Revolution + Love: Measuring the Entanglements of State Violence and Emotions in Early PRC

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Abstract
This paper examines the relationship between violent discourse and emotional intensity in the early revolutionary rhetoric of the People's Republic of China (PRC). Using two fine-tuned *bert-base-chinese* models—one for detecting violent content in texts and another for assessing their affective charge—we analyze over 185,000 articles published between 1956 and 1989 in the *People's Liberation Army Daily* (*Jiefangjun Bao*), the official journal of China's armed forces. We find a statistically significant correlation between violent discourse and emotional expression throughout the analyzed period. This strong alignment between violence and affect in official texts provides a valuable context for appreciating how other forms of writing, such as novels and poetry, can disentangle personal emotions from state power.

Keywords
violent discourse, sentiment analysis, People's Liberation Army Daily, revolutionary rhetoric

1. Introduction

The concept of "Revolution Plus Love" (*geming jia lian'ai* 革命加恋爱) became prominent during the New Culture Movement in China (ca. 1915-1919) and continued to shape Chinese literary practice throughout the long twentieth century. It has also provided a lens through which sinologists have examined socio-political changes in the Republic (1912–1949) and the People's Republic (1949-) of China. Jianmei Liu [25] shows how Chinese writers personalized revolution and revolutionized their romantic adventures, often finding themselves confronted with dilemmas between personal fulfilment and national ideals. Haiyan Lee [21] emphasizes how sentimental discourse replaced the kin-based sociality that defined the pre-modern world with a modern one that transformed strangers into compatriots. Eugenia Lean [20] investigates a startling case of Shi Jianqiao (1905-1979), a woman who murdered the warlord Sun Chuanfang (1885-1935) and then managed to galvanize what Lean calls "public sympathy" to regain freedom. Elizabeth Perry [29] focuses on the "emotion work" launched by the Communist Party as a deliberate strategy of psychological engineering.

The theoretical premise of this paper is that both emotional engagement and violent discourse leave formal traces in texts which can be identified with the help of statistical methods

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of literary inquiry. We build upon existing scholarship on the political signification of sentiments to suggest a computational perspective on the entanglements between violence and affect in Chinese revolutionary discourse. In particular, we focus on the texts published between 1956 and 1989 in the *People's Liberation Army Daily* (*PLA Daily*, or *Jiefangjun Bao* 解放军报), one of the major PRC journals and the official publication of China's armed forces, to analyze how such entanglements manifested in officially sanctioned documents.

2. Related Works

2.1. Violent Discourse and Hate Speech

"Violent discourse" refers to the use of language to inflict harm, perpetuate power structures, and normalize physical violence [27, 1]. While it is closely related to "hate speech," the two categories are not identical. Violent discourse does not need to contain targeted abuse or foul language and is often produced by public institutions rather than private individuals. Conversely, hate speech might include mockery and racial stereotypes without any direct link to violent behavior, let alone military confrontations [36]. The distinction between "hate speech" and "violent discourse" is productive in the analysis of official publications in the early PRC, which often decried racial discrimination in the United States [16, 6]. On the surface, the detailed accounts of US racism contrasted the Chinese revolution with the malfeasance of the capitalist world. In fact, such accounts served to promote state violence against the "enemies of the People" identified within the country. In other words, the anti-hate rhetoric fueled violent behavior.

Automatic hate speech detection includes research related to sexism, racism, cyberbullying, and toxicity in the public realm. The literature focused on these topics is extensive and we refer the reader to multiple surveys for comprehensive overviews [33, 34, 30, 10]. The rise of large language models (LLMs) in hate speech detection research has been a significant development [18], but, as discussed by Elsafoury [7] and Cooper et al. [3], these models continue to struggle with nuanced interpretations, which can perpetuate stereotypes and reinforce harmful narratives. Studies such as those by Röttger et al. [32] and Lee et al. [22] emphasize that hate speech detection models must account for cultural biases to be effective across different linguistic and social contexts. The problem is further compounded by the scarcity of related research in Chinese. There are still relatively few Chinese hate speech datasets available, although the situation seems to be improving [37, 4]. Finally, whereas automatic hate speech detection has been at the forefront of NLP research during the last decade, violent discourse as a theoretical category has been relatively underrepresented in computational literary studies, many projects focusing on extra-literary content such as social media posts or movie dialogues [26, 2, 19, 17].

2.2. Sentiment Analysis in Political Contexts

Similar to hate speech detection, automatic sentiment analysis has seen significant contributions and surveys during the last two decades. Notable studies include those by Liu [24], Wankhade et al. [35], and Zhang et al. [38], which provide comprehensive overviews of the methods and applications of sentiment analysis in various domains. In the context of literary texts, Jockers' work with the *syuzhet* package [15] exemplifies the application of sentiment analysis to understand emotional arcs in literature.

