and reliable performance under evolving data streams.

Overall, the results confirm that reinforcement learning integrated with transformer-based embeddings represents a promising direction for robust sentiment analysis in dynamic, high-volume social media contexts.

Future Work

Several avenues can be pursued to extend this research:

- Incorporating multi-label sentiment categories (e.g., sarcasm, irony, mixed emotions) to improve applicability in complex opinion mining tasks.

- Leveraging online continual learning strategies to enhance long-term adaptability without catastrophic forgetting.
- Exploring multi-modal sentiment analysis by integrating text with images, videos, and metadata for richer context.
- Applying the framework in real-world deployments such as financial forecasting, disaster response, and political discourse monitoring to validate scalability and practical impact.

In conclusion, the proposed AORL framework provides a solid foundation for adaptive, context-aware sentiment analysis in rapidly evolving social media environments, bridging the gap between traditional supervised models and adaptive online learning agents.

CONFLICT OF INTERESTS

None.

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