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Comprehensive Analysis of Sentiment and Toxicity Dynamics in Tourist Vlog Reviews: A CRISP-DM Approach

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Abstract−This research employs the CRISP-DM framework to analyze sentiment and toxicity dynamics in tourist vlog reviews thoroughly. The study delves into sentiment classification and toxicity identification nuances by leveraging machine learning algorithms such as k-NN, SVM, NBC, and DT with SMOTE. Utilizing a dataset comprising a substantial number of posts, the analysis reveals varying levels of accuracy across different algorithms. For instance, k-NN and SVM showcase promising accuracy rates of 85.90% and 86.27% in sentiment classification, while NBC and DT with SMOTE yield 72.52% and 71.14%, respectively. Furthermore, the research elucidates the limitations of toxicity analysis, with NBC demonstrating a precision of 64.96% and DT exhibiting lower recall rates. These findings highlight the importance of robust methodologies for understanding sentiment and toxicity dynamics in online content, particularly in tourist vlog reviews.

Keywords: Sentiment; Reviews; Toxicity; Tourist; Vlog

1. INTRODUCTION

Tourist travel vlogs are a compelling strategy to captivate audiences across various social media platforms, including YouTube. By intricately documenting journeys, these vlogs weave narratives transporting viewers to exotic locales [1]–[3]. This immersive experience fosters a sense of connection and belonging among the audience as they vicariously explore different cultures and landscapes [4]–[8]. Moreover, the dynamic nature of vlogs, characterized by visually appealing content and authentic storytelling, enhances viewer engagement and retention [9]–[12]. As a result, tourist travel vlogs emerge as a potent tool for content creators to forge meaningful connections with the audience, fostering a community of avid followers who eagerly await each new adventure.

Viewer comments on vlog videos serve as valuable indicators of interest in content and storytelling, thus providing insightful data for interpreting tourist destination preferences. These comments often delve into specific aspects of the vlog, ranging from the quality of cinematography to the relatability of the host's experiences, reflecting the audience's engagement with the narrative [13]–[16]. Furthermore, the sentiment expressed in these comments, whether enthusiastic praise or constructive critique, offers nuanced insights into viewer preferences and expectations [17]–[20]. Consequently, by analyzing viewer feedback, content creators and tourism stakeholders glean valuable insights into audience interests, enabling them to tailor future content and promotional strategies to cater to the desires of potential travelers effectively.

Toxicity and sentiment analysis represent pertinent methodologies for discerning viewer responses to tourist vlog videos. These analytical approaches delve into the underlying emotions and attitudes conveyed within viewer comments, allowing for a comprehensive understanding of audience engagement [21]–[24]. By employing toxicity analysis, content creators identify and mitigate harmful or inflammatory discourse within the comment sections, fostering a more positive and constructive online community [25], [26], [26], [27]. Additionally, sentiment analysis enables the extraction of nuanced sentiments, ranging from excitement and admiration to skepticism and criticism, providing invaluable insights into viewer perceptions and preferences [28]. Consequently, integrating these analytical tools empowers content creators and tourism stakeholders to refine strategies, ensuring that tourist vlogs effectively resonate with and cater to the diverse interests of the audience.

This research aims to ascertain toxicity scores and conduct sentiment analysis utilizing the CRISP-DM framework. This structured methodology facilitates the systematic extraction and analysis of data from tourist vlog videos' comment sections, allowing for a comprehensive assessment of viewer responses. By applying CRISP-DM, this research effectively navigates through data understanding, preparation, modeling, evaluation, and deployment, ensuring robust and reliable results [29]. Moreover, using this framework enhances the reproducibility and transparency of the analysis, enabling other scholars and practitioners to replicate and validate the findings [30]. Consequently, adopting CRISP-DM as the analytical framework facilitates the attainment of research objectives and promotes methodological rigor and integrity in the study of viewer engagement with tourist vlog content.

The urgency of this research lies in its potential to inform strategic interventions aimed at enhancing the efficacy of tourist vlog content dissemination and audience engagement. In an era dominated by digital media, where tourist vlogs wield considerable influence over travel decisions, understanding viewer responses and preferences is paramount for content creators and tourism stakeholders [31]. This research provides actionable

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insights into optimizing content strategies and fostering a more positive online environment by deciphering toxicity scores and conducting sentiment analysis within the CRISP-DM framework [32]. Consequently, the timely execution of this research is imperative for leveraging the burgeoning popularity of tourist vlogs to promote sustainable tourism practices and enrich traveler experiences.

This research's theoretical and practical contribution lies in its ability to advance understanding and inform actionable strategies in tourist vlog analysis and audience engagement. This study offers a novel approach for comprehensively evaluating viewer responses to tourist vlog content by integrating toxicity scoring and sentiment analysis within the CRISP-DM framework. Theoretically, this research expands the methodological toolkit available to scholars studying online discourse and audience behavior, contributing to digital media studies' evolving body of knowledge [33]–[36]. The insights gleaned from this research empower content creators and tourism practitioners to optimize content strategies, cultivate positive online communities, and tailor promotional efforts to better resonate with audience preferences [37]. Consequently, this research enriches academic discourse and holds tangible implications for enhancing the effectiveness and ethicality of tourist vlog production and dissemination.

Similar research in the field has predominantly focused on sentiment analysis and viewer engagement in various online contexts, including social media platforms and online forums, albeit with limited emphasis on toxicity scoring and the specific domain of tourist vlogs. While existing studies have provided valuable insights into the factors influencing audience responses and content effectiveness, they often overlook the nuanced interplay between toxicity and sentiment within the unique context of tourist vlog videos [38]–[41]. This highlights a notable gap in the literature this research seeks to address. However, it is essential to acknowledge certain limitations inherent in this study, such as the potential biases introduced by the selection of vlog videos and comment data and the inherent subjectivity involved in interpreting sentiment and toxicity levels. Nevertheless, by transparently acknowledging these limitations, this research contributes to a more nuanced understanding of viewer engagement dynamics in tourist vlogs.

