

Optimized Queuing Modeling in Multimodal Sentiment Analysis: An Examination and Application

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Abstract. This paper introduces an innovative queuing model tailored for multimodal sentiment analysis, designed to swiftly generate a preliminary score by prioritizing influential factors from the most valuable modalities. In a bid to yield reliable results in a compressed timeframe, this model meticulously processes data from the modality possessing the paramount effect factor, concurrently trimming down processing time by omitting data from lesser impactful modalities. This discerning approach allows for a dynamic adjustment of the weights assigned to various modalities based on their respective impact variables, culminating in precise and credible sentiment analysis outcomes. In an era where expediency and accuracy are at a premium, the proposed model stands out by ensuring that the sentiment analysis is not just rapid, but also robust and reliable, reflecting the true emotional tonality with a high degree of reliability. The model's adaptability to fluctuating modalities, ensures its utility across diverse platforms and applications, making it a valuable tool for contemporary sentiment analysis tasks. Amidst a digital landscape that continually evolves, this queuing model for sentiment analysis exemplifies a significant leap forward, proffering enhanced efficiency, accuracy, and reliability in sentiment analysis endeavors.

Keywords: Queuing modeling, Multimodal Sentiment Analysis.

1. Introduction

Multimodal sentiment analysis represents a pivotal task in natural language processing, entailing the aggregation and integration of sentiment information from text, audio, and video data to derive a comprehensive sentiment rating. This challenge has garnered significant attention in recent years, owing to its expansive application potential in arenas such as customer feedback analysis, product review summarization, and social media oversight. Nonetheless, contemporary methods often grapple with balancing accuracy and processing speed, particularly in scenarios where prompt outcomes are paramount [1].

Queuing theory, a mathematical field, delves into the journey of customers or requests through a queueing system [2]. Observable in diverse real-world scenarios like customer service centers, data networks, and manufacturing workflows, the theory concentrates on deciphering the behavior of these systems to augment their efficiency and customer satisfaction.

This research introduces an innovative queuing approach to multimodal sentiment analysis, adept at not only pinpointing the influential variables across multiple modalities but also swiftly leveraging this information to deliver approximate scores [3]. The proposed methodology emphasizes processing inputs from the most impactful modes, enabling the delivery of satisfactory results in a reduced timeframe. By intentionally sidelining information from lesser influential modes, the model ensures minimized processing time. Additionally, the approach considers each modality's degree of influence, dynamically adjusting the weights of different modalities based on their respective influencing variables, culminating in reliable and precise emotional analysis outcomes.

Significant contributions of this research encompass: (1) the introduction of a novel queuing approach for multimodal sentiment analysis that prioritizes information processing from the most influential modality; (2) the employment of influence variables for the identification and estimation of the significance of diverse modalities [4]; and (3) the dynamic modulation of weights for various modalities contingent on their influence variables, optimizing both sentiment analysis accuracy and efficiency.

2. Background and Related Work

2.1. Fundamentals of Queuing Theory and its Practical Implications

Queueing theory is the mathematical examination of waiting lines or queues. This discipline enables the mathematical scrutiny of a host of interconnected activities, such as arrivals at the queue, the duration of waiting within the queue, and the attainment of service from a server. Such comprehensive analysis allows for the extraction and computation of numerous performance metrics, which serve as robust tools for evaluating the efficacy of the examined queueing system [5].

By leveraging mathematical models and principles, queueing theory empowers analysts and professionals to predict and analyze the behavior, stability, and other crucial aspects of queueing systems in various contexts. These insights are invaluable for enhancing efficiency and customer satisfaction in diverse real-world settings. The successful applications of queueing theory abound, underscoring its utility and versatility. It plays a critical role in the design and optimization of CPU scheduling algorithms, ensuring efficient and orderly processing of computer tasks. In telecommunications engineering, queueing theory is pivotal for managing network traffic, reducing latency, and enhancing data throughput, contributing to robust and reliable communication infrastructures. Moreover, it tackles complex issues that demand rigorous mathematical exploration, offering solutions and insights for problem-solving and decision-making [6]. This multifaceted approach underlines the significance and far-reaching impact of queueing theory in addressing contemporary challenges and optimizing various systems and operations.