Related to this article are the numerous studies focused on political contexts, revealing the nuanced ways public opinion is shaped and expressed and highlighting the role of social media in political discourse [5, 23, 31]. Advanced techniques such as emotion mining and aspect-based sentiment analysis (ABSA) have been employed to capture the sentiment in political texts [9, 14]. These approaches facilitate the extraction of sentiment from complex political narratives, providing insights into voter behavior and sentiment polarization.

3. Methodology

3.1. Data Collection

This project used two training datasets:

⇒ **Violent/Non-Violent Texts**: The first dataset was constructed from texts sourced from the *PLA Daily*.[1] Texts were classified as "violent" if they included language depicting physical and military violence, as described in our related work on the distribution of violent discourse in the journal [8], which adopts a dictionary-based approach to detect violent texts for model training. "Non-violent" texts were characterized by the absence of such vocabulary. The dataset includes a total of 5,728 examples, split evenly between the two classes, with no more than 100 examples taken from each year for either class.

⇒ **Strong/Weak Emotion**: The second dataset was derived from the *Douban Dushu* Dataset [39], containing more than 3.7 million Chinese book reviews. As there is no large dataset containing labeled emotional intensity specific to military-related Chinese texts from the mid-20th century, which otherwise would be an ideal training corpus for this project, we searched for a dataset that would capture a broad range of emotional expressions independent of specific subject matter. The *Douban Dushu* Dataset meets this requirement, including reviews of a wide variety of books and thus preventing the trained model from focusing on any particular topic. We labeled 1-star and 5-star comments as representing "strong" emotions due to their clear expression of either negative or positive sentiment, while 3-star comments were considered "weak" emotions. Only the comments that were at least 200 characters long were included, and we selected 62,000 examples from each class ("strong" and "weak" emotion) for training.

3.2. Training & Validation

For this study, we used *PyTorch* to fine-tune two open-source models *bert-base-chinese* on the datasets described above: one for classifying violent versus non-violent texts, and the other for categorizing the strength of emotions within texts. Notice that the sentiment analysis task considered in this project differs from the usual NLP applications which distinguish positive

[1] The *PLA Daily* corpus has been acquired from the digitized version of the journal available through the East View library (https://dlib.eastview.com).

from negative sentiments or categorize them into different classes (anger, surprise, happiness, etc). Here, we focus on the intensity of the expressed sentiments rather than their quality.

Bert-base-chinese is a lightweight model (with 102 million parameters) pre-trained on a large corpus of Chinese text, which makes it suitable for various natural language processing tasks. It requires relatively modest computational resources and enables fast training. For both tasks—violence detection and emotional intensity assessment—we fine-tuned *bert-base-chinese* using sequence classification with the respective dataset, a batch size of 16, a learning rate of 2e-5, and the Adam optimizer. We used validation loss to find the optimal number of training epochs. Texts were tokenized into input sequences using the *bert-base-chinese* tokenizer, which splits by Chinese character (there are no spaces in Chinese). We have achieved F1 score of **0.981** for violence analysis (600 test samples) and **0.926** for sentiment analysis (12,000 test samples).

3.3. Quantitative Analysis

After training, the 185,472 articles from the *PLA Daily* published between 1956 and 1989 were segmented into non-overlapping chunks of 500 characters, yielding 629,734 texts in total. The period in question begins with the establishment of the journal in 1956 and ends in 1989, a year marked by nation-wide pro-democratic protests. Each text was evaluated by the two models for the probability of being classified as "violent" or "strong" (emotionally intense), respectively. We then computed the average monthly probability of the "violent" class and the "strong" class.