2. RESEARCH METHODOLOGY

2.1 Gap Analysis

Gap analysis is essential for identifying discrepancies in previous research, particularly those about sentiment analysis in tourist travel vlogs. While existing studies have explored various aspects of audience engagement and content effectiveness in digital media contexts, there remains a noticeable gap in the literature regarding the nuanced sentiment analysis within the specific domain of tourist travel vlogs. This research pinpoints areas where existing knowledge falls short by conducting a thorough gap analysis, guiding future research endeavors. This proactive approach is crucial for advancing understanding and addressing the complexities inherent in viewer responses to tourist travel vlog content.

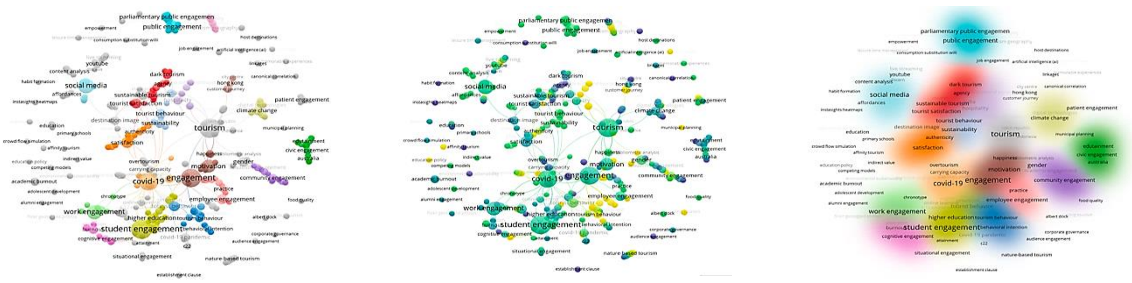

Figure 1. Network, Density, and Overlay visualisation of Tourist Travel Vlog and Viewer Engagement

Figure 1 shows the network, density, and overlay visualization of similar topics of sentiment analysis in the tourism sector. Keywords utilized in literature searches related to tourist travel vlogs, tourist behavior, and viewer engagement are processed using Vosviewer to analyze the interrelations among topics and current trends in scholarly research. By employing a systematic approach to keyword selection and advanced visualization tools like Vosviewer, this research uncovers intricate patterns and connections within the vast literature landscape. This facilitates a deeper understanding of the evolving discourse surrounding tourist travel vlogs and sheds light on emerging areas of interest and investigation. Thus, leveraging such computational techniques enhances the efficiency and efficacy of literature review processes, enabling scholars to stay abreast of the latest developments and insights.

Based on the gap analysis results, it is evident that the study of sentiment analysis in the tourism sector warrants enhancement, considering the escalating demand in the tourism market over time. As tourism continues to evolve and diversify, fueled by increasing globalization and technological advancements, a pressing need arises to understand better and respond to travelers' changing preferences and sentiments. By refining sentiment analysis methodologies within the tourism context, this research provides valuable insights that inform content-

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creation strategies and contribute to the sustainable development and promotion of tourist destinations. Thus, investing in advancing sentiment analysis in the tourism sector is imperative for staying attuned to the dynamic landscape of travel and hospitality.

2.2 Cross-Industry Standard Process for Data Mining (CRISP-DM)

This research adopts the CRISP-DM framework to analyze content, sentiment, and toxicity scores within Sumba culture video reviews. CRISP-DM, or Cross-Industry Standard Process for Data Mining, provides a structured approach to data analysis, encompassing phases such as business understanding, data understanding, data preparation, modeling, evaluation, and deployment. By applying this framework, this research systematically navigates the complexities of content analysis, sentiment classification, and toxicity assessment within cultural media datasets. Moreover, using CRISP-DM ensures methodological rigor and facilitates the reproducibility of findings, thereby enhancing the credibility and reliability of research outcomes. Thus, leveraging the CRISP-DM framework underscores the commitment to rigorous and systematic inquiry, ultimately contributing to a deeper understanding of audience perceptions and reactions toward cultural representations in digital media.

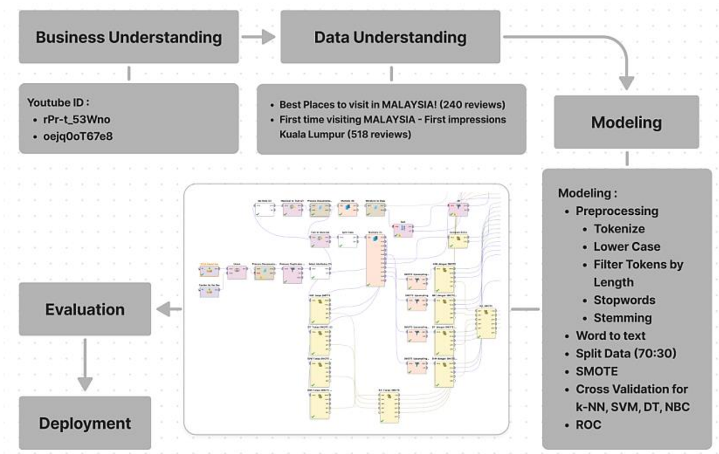

Figure 2. Implementaiton of CRISP-DM Framework

Figure 2 shows the implementation of the CRISP-DM framework. The framework utilized in this research is CRISP-DM, renowned for its contextual elaboration, particularly in the business understanding stage concerning sentiment analysis for tourist travel vlog video reviews. CRISP-DM's structured approach enables this research to systematically navigate through various stages of data mining, including understanding the business context, data understanding, data preparation, modeling, evaluation, and deployment. Within the business understanding stage, CRISP-DM encourages delving into the project's specific objectives and requirements, thereby facilitating a nuanced comprehension of sentiment analysis's contextual intricacies in tourist travel vlogs. Consequently, leveraging CRISP-DM enhances the rigor and relevance of the research process, ensuring that insights gleaned from sentiment analysis contribute meaningfully to the understanding and optimizing tourist vlog content.

The adoption of the CRISP-DM framework is tailored to the central theme of this research, which revolves around analyzing viewer sentiments regarding tourist travel vlogs using k-NN, DT, NBC, and SVM algorithms, augmented by the SMOTE technique. By aligning with CRISP-DM, this research systematically guides the process of data understanding, preparation, modeling, evaluation, and deployment, ensuring a structured and methodical approach to sentiment analysis. This framework offers a comprehensive methodology for navigating the complexities inherent in analyzing viewer sentiments within the context of tourist travel vlogs, facilitating the integration of diverse analytical techniques to yield robust and actionable insights. Consequently, adopting CRISP-DM enhances the efficiency and effectiveness of the research endeavor, ultimately contributing to a deeper understanding of viewer engagement dynamics in tourist vlog content.