2.2. Insights into Multimodal Sentiment Analysis and its Inherent Challenges

Sentiment analysis is a growing technique that seeks to ascertain people's feelings or views regarding a specific object. It has multiple uses in a variety of contexts and industries, including risk assessment, psychological profiling, public opinion research, and product review analysis. However, irony and hyperbole are more difficult to understand when only text is provided [7]. To provide a more robust analytical framework, multimodal sentiment analysis (MSA) blends textual data with visual and audio input. The suggested sentiment polarity, which might be positive, neutral, or negative, is more precisely determined using this approach, which makes use of fusion techniques [8].

2.3. Bridging the Gap: Queuing Theory's Role in Multimodal Sentiment Analysis

A major issue in multimodal sentiment analysis, the imbalance of data between various patterns, can be resolved using the queuing theory. Some patterns in multimodal data may have significantly richer data than others, which could cause sentiment analysis results to be skewed in favor of these rich patterns. Queuing theory could assist in our comprehension, forecasts, and solution of this data imbalance issue.

A study that suggests a modal sequential perception network with global acoustic feature enhancement to address the issues of equal processing of modalities and global acoustic information loss in multimodal sentiment analysis, which performs at the cutting edge on two widely used datasets, is one example that can demonstrate the importance of processing data imbalance [9].

3. Systematic Exploration and Application

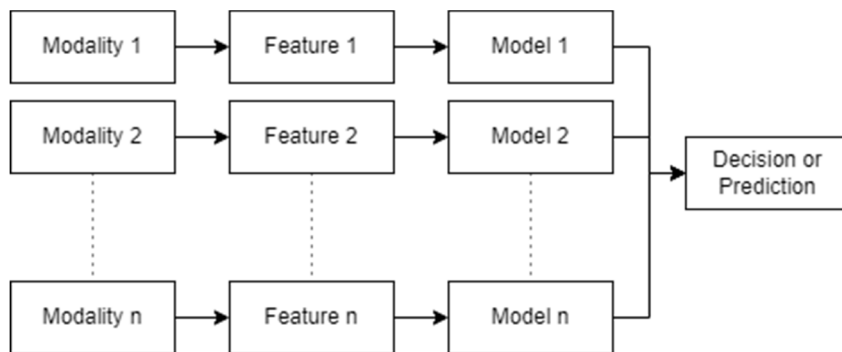


Figure 1. Post fusion method (Photo/Picture credit: Original).

3.1. Architectural Framework of Multimodal Sentiment Analysis

Referring to Figure 1, post-fusion method refers to integration that occurs only after each modality has made a judgment (classification or regression). To conduct post-fusion method, models are trained on various modalities and their output results are combined. In comparison to pre-fusion, this method can handle simple data asynchrony and enables for the adoption of the most appropriate method for evaluating each specific modality, such as HMM for audio and SVM for images [10].

