Toward Automating the Classification of Films' Narrative Structures

Nuttanai Lertpreechapakdee, Chulalongkorn University, Thailand
Tatri Taiphapoon, Chulalongkorn University, Thailand
Sukree Sinthupinyo, Chulalongkorn University, Thailand

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Abstract
Traditional methods of analyzing film narrative structure typically involve qualitative analyses of script and film elements as well as quantitative assessments of editing patterns. These approaches are limited by scalability and efficiency due to the extensive manual human labor required, making them impractical for analyzing large datasets. This paper examines how machine learning techniques can be leveraged to classify film narrative structures in a more scalable and efficient manner, particularly when dealing with extensive collections of films. To address the limitations of traditional methods, two main approaches are proposed. The first approach utilizes natural language processing (NLP) to perform script sentiment analysis and identify the hidden emotional structures across a large body of film scripts. The second approach uses computer vision techniques to detect editing elements such as transitions and shot duration patterns, which are then analyzed to uncover the underlying narrative structures within a corpus of films. Each approach has its strengths and limitations depending on the availability of samples and practical considerations. These machine learning techniques offer a scalable and efficient way to analyze narrative structures, enabling film scholars to uncover hidden complex patterns within large datasets of films. Practically, these techniques can also assist filmmakers in fine-tuning their work, ensuring that the pacing and emotional impact align with their creative vision. Overall, this integration of technology into film studies and production enhances traditional methods of film study and helps filmmakers make more informed decisions.

Keywords: Machine Learning in Film Studies, Film Analysis Automation, Computer Vision in Film, Data-Driven Film Studies

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Introduction

The analysis of narrative structures in film has long been a cornerstone of film studies, offering profound insights into how stories are crafted and experienced. Traditionally, these analyses have been conducted through qualitative methods, where researchers engage in a meticulous examination of film elements to uncover the narrative framework. For instance, Thompson (1999)'s analysis involves segmenting films into distinct acts to understand the progression and organization of the story. While this method yields rich, detailed insights, it is inherently time-consuming and subject to individual interpretation, which can limit its scalability and consistency across different studies.

Quantitative approaches have also made significant contributions to the field by providing a more objective lens through which to view narrative structures. Cutting et al. (2011)'s work, for example, demonstrates that shot duration and the frequency of cuts are closely tied to the narrative intensity of films. This analysis suggests that longer shot durations are often used at the beginning and end of a movie, as well as at key transitional points, such as act boundaries, highlighting how variations in editing rhythms can significantly affect the emotional and narrative flow of a film. However, despite these advancements, quantitative methods still require extensive manual effort to collect and analyze data, limiting their practical application on a larger scale.

In recent years, the convergence of increased computational power and the availability of vast datasets has opened new possibilities for film analysis. Machine learning, with its ability to process and analyze large volumes of data efficiently, offers a transformative approach to studying narrative structures (Fan, 2018). By automating aspects of narrative analysis, machine learning addresses the limitations of traditional methods, providing a scalable, objective means of analyzing films that can be applied across large datasets.

This paper introduces two innovative approaches to film narrative classification: natural language processing (NLP) for script sentiment analysis and computer vision for analyzing editing elements such as shot duration and transitions. These methods, grounded in machine learning, offer the potential to not only enhance the efficiency and scale of narrative analysis but also to provide new insights into the structure and pacing of films. Through these approaches, this paper seeks to demonstrate how the integration of machine learning into film studies can revolutionize both academic research and practical filmmaking, enabling a deeper and more nuanced understanding of narrative structures.

Traditional Qualitative and Quantitative Approaches in Film Studies

Traditional approaches to film studies have been the bedrock of the discipline, encompassing both qualitative and quantitative methods that provide scholars with tools to dissect and interpret films from various perspectives. These methods allow researchers to explore a wide range of film elements, including visual styles, thematic content, cultural contexts, and narrative structure.

Narrative structure refers to the way in which a story is organized and presented to the audience, shaping how the plot unfolds over time. Narrative structure is central to guiding the audience's experience, helping to create tension, build characters, and deliver thematic messages. Common structures, such as the three-act framework, divide a story into distinct sections—beginning, middle, and end—each with its own purpose in advancing the plot. This structure serves as the backbone of many films, influencing how stories are told and how audiences perceive them (Chatman, 1980).