2.2.1 Business Understanding

During the business understanding stage, the context of the dataset pertains to tourism content, wherein travelers create vlogs documenting Malaysia. Consequently, the focus of the discussion context emphasizes viewer responses to tourist vlog content. This contextualization underscores the significance of understanding audience engagement dynamics within tourist travel vlogs, as it enables this research to discern the impact of content on viewer perceptions and preferences. By delineating the scope of the dataset within the tourism context, this research effectively aligns analytical methodologies and objectives with the overarching aim of comprehensively analyzing viewer responses to tourist vlog content.

The dataset earmarked for processing into information comprises textual data extracted from viewer comments on vlog videos with predetermined IDs. These comments provide valuable insight into viewer

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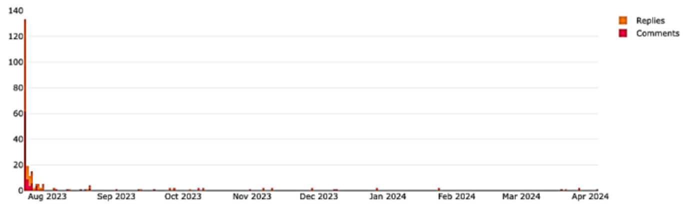
sentiments, opinions, and reactions toward the tourist vlog content. By analyzing the textual data within the comments, this research gleaned a nuanced understanding of audience engagement dynamics, discerning patterns, trends, and preferences that inform the broader discourse surrounding tourist travel vlogs. Thus, converting this dataset into actionable information facilitates the elucidation of viewer perceptions and optimizing content strategies to better resonate with audience interests. The videos earmarked for analysis are identified by the unique IDs: "rPr-t_53Wno" and "oejq0oT67e8". These videos, titled "Best Places to Visit in MALAYSIA!" and "First time visiting MALAYSIA - First Impressions Kuala Lumpur," respectively, have garnered significant attention, as evidenced by the respective numbers of reviews: 240 and 518. This preliminary assessment of the videos provides crucial context for understanding the scope and scale of viewer engagement, guiding subsequent steps in the research process.

Video 1 : https://www.youtube.com/watch?v=rPr-t_53Wno

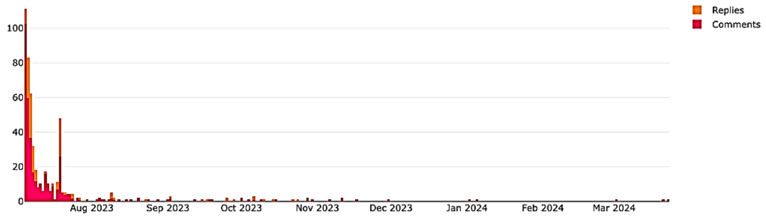


Frequently used Words

Figure 3. Post-per-day Statistic and Frequently Used Words of First Video (rPr-t_53Wno)

Figure 3 shows the first video's post-per-day statistic and frequently used words (rPr-t_53Wno). Based on the post-per-day statistics provided, it is evident that there was a notable spike in activity on July 22, 2023, with 62 posts recorded. However, this activity level sharply declined in the subsequent days, with only single-digit numbers of posts on July 23 and 25 and even fewer on July 24 and 27. This fluctuation in posting frequency may indicate a transient surge of interest or engagement on July 22, followed by a subsequent decrease in activity. Based on the data of frequently used words provided, specific patterns emerge regarding the vocabulary employed in the analyzed content. The word "Thank" appears to be the most frequently used, occurring 42 times, followed closely by "Malaysia" with 36 instances. Other commonly used terms include "guys" (28), "KL" (20), and "Thanks" (20). These findings suggest that gratitude and references to the destination, Malaysia, are prevalent throughout the content. Additionally, terms like "visit," "much," and "like" indicate a positive tone and enthusiasm towards travel experiences. However, it is noteworthy that certain specific names, such as "Ann," "Jan," and "French," appear frequently, potentially indicating the presence of recurring characters or themes within the content.

Video 1 : https://www.youtube.com/watch?v= oejq0oT67e8



Frequently used Words

Figure 4. Post-per-day Statistic and Frequently Used Words of Second Video (oejq0oT67e8)

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Figure 4 shows the post-per-day statistic and frequently used words of the second video (oejq0oT67e8). Based on the data of post-per-day statistics for the second video, it is discernible that there was a notable peak in activity on July 5, 2023, with 103 posts recorded. Subsequently, there was a gradual decline in posting frequency over the following days, with 60 posts on July 6, 37 posts on July 7, and further decreases on subsequent dates. However, activity was resurgent on July 19, 2023, with 26 posts recorded, followed by a slight decrease on July 8, with 17 posts. This fluctuation in posting frequency may reflect variations in viewer engagement and interest levels over time, indicating potential factors influencing audience interaction with the video content. Based on the data of frequently used words provided, a discernible pattern emerges regarding the vocabulary employed within the analyzed content. The term "Malaysia" appears to be the most frequently used, occurring 128 times, suggesting a significant focus on the destination within the discourse. Other prevalent terms include "country" (56), "India" (50), and "Welcome" (43), indicating a broad geographical scope and potential themes related to travel and cultural exchange. Additionally, terms such as "visit," "love," "like," and "beautiful" convey positive sentiments and appreciation for the experiences shared within the content. However, it is noteworthy that variations in spelling, such as "malaysia" and "Malingsial," may introduce ambiguity and require careful consideration during analysis.

Understanding the dataset's context sharpens this research's analysis and discussion. This research gains valuable insights into audience engagement dynamics and preferences by contextualizing the dataset within the realm of tourist travel vlogs, explicitly focusing on viewer responses to content related to visits to Malaysia. This contextual understanding enables a more nuanced interpretation of the data, allowing for the identification of recurring themes, sentiment patterns, and areas of interest among viewers. Consequently, incorporating contextual knowledge enhances the depth and relevance of the analysis, ultimately contributing to a richer understanding of viewer engagement with tourist travel vlog content.