4. Results

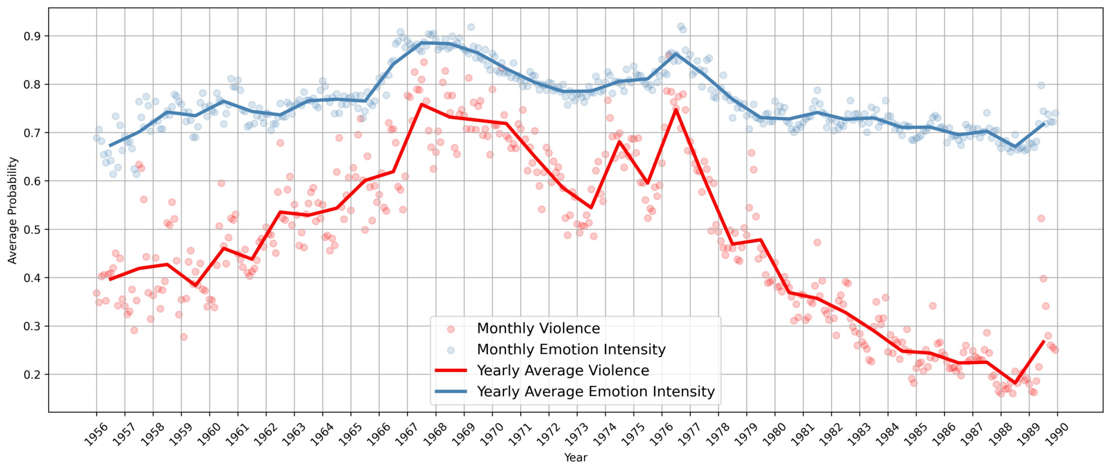

Figure 1: Yearly average and monthly probabilities of violence and emotional intensity in *PLA Daily* texts from 1956 to 1989.

As illustrated in Figure 1, there is a clear alignment between violent discourse and emotional expression in the journal. Affectively-charged texts are often about violence, and violence is described in affective terms. Both lines demonstrate an increasing trend from the late 1950s, peaking around 1968, followed by a decline through the late 1970s and 1980s. This trend indicates heightened periods of violence-related, emotionally-charged content published in the journal during the Cultural Revolution (1966-1976) and a subsequent decrease as China moved towards more stabilized periods in the post-Mao era. A very strong Pearson correlation between the monthly averages (408 months; *r*: 0.8468, *p-value*: 2.4296e-113) and yearly averages (34 years; *r*: 0.9092, *p-value*: 1.0183e-13) of violent discourse and emotional intensity can be observed, demonstrating how the *People's Liberation Army Daily* "emotionalized revolution and revolutionized emotions" in the early PRC.[2] This relationship can be further illustrated by plotting the percentage of articles displaying both high-violence and high-emotion scores throughout the analyzed period (Figure 2). Between 1966 and 1968, the number of such articles rises to nearly 50% of the total published content.

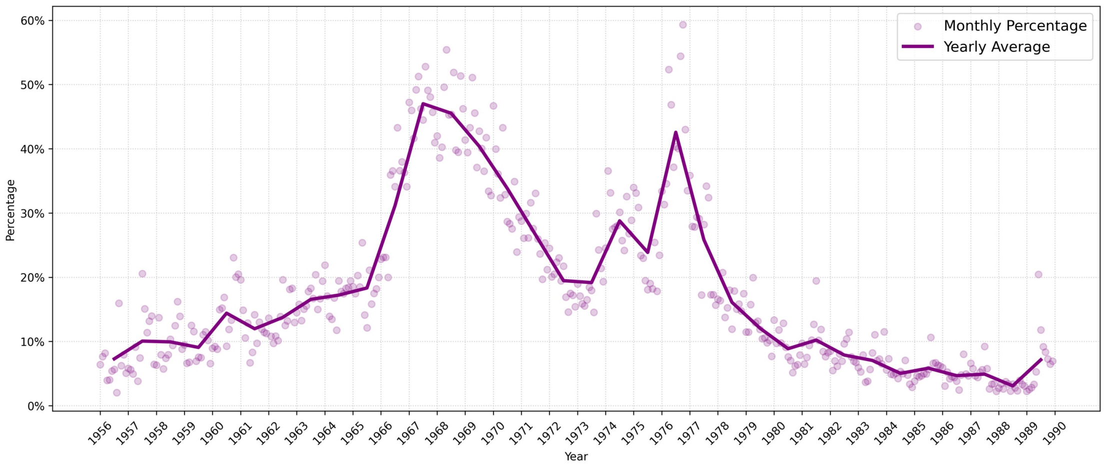

Figure 2: Percentage of articles with both violence and emotion scores exceeding 0.9, published in the *PLA Daily* between 1956 and 1989. Prior to plotting, the values in each category have been normalized to map onto a [0, 1] scale based on the actual observed ranges.

Examples from the extrema of the distribution have been provided in Table 1 in the Appendix. In high-violence, high-emotion texts, the sentiments are channelled towards the Communist Party and the leader Mao Zedong in the *yiku-sitian* 忆苦思甜 ("remember the bitter past and think of the sweet present") mode. In the high-violence, low-emotion texts, the focus is placed on military matters analyzed from a professional perspective. The low-violence, high-emotion passages convey gratitude to the Communist Party and its members, with little to no mention of military history. The low-violence, low-emotion texts focus on civilian matters.