Qualitative methods emphasize an in-depth exploration of themes, visual compositions, and how films communicate their messages to audiences (Bordwell et al., 2004). Researchers using qualitative approaches typically engage in close readings of films, meticulously analyzing elements such as cinematography, editing, and sound design to uncover deeper meanings and artistic intentions. For example, Thompson (1999)'s analysis of narrative structures involves dissecting formal elements like shot composition, editing patterns, and narrative devices, which are then segmented into act structures such as the four-act model. This model divides a film into setup, complication, development, and climax, providing a clear framework for understanding the flow and progression of a film's story.

In addition to narrative structure, qualitative methods also encompass other critical approaches such as auteur theory, which focuses on the director's personal influence and recurring themes throughout their body of work (Sarris, 1962). For instance, analyzing recurring motifs and directorial styles in the films of Alfred Hitchcock offers valuable insights into his impact on the thriller genre. Psychoanalytic film theory, as applied by scholars like Mulvey (2013), examines how films reflect and shape unconscious desires and societal norms, particularly through concepts like the "male gaze." These qualitative methods allow for a thorough exploration of the filmmaker's techniques and the audience's emotional and intellectual responses. However, such analysis is often time-consuming and subject to the analyst's personal biases and interpretations, which can limit its objectivity and scalability (Denzin & Lincoln, 2011).

Quantitative methods in film studies, in contrast, involve the systematic and empirical investigation of film-related phenomena through statistical, mathematical, or computational techniques. These methods provide objective data that can reveal trends, patterns, and correlations, complementing the subjective insights gleaned from qualitative analysis (Redfern, 2014). For instance, box office statistical analysis can reveal the financial success of films over time and across different markets. Researchers might use regression analysis to determine the factors contributing to a film's success, such as genre, star power, or marketing expenditure (Liu & Xie, 2019).

Quantitative approaches have also been essential in analyzing stylistic elements like shot length, camera movement, and scene transitions. Salt (1974)'s pioneering work in statistical style analysis offers an objective approach to understanding film style, where he quantified variables, such as shot length and camera movement across a diverse sample of films. This method revealed subtle stylistic patterns and variations among directors, which traditional qualitative analysis might overlook. Similarly, the study of shot length and pacing by Cutting (2016) has shed light on how editing rhythms influence narrative intensity. For example, longer shot durations often occur at significant narrative junctures, such as act boundaries, highlighting how variations in editing rhythms can greatly affect the emotional and narrative structure of a film. These quantitative methods uncover trends and patterns that may not be immediately evident through qualitative analysis alone. However, despite their objectivity, traditional quantitative methods often rely on manual data collection, which limits their scalability and efficiency.

While traditional qualitative and quantitative approaches have significantly contributed to the field of film studies, they also present challenges related to labor-intensive data collection and limited scalability. These limitations underscore the need for innovative methodologies that can overcome these challenges. Integrating machine learning techniques into film studies offers a promising solution by automating data collection and analysis processes. This technological advancement not only enhances the scalability and efficiency of film analysis but also complements traditional methods, paving the way for more comprehensive and nuanced explorations of elements like narrative structures.

Machine Learning Approaches in Film Studies

One of the earliest and most impactful applications of machine learning in film studies has been genre classification. Traditionally reliant on manual coding of film characteristics—a process that is both inconsistent and labor-intensive—genre classification has been revolutionized by machine learning. Models trained using supervised learning techniques have proven highly effective in automatically categorizing films into genres such as action, comedy, or drama by analyzing dialogue, plot summaries, visual style, and external metadata like posters and trailers (Kumar et al., 2023). Deep learning, particularly through convolutional neural networks (CNNs), has further advanced this field by recognizing complex patterns in both text-based and visual components of films, thus providing a fast and scalable alternative to human classification (Simões et al., 2016).

Beyond genre classification, sentiment analysis has emerged as another significant application. Originally developed for assessing the emotional tone of text, sentiment analysis has been adapted to analyze film scripts and viewer reviews, offering insights into how films resonate emotionally with audiences (Narendra et al., 2016). Machine learning models, particularly those based on natural language processing (NLP), have been instrumental in mapping the emotional trajectories within scripts, revealing narrative pacing and intensity contribute to the audience's overall experience. These models, using techniques like sentiment lexicons and advanced methods such as recurrent neural networks (RNNs) and transformers, allow for the automated analysis of the emotional dynamics across large datasets, identifying common narrative structures like the "hero's journey" arc often found in dramas (Reagan et al., 2016).