2.2.2 Data Understanding

During the data understanding stage, the comments collected from the videos will undergo cleaning and extraction. This initial step is crucial for preparing the data for further analysis, involving removing irrelevant or duplicate comments, standardizing formatting, and extracting relevant information. By meticulously cleaning and extracting the comments, this research ensures the integrity and quality of the dataset, laying a solid foundation for subsequent analytical procedures. Consequently, this meticulous approach enhances the reliability and validity of the findings derived from the data, facilitating more robust insights into viewer engagement with tourist travel vlog content.

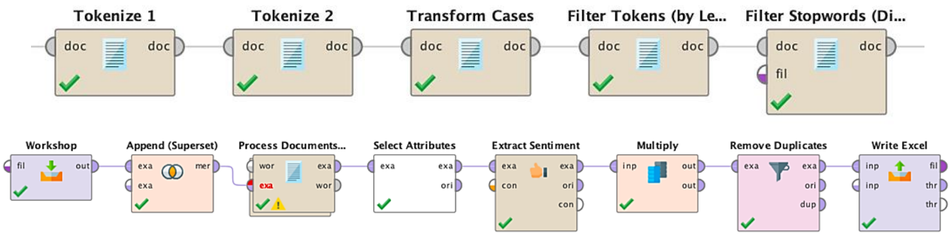

Figure 5. Data Cleaning and Extract Sentiment

Figure 5 shows the data cleaning and extract sentiment process in Rapidminer. The extracted data will yield string and total scores within the classification of negative and positive classes. This classification process is essential for categorizing viewer sentiments expressed in the comments associated with the tourist travel vlog videos. By assigning string scores and total scores to each comment, this research quantitatively assesses the polarity and intensity of sentiment, distinguishing between negative and positive feedback. This systematic classification enables a structured analysis of viewer responses, facilitating a deeper understanding of audience engagement dynamics and preferences within the context of tourist travel vlogs.

The results of the classification into negative and positive classes will be advanced to the modeling stage to analyze the performance of the best algorithms. This crucial step involves assessing machine learning algorithms, such as k-NN, DT, NBC, and SVM, to determine effectiveness in accurately predicting sentiment classifications based on the extracted data. By rigorously evaluating the performance of different algorithms, this research identifies the most suitable model for sentiment analysis within the context of tourist travel vlogs. Consequently, this modeling phase plays a pivotal role in refining analytical methodologies and enhancing the reliability of insights derived from the data.

2.2.3 Modeling

During the modeling stage, the performance of classification algorithms will be assessed, including k-NN, DT, NBC, and SVM, augmented by the Synthetic Minority Over-sampling Technique (SMOTE), with a data split of 30% for training and 70% for testing. This rigorous evaluation process aims to determine the efficacy of each

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algorithm in accurately classifying sentiment within the dataset of tourist travel vlog comments. This research ensures the robustness and generalizability of the model's performance by employing SMOTE to address potential class imbalance issues and adopting a standardized data split for training and testing. Consequently, this meticulous approach to algorithm evaluation enhances the reliability and applicability of insights derived from the sentiment analysis of tourist travel vlog content.

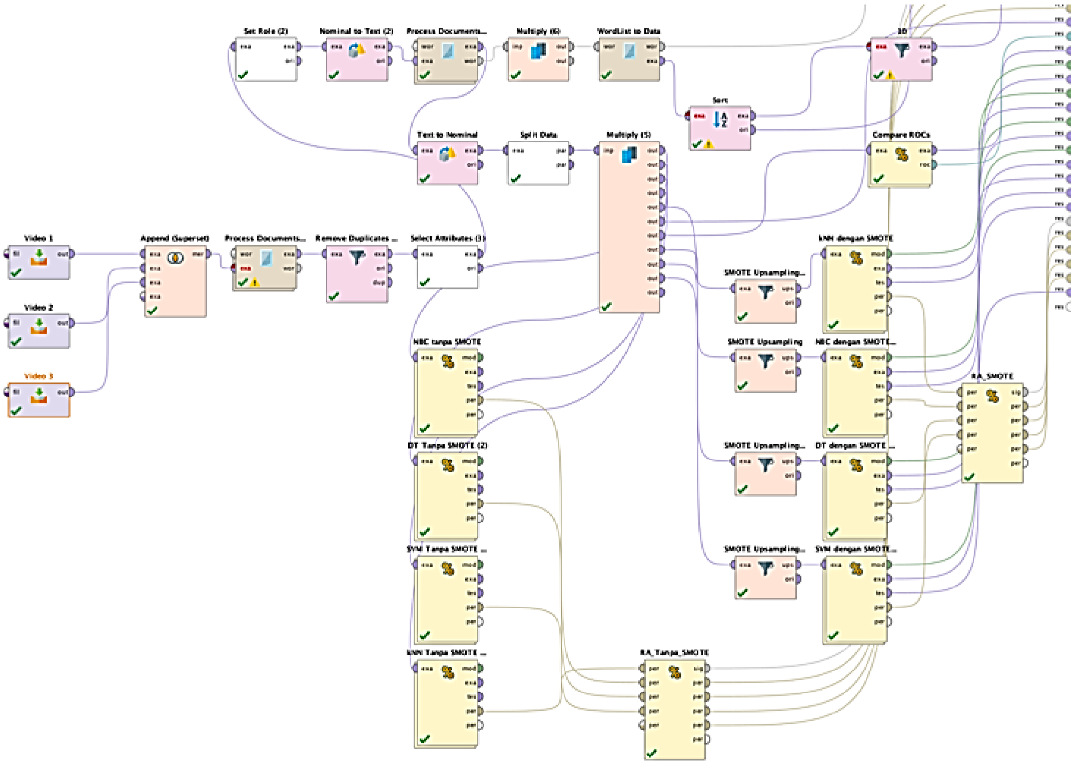

Figure 6. Implementation of k-NN, DT, NBC, and SVM with SMOTE

Figure 6 shows the Implementation of k-NN, DT, NBC, and SVM with SMOTE. The SMOTE operator addresses the class imbalance between negative and positive classes within the dataset. By generating synthetic samples for the minority class, SMOTE effectively mitigates the imbalance, thereby improving the performance of classification algorithms and enhancing the accuracy of sentiment analysis. This strategic use of SMOTE ensures that the model is trained on a more representative dataset, enabling it to capture better the nuances and complexities of viewer sentiments expressed in tourist travel vlog comments. As a result, SMOTE serves as a vital tool in overcoming class imbalance challenges and optimizing the reliability of sentiment analysis outcomes.