[2] It is important to notice that the relative values (trends) *within* models are more informative than absolute comparisons *between* the models, as they have been trained on different amounts and types of data. For example, emotional intensity of 0.7 and violence score of 0.5 does not entail that a given text is "more emotional than violent."

5. Discussion

The above findings offer additional evidence that emotional mobilization was one of the crucial aspects of revolutionary violence in modern China, fostering a collective identity among the populace confronted with state-designated enemies [29, 28]. Although well-documented in non-DH sinology, the discovered alignment between emotion and violence is surprising insofar as the sentiment-analysis model has been trained on texts (book reviews) that have little in common with the military-related content published in the *PLA Daily*. The results demonstrate the applicability of out-of-distribution datasets in quantitative explorations of literary phenomena, including even such intangible features as emotional valence of political texts. Moreover, the focus on continuous intensity rather than discrete flavors of emotions mitigates some of the shortcomings of computational sentiment analysis. By identifying highly-emotional moments in texts rather than labeling them as either "positive" or "negative," we give some of the interpretive power back not only to the researcher but also the individuals who actually read those texts.

This last point is particularly important given that the intended reader was supposed to not only sympathize with the suffering of proletarian heroes (Patrick Hogan's "complementary emotions" [11]) but also empathize with them by partaking in the revolutionary fervor ("parallel emotions"). These reactions could thus simultaneously feature sentiments at the extrema of the positive-negative spectrum. Consider the following excerpt from the article "A Communist Party Member Must Fight," published on October 12th, 1969:

> Fire means a command, and the scene of the fire is a battlefield! Lu Bingyi and his comrades from the propaganda team were the first to arrive at the site. A raging fire was engulfing a local alleyway's plastic processing factory. Through the thick, acrid smoke, they could hear the desperate cries of women trapped inside. [...] The fire, fanned by plastic products, raged ever higher. Thick black smoke, carrying a pungent odor, stung Lu's nose, causing it to bleed. With the combined heat of the flames and the suffocating smoke, Lu felt dizzy and gasped for breath. Over and over, he silently recited, "Be resolute, fear no sacrifice, overcome all difficulties to win victory." Chairman Mao's teachings, heavy with meaning, strengthened Lu as he charged into the flames and fought bravely. Foam from the fire extinguishers sprayed into Lu's left eye, causing sharp pain, yet he persisted, helping Master Zhou rescue five class sisters in quick succession.
>
> 火光就是命令，火场就是战场！小陆和宣传队的同志首先赶到现场。烈火，在里弄塑料加工厂里熊熊地燃烧。从浓浓的臭烟里发出了姐妹们焦急的呼救声... 熊熊的烈火，卷着塑料制品，越烧越旺，浓浓的乌烟，发出一股特殊的臭味，呛得小陆的鼻子直流血。又是火烤，又是烟熏，小陆感到头昏脑胀，窒息得喘不过气来。他一遍又一遍地背诵着“下定决心，不怕牺牲，排除万难，去争取胜利”。毛主席的教导，字字重千斤，鼓励着小陆出入火海，英勇战斗。外边射进火海的泡沫酸碱喷进了小陆的左眼，痛得厉害，他仍坚持和周师傅一起接连救出了五个阶级姐妹。

In this and similar passages, the vicarious details are meant to invoke both positive and negative responses in the reader, embedding ideological instruction at an affective level. A binary understanding of emotions risks oversimplifying such emotional dynamics and missing the nuanced ways in which political power can be intertwined with affect.

Our paper thus suggests a special role that can be played by narrative arts. If literature has the potential to "personalize revolution and revolutionize romantic adventures," as Liu puts it [25], it can also disentangle private passions from violent discourse and redirect feelings towards other facets of life [12, 13]. Depictions of simple everyday interactions, deliberately paired with non-violent sentiment, may generate affective-discursive spaces that resist political manipulation. The computational approach proves useful not only in conceptualizing such spaces in quantitative terms but also identifying them within large textual corpora. We will further explore this line of thought in the sequels to this paper.

Limitations

Several limitations of this project must be acknowledged. Our primary dataset consists of articles from the *PLA Daily*, a single source that does not represent the full spectrum of revolutionary discourse in the PRC. Furthermore, the binary classification of texts as either violent or non-violent and as conveying strong or weak emotions simplifies the complex nature of human language. More refined classification systems could be developed to capture such subtleties.