In addition to text-based analysis, machine learning has significantly advanced the stylistic analysis of films through computer vision techniques. Computer vision enables the automatic extraction and interpretation of visual data, which is critical for understanding the aesthetic and narrative structure of films (Rasheed & Shah, 2005). CNNs trained on large datasets of film frames can identify distinct visual styles, analyze editing rhythms and shot compositions (Karpathy et al., 2014). Another key application of computer vision is in the analysis of shot length and pacing, where machine learning models can automatically detect cuts and transitions, revealing editing patterns that are often linked to a film's narrative structure (Brunick et al., 2013). For instance, faster editing may correlate with high-intensity sequences, while longer shots might be used to build tension.

By complementing traditional methods, these machine learning techniques open up new avenues for film studies, offering insights into narrative structures that were previously inaccessible. The automation of narrative analysis not only enhances the efficiency of film studies but also deepens our understanding of how films are constructed and resonate with audiences. This, in turn, contributes significantly to both academic research and practical filmmaking.

Proposed Methodologies

To address these challenges and harness the potential of machine learning for movies' narrative structure analysis, this section outlines two methodologies: Script sentiment analysis and Editing pattern analysis using computer vision techniques. These methodologies are designed to work at different stages of film's production, providing a comprehensive approach to automating the classification of film narrative structures through both script analysis in pre-production and the examination of editing patterns in post-production.

Script Sentiment Analysis for Narrative Structure Classification

The first proposed approach leverages natural language processing (NLP) techniques to systematically analyze the emotional and narrative structures embedded within film scripts, aiming to automate the identification of narrative patterns by examining sentiment dynamics throughout a script, which can reveal underlying emotional arcs and structural elements critical to understanding a film's overall narrative framework (Eliashberg et al., 2007). This methodology begins with the extensive collection and preprocessing of a diverse corpus of film scripts, ensuring the selection encompasses a broad range of genres, historical periods, and narrative styles to allow the model to generalize across various film types. These scripts, sourced from publicly available databases, screenwriting forums, and licensed repositories, will be meticulously cleaned and standardized, a process that includes removing extraneous elements like stage directions, character names, and annotations not directly relevant to narrative analysis. Tokenization will then break down the text into individual words or phrases, followed by part-of-speech tagging to focus the sentiment analysis on the most narratively significant components of the script, particularly dialogue and descriptive passages.

The development of a sentiment analysis model specifically tailored to the language of film scripts is central to this methodology. Traditional sentiment analysis models, typically trained on generic text corpora, may not fully capture the nuances of cinematic language, necessitating the fine-tuning of a pre-trained transformer-based model, such as BERT (Bidirectional Encoder Representations from Transformers), on a domain-specific dataset of film scripts (Devlin et al., 2018). This fine-tuning process enables the model to adapt to the unique language patterns, emotional cues, and narrative structures present in screenplays, with supervised training using labeled data, where segments of scripts are annotated with sentiment labels to guide the model in recognizing similar patterns in unseen scripts.

Once the sentiment analysis model is in place, scripts will be segmented into scenes or acts based on standard screenplay formatting cues, such as "INT." and "EXT." for scene changes. Each segment will undergo sentiment analysis to generate a sentiment score that reflects the emotional tone of that particular scene. These scores will then be aggregated to produce an emotional arc for the entire film, capturing narrative patterns such as rising tension, climactic moments, and resolutions. Advanced sentiment analysis techniques, including contextual sentiment scoring, will be employed to account for the broader narrative context of each sentiment-laden word or phrase, ensuring a more nuanced and accurate depiction of the film's emotional landscape (Zhang et al., 2018).

Following the mapping of emotional arcs, key features will be extracted from these sentiment trajectories, including the frequency and intensity of emotional peaks and troughs, the overall emotional polarity, and the rate of emotional change between scenes or acts. These features will serve as inputs for a machine learning classifier designed to categorize films based on their narrative structure. Various algorithms, such as support vector machines (SVM), random forests, or neural networks, will be explored to determine the most effective approach for this classification task, with the classifier trained on a portion of the dataset and tested using cross-validation to ensure it generalizes well across different types of scripts and narrative styles (Li et al., 2009).