The outcomes of the modeling process will be evaluated based on the confusion matrix and F-measure. These evaluation metrics provide comprehensive insights into the performance of classification algorithms by quantifying the ability to classify sentiments into negative and positive categories accurately. The confusion matrix offers a detailed breakdown of true positives, false positives, and false negatives, enabling a nuanced understanding of classification errors and model efficacy. Additionally, combining precision and recall, the F-measure provides a single score representing the model's overall performance. By utilizing these robust evaluation techniques, this research effectively assesses the reliability and effectiveness of sentiment analysis algorithms in capturing viewer sentiments expressed in tourist travel vlog comments.

2.2.4 Evaluation

Evaluation is conducted under accuracy, precision, recall, F-measure, and Area Under the Curve (AUC). These comprehensive assessment criteria provide a thorough understanding of the performance of sentiment analysis models by measuring different aspects of predictive capabilities. Accuracy quantifies the overall correctness of predictions, while precision measures the proportion of correctly identified positive instances among all instances classified as positive. Conversely, recall assesses the proportion of valid positive instances the model correctly identified. F-measure combines precision and recall into a single score, offering a balanced assessment of model performance. Additionally, AUC summarizes the model's ability to distinguish between positive and negative instances across various threshold values. By considering these diverse evaluation metrics, this research gains nuanced insights into the strengths and weaknesses of sentiment analysis models, facilitating informed decision-making in model selection and refinement.

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Subsequently, each algorithm's performance vectors are compared when utilizing SMOTE and when not utilizing SMOTE. This comparative analysis allows for an assessment of the effectiveness of SMOTE in enhancing the classification performance of sentiment analysis algorithms. By evaluating the performance of each algorithm under both conditions, this research discerns the impact of SMOTE on mitigating class imbalance issues and improving the accuracy of sentiment predictions. Consequently, this comparative analysis provides valuable insights into the efficacy of SMOTE as a technique for optimizing sentiment analysis models, informing decision-making processes regarding its incorporation into analytical methodologies.

2.2.5 Deployment

During the deployment stage, the data processed into sentiment analysis results and average toxicity scores within the dataset will serve as valuable knowledge for information users, particularly content creators. This information equips content creators with actionable insights into the sentiment dynamics of viewer responses and the overall toxicity levels within the content. By leveraging this knowledge, content creators make informed decisions regarding content creation strategies, tailoring the approaches to align with audience preferences and expectations. Consequently, deploying sentiment analysis and toxicity identification outcomes empowers content creators to enhance the quality and relevance of content, fostering greater engagement and resonance with an audience.

Thus, practical implications benefit the sustainability of tourism travel vlog content creation across various destinations. By leveraging sentiment analysis results and toxicity identification, content creators tailor content strategies to resonate more effectively with the audience, enhancing viewer engagement and loyalty. This strategic alignment with audience preferences and perceptions contributes to the longevity and success of tourist travel vlog content, fostering continued interest and support from viewers. As a result, content creators sustain and grow in the competitive landscape of destination-based content creation, ultimately contributing to the vitality of the tourism industry.

3. RESULT AND DISCUSSION

The discussion in the research is divided into two parts: the toxicity score identification results and algorithm implementation outcomes in sentiment analysis. This partitioning allows for a comprehensive examination of the findings, enabling a focused exploration of the toxicity levels within the dataset and the effectiveness of the applied algorithms in analyzing sentiment. By structuring the discussion in this manner, the research ensures a systematic and coherent presentation of the results, facilitating a nuanced understanding of the implications and insights derived from the study. Consequently, this approach enhances the clarity and rigor of the research findings, contributing to the advancement of knowledge in sentiment analysis within the context of tourist travel vlogs.

3.1 Toxicity Analysis

Based on identifying toxicity scores from 199 out of 240 posts using the Perspective API on the first video, it is discernible that various toxicity indicators are present within the comments. The toxicity score for the entire dataset ranges from 0.05541 to 0.58852, indicating a spectrum of toxicity levels across the comments. Additionally, specific toxicity categories such as severe toxicity, identity attack, insult, profanity, and threat exhibit varying scores, suggesting different degrees of harmful language or behavior within the comments. This comprehensive analysis provides valuable insights into the nature and prevalence of toxicity within the dataset, enabling a nuanced understanding of the discourse surrounding the video content.

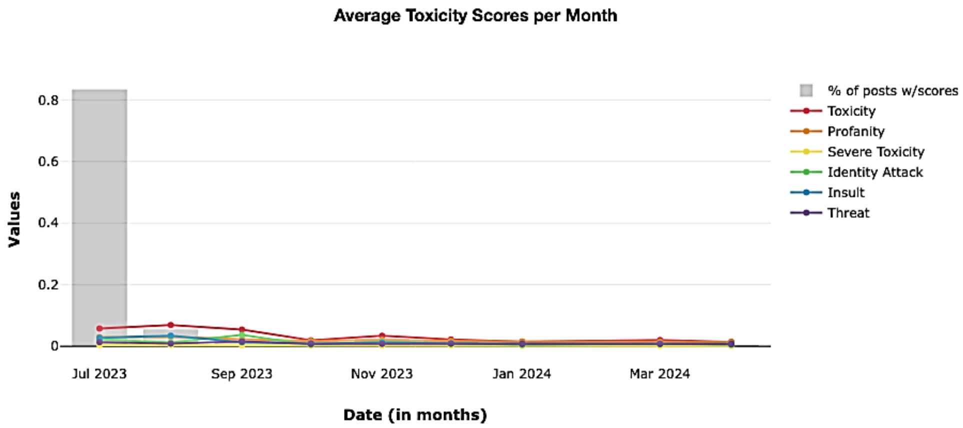

Figure 7. Toxicity Score of the First Video (rPr-t_53Wno)

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Figure 7 shows the toxicity score of the first video (rPr-t_53Wno). The provided data presents toxicity scores for various categories extracted from a subset of comments on the first video, as identified by the Perspective API. The toxicity scores range from 0.05541 to 0.58852, indicating the presence of varying degrees of toxic language or behavior within the comments. The highest toxicity score is observed for the "Identity Attack" category (0.58355), followed by "Toxicity" (0.58852), suggesting that comments containing attacks on identity or personal characteristics are particularly prevalent and have a significant impact on the overall toxicity score. Meanwhile, the lowest toxicity scores are for "Severe Toxicity" (0.16960) and "Threat" (0.42643), indicating that comments with severe language or explicit threats are less common in the dataset. Overall, the analysis highlights the diverse nature of toxic language within the comments, with varying levels of severity across different toxicity categories. This information is valuable for content creators and platform moderators in understanding the dynamics of toxic discourse and implementing measures to foster a healthier online environment.