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Appendix

Excerpt	Source	V	E
The heavens and earth are not as great as the Party's kindness; Chairman Mao is truly the most dear person to us poor and lower-middle peasants. In the wicked old society, eleven of my relatives were killed. When I was fourteen, my father was beaten to death by a heartless landlord while working for him. After my father's death, my mother led us siblings to beg for food. [...] A few years after joining my husband's family, four members of his family died from hunger and exhaustion. I gave birth to eight sons, but two of them starved to death. I begged for food from Shandong to Guandong, from a young child until I was over fifty years old. A landlord's vicious dog bit off my right ear, leaving me covered in wounds and nearly dead. 我想，天大地大不如党的恩情大，毛主席真是咱贫下中农最亲的人。万恶的旧社会，活活坑死了我十一个亲人。我十四岁那年，爹爹在给地主扛活时，被狼心狗肺的地主活活打死了。爹爹死后，妈妈领着我们姊妹几个到处要饭... 过门后不几年，婆家又饿死和累死了四口人。我生了八个儿子，也活活饿死两个。我要饭从山东要到关东，从不懂事的孩子要到五十多岁。地主的恶狗咬掉了我的右耳朵，咬得我满身是伤，险些送了命。	"Don't Forget Class Bitterness: Always Loyal To Chairman Mao" 不忘阶级苦: 永远忠于毛主席 Jun 17, 1968	0.9955	0.9941
In recent years, the Soviet military has paid great attention to the synchronization of air defense weapons and combat units, studying issues such as the deployment, firing, and logistical support of air defense units during movement to ensure the success of their large-scale mobile operations. However, Western analysts believe that the mobility of the Soviet field air defense is far from meeting the requirements of rapid army offensives. When the troops begin to move, the effectiveness of the air defense drops sharply. Combined with a low level of electronic warfare capabilities, significant technical and tactical improvements are still needed. 近年来，苏军很注意防空武器与作战部队的同步运动，研究运动中防空部队的展开、发射和补充保障等问题，以保证其大规模机动作战的胜利。但西方认为，苏军野战防空的机动性远没有达到陆军快速进攻的要求。部队一运动起来，防空的效能骤减，加上电子战水平低，在技术、战术上还需大大改进。	"Three Characteristics of Soviet Army Field Air Defense" 苏陆军野战防空三个特点 Aug 24, 1984	0.9995	0.2271
I was so emotional that I couldn't speak. I lost my mother when I was very young, and my father was constantly running around to make ends meet, leaving no one to take care of me as I was tormented by illness. But today, in the revolutionary forces, my superiors care for and look after me with such meticulous attention, like my own parents. As I thought about this, tears welled up in my eyes. With trembling hands, I accepted the fruits and snacks brought by Section Chief Yang. These were not just fruits and snacks, but a symbol of the heartfelt care from revolutionary comrades to their fellow soldiers, continually warming my heart. Dear Section Chief Yang, you worked tirelessly for the revolutionary cause, exhausting yourself to the point of illness, and now you have left us forever! 我激动得说不出话来。我在很小的时候失去了母亲，父亲整天为我们的生活奔跑，疾病把我折磨得死去活来，也无人照顾。而今天在革命部队里，上级对自己是这样无微不至地体贴和照顾，象亲生父母一样。我想着想着，热泪禁不住夺眶而出。我用颤抖的手接过股长送来的水果和点心。这不是水果，也不是点心，而是革命同志对战友的一颗火热的心，它不断地温暖着我。亲爱的杨股长，为了革命事业废寝忘食，劳累成疾，终于和我们永别了！	"When Section Chief Yang and I Were Together" 杨股长和我在一起的时候 Jun 6, 1959	0.0079	0.9948
Systematically and in an organized manner, military officers are being dispatched to civilian enterprises and local universities to gain life experience and learn from the strengths of these institutions. This initiative aims to enhance and improve the educational work of military academies. The main considerations for this new attempt by the Air Self-Defense Force Officers School are: first, to broaden the horizons of young military officers, helping them understand society, learn from the strengths of civilian enterprises and local institutions, and address their own shortcomings; second, to deepen the understanding of the military within local and civilian communities... 有计划、有组织地把军队干部派往民间企业、地方大学体验生活，吸取民间企业、地方大学的长处，以加强和改善军队院校的育人工作。航空自卫队干部学校进行新尝试的主要考虑是：一、使年轻军队干部开阔视野，了解社会，取地方、民间之长，补自己之短；二、加深地方、民间对军队的了解...	"Japan Air Self-Defense Force's New Attempt to Train Command Officers" 日本航空自卫队培养指挥干部的新尝试 Oct 10, 1988	0.0007	0.2716

Table 1
Sample texts with corresponding violence (V) and emotion (E) scores.