To validate the effectiveness of the proposed methodology, the classified narrative structures will be compared against manually annotated ground truth data, which may be provided by film scholars or based on established narrative theory frameworks. The model's performance will be evaluated using metrics such as accuracy, precision, recall, and F1-score to provide a quantitative measure of its effectiveness (Powers, 2020). Additionally, qualitative assessments will be conducted by examining cases where the model's predictions align or diverge from traditional narrative analyses, offering insights into the model's interpretability and identifying potential areas for refinement.

Editing Pattern Analysis Using Computer Vision Techniques

The second proposed approach utilizes advanced computer vision techniques to analyze the editing patterns of films, with a particular focus on shot duration—a key element that significantly influences a film's narrative structure and pacing (Cutting & Candan, 2015). This methodology automates the detection and analysis of shot transitions, such as cuts, fades, and dissolves, to uncover the underlying temporal patterns that contribute to a film's pacing and narrative flow. The analysis begins with the detection of shot boundaries, known as shot boundary detection (SBD), which are transitions between consecutive shots in a film. This process is crucial for determining the duration of each shot and subsequently constructing the shot duration pattern of a film (Abdulhussain et al., 2018). SBD algorithms analyze visual and audio features in the video to identify the points where these transitions occur. Basic SBD methods compare consecutive frames based on pixel intensity, color histograms, or edge detection, while more advanced methods leverage machine learning models, such as convolutional neural networks (CNNs), which are trained on large datasets of annotated videos. These models learn to recognize patterns associated with various types of transitions, enabling them to detect shot boundaries with high accuracy. The integration of multimodal approaches, which combine visual and audio data, enhances detection accuracy by providing a more robust analysis of transitions. Once the shot boundaries are detected, the shot durations are calculated by measuring the time intervals between consecutive boundaries. These durations are then organized into a chronological sequence, representing the shot duration pattern of the film. This sequence offers a temporal overview of the film's pacing, where shorter durations indicate faster-paced sections and longer durations reflect slower, more deliberate moments.

The next phase of the methodology involves extracting key features from the shot duration data that characterize the film's editing patterns. These features may include the average shot duration, the variance in shot lengths, and the frequency of transitions, all of which contribute to the film's overall pacing and narrative intensity. Additional features, such as the distribution of shot durations across different sections of the film, are analyzed to identify patterns related to the film's emotional arcs or narrative structure. Given the sequential nature of shot duration data, time-series analysis techniques are employed to group films with similar editing patterns. Time-Series K-Means, for example, modifies the traditional K-Means algorithm by incorporating temporal information into the clustering process. By using distance metrics like Dynamic Time Warping (DTW), which accounts for variations in timing and sequence among the shot duration patterns, the method helps to identify clusters of films with similar editing rhythms (Petitjean et al., 2011). Time-Series K-Medoids offers a robust alternative by using actual data points as cluster centers, enhancing the algorithm's resistance to outliers (Huy & Anh, 2016). Additionally, methods such as Spectral Clustering and Agglomerative Clustering provide further means of grouping films based on their shot duration patterns, with each method offering unique strengths in handling the complex dynamics of time-series data (Rani & Sikka, 2012).

The results of the clustering process are evaluated for validity and consistency through multiple approaches. The first step involves a visual inspection, where the centroids of each cluster—representing the average shot duration pattern of the films within that cluster—are compared to the individual shot duration patterns of the films. This comparison assesses whether the centroids effectively capture the key features of the editing patterns. Further validation involves cross-cluster comparisons using metrics such as Adjusted Mutual Information (AMI) to measure the similarity between different clustering results (Romano et al., 2016). By comparing the outcomes of various clustering methods, researchers can ensure that the identified patterns are robust and not artifacts of a single algorithm. Additionally, methodological triangulation, which involves comparing the clustering results with those obtained from alternative methods like Spectral Clustering or Agglomerative Clustering, provides further confidence in the reliability of the findings (Monti et al., 2003).