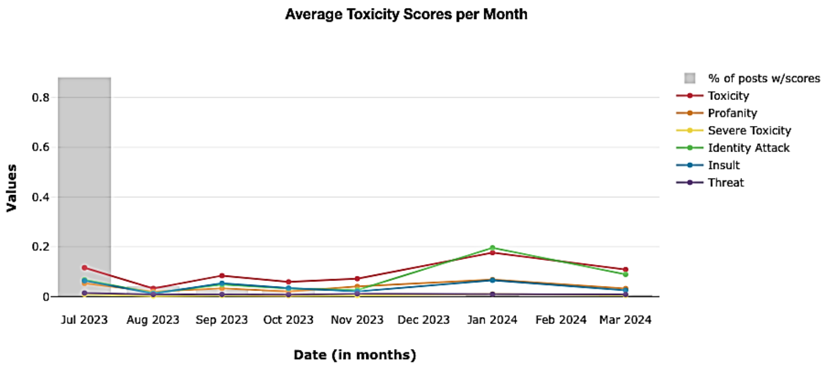

Figure 8. Toxicity Score of the Second Video (oejq0oT67e8)

Figure 8 shows the toxicity score of the Second video (oejq0oT67e8). The provided data offers toxicity scores derived from the Perspective API for a subset of comments on the second video, totaling 437 out of 518 posts. These scores indicate the presence and intensity of various forms of toxic language within the comments. The overall toxicity score for the entire dataset ranges from 0.10953 to 0.66672, suggesting a diverse spectrum of toxicity levels across the comments. Notably, the highest toxicity scores are observed for the "Toxicity" (0.66672) and "Insult" (0.65866) categories, indicating a prevalence of comments containing toxic language or behavior intended to belittle or offend others.

Conversely, the lowest toxicity scores are observed for the "Severe Toxicity" (0.34970) and "Threat" (0.44827) categories, indicating a relatively lower incidence of comments containing severe language or explicit threats. Overall, this analysis sheds light on the prevalence and varying degrees of toxic language within the comments, providing insights into the nature of discourse surrounding the second video. Such insights are valuable for content creators and platform moderators in understanding and addressing toxic behaviors within online communities.

The weakness of toxicity analysis in this study lies in its reliance on automated tools, such as the Perspective API, which may not fully capture the nuanced context and intent behind comments. While these tools provide quantitative scores for toxicity levels, they may overlook subtleties in language, cultural nuances, and sarcasm, leading to potential misinterpretations or inaccuracies in toxicity assessment. Additionally, automated tools may struggle with detecting evolving forms of toxic behavior or identifying disguised toxic language, limiting the comprehensiveness and accuracy of toxicity analysis. Therefore, while toxicity analysis offers valuable insights into the prevalence of hostile language, its reliance on automated tools necessitates careful interpretation and supplementation with qualitative analysis to ensure a thorough understanding of toxic discourse.

3.2 Sentiment Analysis

Based on the implementation results of the k-NN, SVM, NBC, and DT algorithms using SMOTE, it is evident that these methods offer relevant approaches for analyzing the research dataset. The utilization of SMOTE addresses the imbalance between negative and positive classes within the dataset, enhancing the robustness of the classification process. Furthermore, the diverse nature of these algorithms allows for comprehensive analysis, leveraging distinct computational techniques to uncover patterns and relationships within the data. Consequently, applying these methods yields valuable insights into the characteristics and dynamics of the dataset, contributing to a deeper understanding of the research context and facilitating informed decision-making in subsequent analyses.

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SVM Using SMOTE

```
PerformanceVector:
accuracy: 86.27% +/- 8.22% (micro average: 86.24%)
ConfusionMatrix:
True:   Positive        Negative
Positive:       251     35
Negative:       47      263
AUC (optimistic): 0.937 +/- 0.043 (micro average: 0.937) (positive class: Negative)
AUC: 0.924 +/- 0.046 (micro average: 0.924) (positive class: Negative)
AUC (pessimistic): 0.911 +/- 0.052 (micro average: 0.911) (positive class: Negative)
precision: 86.75% +/- 10.72% (micro average: 84.84%) (positive class: Negative)
ConfusionMatrix:
True:   Positive        Negative
Positive:       251     35
Negative:       47      263
recall: 88.24% +/- 7.28% (micro average: 88.26%) (positive class: Negative)
ConfusionMatrix:
True:   Positive        Negative
Positive:       251     35
Negative:       47      263
f_measure: 86.89% +/- 6.30% (micro average: 86.51%) (positive class: Negative)
ConfusionMatrix:
True:   Positive        Negative
Positive:       251     35
Negative:       47      263
```

DT Using SMOTE

```
PerformanceVector:
accuracy: 71.14% +/- 3.44% (micro average: 71.14%)
ConfusionMatrix:
True:   Positive        Negative
Positive:       296     170
Negative:       2       128
AUC (optimistic): 0.997 +/- 0.007 (micro average: 0.997) (positive class: Negative)
AUC: 0.500 +/- 0.000 (micro average: 0.500) (positive class: Negative)
AUC (pessimistic): 0.426 +/- 0.076 (micro average: 0.426) (positive class: Negative)
precision: 98.73% +/- 2.70% (micro average: 98.46%) (positive class: Negative)
ConfusionMatrix:
True:   Positive        Negative
Positive:       296     170
Negative:       2       128
recall: 42.89% +/- 7.97% (micro average: 42.95%) (positive class: Negative)
ConfusionMatrix:
True:   Positive        Negative
Positive:       296     170
Negative:       2       128
f_measure: 59.35% +/- 7.51% (micro average: 59.81%) (positive class: Negative)
ConfusionMatrix:
True:   Positive        Negative
Positive:       296     170
Negative:       2       128
```