3.2. Strategies for Optimizing the Queuing Model

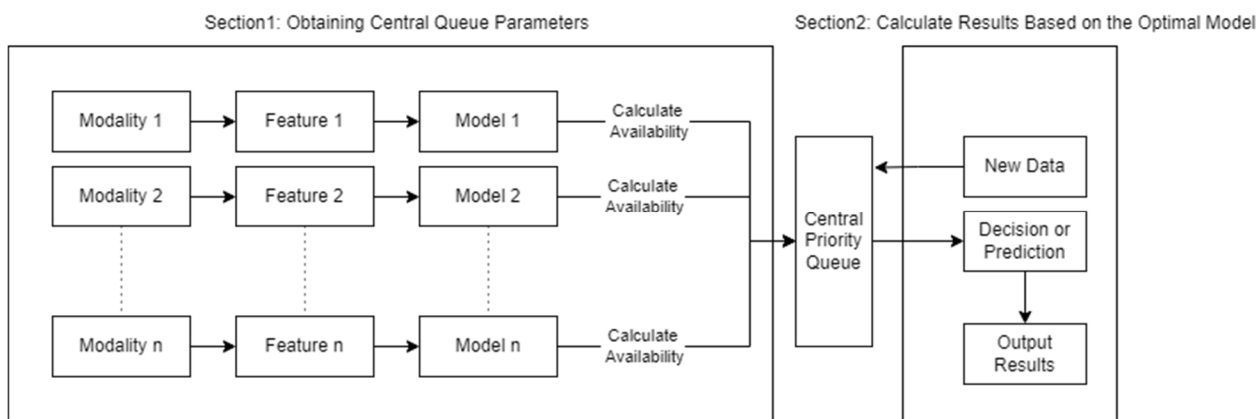


Figure 2. (Photo/Picture credit: Original).

According to Figure 2, first computes each model's availability during the training process, taking into account the accuracy and time required for each model. This article evaluates its availability by dividing its accuracy by the average processing time of its data using a basic confusion matrix.

$$Availability = \frac{Accuracy}{Average Processing Time} \quad (1)$$

3.3. Metrics for Evaluation and Experimental Design

The model used accuracy and average completion time as the primary evaluation indicators to assess the performance of the algorithm. We employed randomly generated data in the experimental design and compared its performance and accuracy to established processing methods.

This model primarily measures a variable parameter k , which means that only the most effective first $k * 100\%$ of the data is chosen for analysis, and their total effectiveness and total consumption

time are calculated and compared to the case of processing all the data to obtain an availability ratio and a time ratio as the effectiveness obtained by processing these data.

4. Results from the Experiments

Table 1. Experimental result, where k represents the first k * 100% of the data are chosen for analysis

Group	1	2	3	4	5	6	7
k	0	0.5	0.6	0.7	0.8	0.9	1
Availability Ratio	0.000	0.480	0.613	0.664	0.784	0.894	1.000
Time Ratio	0.000	0.332	0.502	0.518	0.639	0.833	1.000

According to the experimental measurement results, processing data with this queueing model optimization strategy ignored several low-impact modalities and sacrificed some expression effectiveness while drastically reducing total processing time, fulfilling the experimental target. However, more research is required to investigate the use of this approach in different settings, as well as its long-term effects on expression effectiveness. As shown in Table 1.

5. Conclusion

According to the study's findings, the queueing model optimization technique substantially curtails overall processing time, meeting the experimental data processing objectives effectively. Despite these advancements, it tends to neglect some low-effect modes and compromises specific expression impacts. This limitation underscores a pressing need to scrutinize the method's applicability across diverse circumstances and assess its prolonged impact on expression performance.

Given these considerations, it is imperative to delve into a comprehensive examination of the method's operational efficacy. A proposed avenue for future research involves a meticulous investigation and discourse regarding the enhancement technique of this methodology's performance. This exploration should encompass an extensive range of types and sizes of datasets to ascertain its broader applicability and versatility. Understanding the potential limitations and areas of improvement will offer invaluable insights for refining the model for more robust, versatile, and comprehensive utilization in multimodal sentiment analysis. Further, an in-depth exploration may unearth nuanced strategies to counterbalance the oversight of low-effect modes, ensuring a more holistic and inclusive analysis. Additionally, the study should illuminate the prospective long-term repercussions of employing this queueing model optimization technique on expression performance, encompassing both the positive enhancements and possible compromises. This inquiry will furnish a well-rounded perspective, facilitating informed decisions for the method's application in diverse contexts and contributing to the ongoing enhancement and refinement of multimodal sentiment analysis techniques. This multifaceted exploration holds the promise of propelling the field forward, offering advanced, efficient, and more precise solutions for multimodal sentiment analysis, bolstering the analytical capabilities, and contributing substantially to diverse applications in various sectors.

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