Implications for Film Studies

The integration of machine learning into the analysis of film narrative structures represents a transformative shift in film studies, moving from traditional, labor-intensive methodologies to more scalable and data-driven approaches. By automating the processes of script sentiment analysis and editing pattern detection, the methodologies proposed in this paper have the potential to significantly broaden and deepen our understanding of cinematic storytelling.

One of the implications of these methodologies is their ability to democratize film analysis. Traditionally, in-depth narrative analysis has been accessible primarily to scholars with the time and resources to engage in close readings of films. However, by utilizing machine learning, these methodologies make it possible to analyze vast datasets of films quickly and efficiently, thus broadening the scope of analysis to include a wider range of cinematic works. This democratization could lead to a more inclusive understanding of global cinema, allowing for the study of films from diverse cultures and genres that have historically been underrepresented in academic discourse.

Moreover, the scalability of these methodologies is one of their key strengths. Their ability to handle large datasets enables researchers to uncover trends and patterns that would be difficult to identify through manual analysis alone. This scalability is particularly important in an era where digital archives of films are expanding rapidly, necessitating tools that can keep pace with the growing volume of cinematic works. By processing and analyzing vast amounts of data, these methodologies not only enhance the efficiency of film studies but also allow for a more comprehensive exploration of narrative structures across different genres, cultures, and time periods.

Another significant strength of these methodologies is their capacity to integrate different types of data—namely, textual data from film scripts and visual data from editing patterns—

into a unified analytical framework. This multimodal approach provides a more holistic understanding of narrative structures, capturing both the emotional arcs conveyed through dialogue and the pacing effects created by editing. By combining these elements, the proposed methodologies offer a comprehensive view of how narrative structures are constructed and how they function within the broader context of a film.

The use of advanced machine learning techniques, such as BERT for sentiment analysis and CNNs for shot boundary detection, further enhances the sophistication and accuracy of the analysis. These models are capable of capturing the nuanced and complex nature of cinematic language and visuals, leading to more reliable results that can inform both academic research and practical filmmaking. This integration of cutting-edge technology into film studies not only provides new insights but also aligns with contemporary shifts towards data-driven research methodologies across various disciplines.

In practical terms, these methodologies also offer significant benefits to filmmakers and the broader film industry. By providing tools to analyze and optimize narrative structures, filmmakers can use these insights to align their creative vision with audience expectations, enhancing the emotional and narrative impact of their work. Additionally, the ability to analyze editing patterns in detail can inform decisions about pacing and shot composition, leading to more effective storytelling techniques that resonate with viewers.

Conclusion

The integration of machine learning into the analysis of film narrative structures presents a transformative opportunity for film studies. Traditional methods, while rich in detail and depth, are often limited by the extensive manual effort required, making them impractical for analyzing large datasets. By leveraging machine learning techniques such as natural language processing for script sentiment analysis and computer vision for editing pattern detection, this paper proposes a scalable and efficient approach to classifying narrative structures across extensive collections of films.

These methodologies not only address the limitations of traditional approaches but also offer new insights into the construction and function of narrative structures in cinema. The ability to process and analyze vast amounts of data enables a more comprehensive understanding of narrative trends and patterns across different genres, cultures, and historical periods. Additionally, the integration of textual and visual data into a unified analytical framework provides a holistic perspective on how narrative elements such as emotional arcs and pacing contribute to the overall storytelling experience.

The implications of these advancements extend beyond academic research, offering practical tools for filmmakers to optimize their creative work. By aligning narrative structures with audience expectations, filmmakers can enhance the emotional and narrative impact of their films, ultimately contributing to a richer and more nuanced cinematic experience.

However, as with any emerging technology, there are challenges to be addressed. The reliance on the quality and diversity of training data, the interpretability of machine learning models, and the need for human expertise in certain aspects of the analysis are all factors that require ongoing attention and refinement. Future research will need to focus on these areas to further develop and enhance the methodologies proposed in this paper.

In conclusion, the integration of machine learning into film studies represents a significant advancement in the field, providing both scholars and practitioners with powerful new tools for analyzing and understanding narrative structures. As these technologies continue to evolve, they will undoubtedly play an increasingly important role in shaping the future of film analysis, offering new ways to explore, interpret, and create cinematic works.

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