k-NN Using SMOTE

```
PerformanceVector:
accuracy: 85.90% +/- 8.23% (micro average: 85.91%)
ConfusionMatrix:
True:   Positive        Negative
Positive:       273     59
Negative:       25      239
AUC (optimistic): 0.965 +/- 0.035 (micro average: 0.965) (positive class: Negative)
AUC: 0.917 +/- 0.056 (micro average: 0.917) (positive class: Negative)
AUC (pessimistic): 0.886 +/- 0.070 (micro average: 0.886) (positive class: Negative)
precision: 90.65% +/- 8.62% (micro average: 90.53%) (positive class: Negative)
ConfusionMatrix:
True:   Positive        Negative
Positive:       273     59
Negative:       25      239
recall: 80.21% +/- 11.15% (micro average: 80.20%) (positive class: Negative)
ConfusionMatrix:
True:   Positive        Negative
Positive:       273     59
Negative:       25      239
f_measure: 84.84% +/- 9.16% (micro average: 85.05%) (positive class: Negative)
ConfusionMatrix:
True:   Positive        Negative
Positive:       273     59
Negative:       25      239
```

NBC Using SMOTE

```
PerformanceVector:
accuracy: 72.52% +/- 6.50% (micro average: 72.48%)
ConfusionMatrix:
True:   Positive        Negative
Positive:       134     0
Negative:       164     298
AUC (optimistic): 1.000 +/- 0.000 (micro average: 1.000) (positive class: Negative)
AUC: 0.522 +/- 0.071 (micro average: 0.522) (positive class: Negative)
AUC (pessimistic): 0.452 +/- 0.124 (micro average: 0.452) (positive class: Negative)
precision: 64.96% +/- 6.27% (micro average: 64.50%) (positive class: Negative)
ConfusionMatrix:
True:   Positive        Negative
Positive:       134     0
Negative:       164     298
recall: 100.00% +/- 0.00% (micro average: 100.00%) (positive class: Negative)
ConfusionMatrix:
True:   Positive        Negative
Positive:       134     0
Negative:       164     298
f_measure: 78.61% +/- 4.43% (micro average: 78.42%) (positive class: Negative)
ConfusionMatrix:
True:   Positive        Negative
Positive:       134     0
Negative:       164     298
```

Figure 9. Performance of SVM, DT, k-NN, and NBC Using SMOTE

Figure 9 shows the performance of each algorithm using SMOTE. The performance evaluation of SVM with SMOTE indicates promising results, with an accuracy rate of 86.27% +/- 8.22%, demonstrating its effectiveness in classification tasks. The confusion matrix reveals balanced predictions, with a notable precision of 86.75% +/- 10.72% and recall of 88.24% +/- 7.28%, highlighting the model's ability to classify instances across both positive and negative classes correctly. Moreover, the f-measure of 86.89% +/- 6.30% underscores the robustness of the model's predictive capabilities. These metrics collectively affirm the suitability of SVM with SMOTE for handling imbalanced datasets, offering reliable performance in discerning patterns and making informed decisions in classification tasks.

The evaluation of DT with SMOTE reveals mixed performance metrics, with an accuracy rate of 71.14% +/- 3.44%, indicating moderate success in classification tasks. However, the model exhibits imbalanced predictions, as evidenced by the confusion matrix, with a notably high precision of 98.73% +/- 2.70% but a relatively low recall of 42.89% +/- 7.97%. Additionally, the f-measure of 59.35% +/- 7.51% reflects the model's uneven performance in achieving a balance between precision and recall. Furthermore, the AUC values suggest varying degrees of model performance, with the optimistic AUC score indicating predictive solid capability. Still, the pessimistic AUC and micro average AUC indicate potential limitations in handling imbalanced datasets. Despite its drawbacks, DT with SMOTE demonstrates the potential for classification tasks, albeit with the need for further refinement to address imbalanced predictions and optimize overall performance.

The analysis of NBC with SMOTE reveals notable performance metrics, with an accuracy rate of 72.52% +/- 6.50%, indicating moderate success in classification tasks. The model demonstrates high precision, with a value of 64.96% +/- 6.27%, suggesting its effectiveness in correctly identifying negative instances. Moreover, the recall rate of 100.00% +/- 0.00% indicates that the model successfully captures all valid negative instances. However, the AUC values present a mixed picture, with an optimistic AUC score of 1.000, indicating predictive solid capability. In contrast, the pessimistic AUC and micro average AUC values of 0.452 and 0.522 suggest potential limitations in handling imbalanced datasets. Despite these limitations, NBC with SMOTE exhibits promising performance in correctly identifying negative instances, albeit with the need for further optimization to address potential biases and improve overall classification accuracy.

The evaluation of k-NN with SMOTE reveals promising performance metrics, with an accuracy rate of 85.90% +/- 8.23%, suggesting its efficacy in classification tasks. The model demonstrates high precision, with a value of 90.65% +/- 8.62%, indicating its ability to classify negative instances correctly. Additionally, the recall rate of 80.21% +/- 11.15% suggests that the model effectively captures actual negative instances. Despite slight fluctuations in performance, the AUC values, including the optimistic AUC of 0.965, micro average AUC of 0.917, and pessimistic AUC of 0.886, underscore the model's robustness in distinguishing between positive and

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negative classes. Overall, k-NN with SMOTE performs commendably accurately in classifying negative instances, highlighting its potential utility in sentiment analysis tasks and underscoring its relevance to the dataset under study.

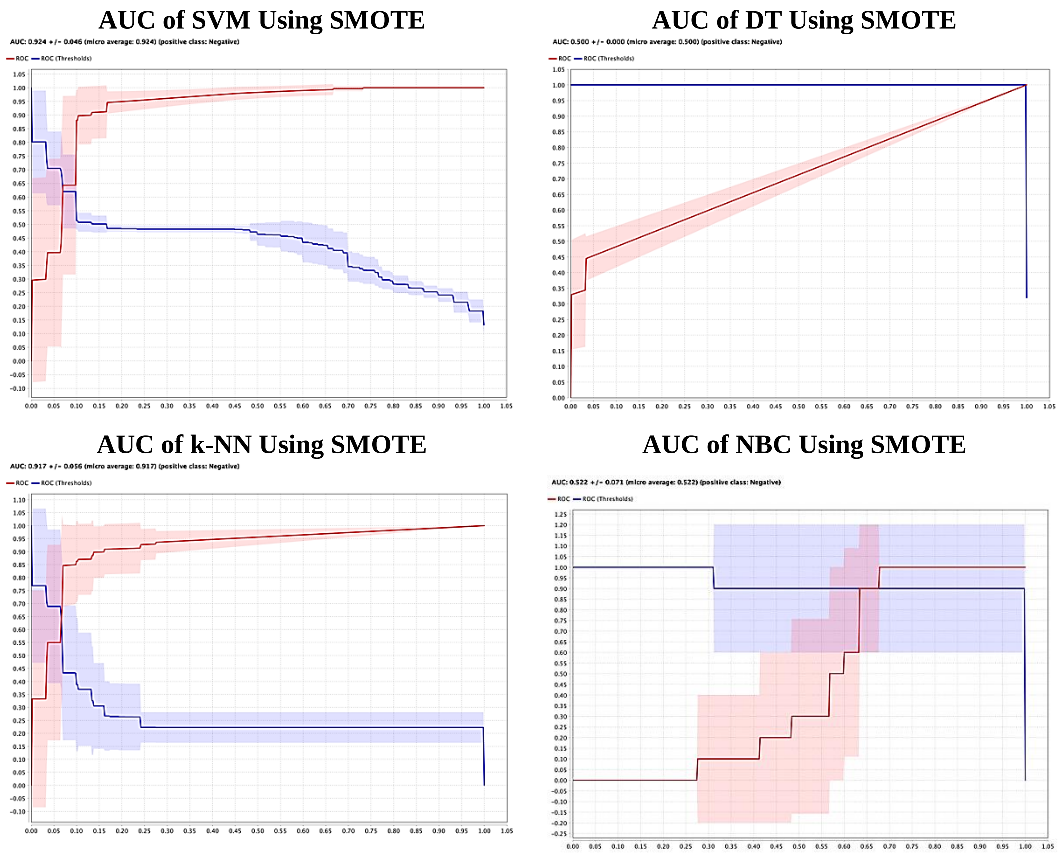

Figure 10. The AUC of SVM, DT, k-NN, and NBC Using SMOTE

Figure 10 shows the Area Under the Curve of SVM, DT, k-NN, and NBC Using SMOTE. The AUC values of each algorithm provide insights into discriminative capabilities in classifying positive and negative instances. SVM with SMOTE demonstrates the highest AUC values, with an optimistic AUC of 1.000, micro average AUC of 1.000, and pessimistic AUC of 0.911, indicating its robustness in distinguishing between the two classes. Following closely is k-NN with SMOTE, with an optimistic AUC of 0.965, micro average AUC of 0.917, and pessimistic AUC of 0.886, suggesting its discriminatory solid power. Meanwhile, NBC with SMOTE exhibits moderate AUC values, with an optimistic AUC of 1.000, micro average AUC of 0.522, and pessimistic AUC of 0.452, implying its relatively lower ability to distinguish between positive and negative classes. Notably, DT with SMOTE shows the lowest AUC values across the algorithms, with an optimistic AUC of 0.997, micro average AUC of 0.500, and pessimistic AUC of 0.426, indicating its limited discriminatory performance. Overall, the comparison underscores SVM with SMOTE as the most effective algorithm in classifying sentiments, followed by k-NN with SMOTE. NBC with SMOTE and DT with SMOTE exhibit comparatively lower discriminative capabilities.

Based on the comparison of AUC values, the recommendation would be to prioritize SVM with SMOTE and k-NN with SMOTE for sentiment classification tasks. These algorithms demonstrate higher discriminative capabilities in distinguishing between positive and negative sentiments compared to NBC with SMOTE and DT with SMOTE. However, the choice between SVM and k-NN may depend on other factors such as computational efficiency, interpretability, and specific task requirements. Therefore, it's advisable to conduct further experimentation and analysis to determine the most suitable algorithm based on the specific needs and constraints of the sentiment analysis project. In analyzing sentiment in tourist vlog reviews, the recommendation based on comparing AUC values suggests that SVM with SMOTE and k-NN with SMOTE are particularly effective algorithms. These algorithms are instrumental in accurately classifying sentiments expressed in viewer comments regarding tourist destinations showcased in vlogs. By employing these algorithms, content creators and tourism stakeholders gain valuable insights into the reception and perception of the content, helping them to tailor the vlogs better to meet the preferences and expectations of the audience. Moreover, utilizing these advanced algorithms enhances the quality and relevance of tourist vlog reviews, ultimately contributing to a more engaging and informative experience for viewers.

The limitations of sentiment analysis based on this dataset are twofold. Firstly, the dataset may lack diversity regarding the viewers' languages, cultures, and demographics, leaving comments on the tourist vlogs. This lack of diversity could lead to biases in the sentiment analysis results, as the algorithms may not accurately capture the nuances and variations in sentiment across different audience groups. Secondly, the dataset may suffer from inherent subjectivity in interpreting sentiments expressed in the comments. Sentiment analysis algorithms may struggle to accurately discern the true sentiment behind ambiguous or sarcastic comments, leading to potential misclassification of sentiments. Therefore, while sentiment analysis provides valuable insights, these limitations underscore the importance of contextual understanding and human interpretation in accurately gauging sentiment in tourist vlog reviews.

4. CONCLUSION

In conclusion, employing the CRISP-DM framework, this research has shed light on tourist vlog reviews' sentiment and toxicity analysis. Insightful conclusions have been drawn by utilizing various machine learning algorithms such as k-NN, SVM, NBC, and DT with SMOTE. The sentiment analysis revealed notable accuracy rates, with k-NN achieving an accuracy of 85.90%, SVM 86.27%, NBC 72.52%, and DT 71.14%. However, the toxicity analysis indicated varying performance levels, with some algorithms exhibiting shortcomings. For instance, NBC with SMOTE displayed an accuracy of 72.52%, whereas DT exhibited lower precision and recall rates. These findings underscore the significance of employing robust methodologies like CRISP-DM in analyzing tourist vlog reviews, allowing for a comprehensive understanding of sentiment and toxicity dynamics in online content.

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