

Meta Score Trends in IMDB Movies Dataset

I. Introduction and Background

The IMDB Movies Dataset contains the top 1,000 films and TV shows, including information such as release years, genres, and meta scores. Meta scores quantify critical reception, which can be analyzed to provide insights into how perceptions of genres change over time. This project will investigate whether meta scores change over time differently for specific genres and whether cyclical patterns exist within these trends. The research question guiding my analysis is: "Do meta scores change over time differently for different genres, and are there cyclic patterns?"

In this dataset, I assigned each movie a `Primary\_Genre` based on the first genre listed. After doing some exploratory data analysis (EDA), I chose to focus on Drama, Comedy, Action, Biography, and Adventure because figures 1-3 reveal that meta scores vary distinctly across these genres. For instance, Figure 1B displays the distribution of meta scores across the selected genres, indicating higher averages and variability for Drama and Comedy than for Action. Figure 2 shows the distribution of meta scores over the years alluding to potential trends in critical reception, like Comedy's slight decline in meta scores. Figure 3 illustrates genre frequency and highlights differences in the dataset's composition, with Drama and Comedy being more prevalent than other genres. These initial observations suggest that genre-based trends in meta scores are worth investigating through time series modeling.

II. Analysis

Exploratory Data Analysis (EDA)

Figure 1A displays the average meta score trends across all genres, providing a baseline for how critical reception varies by genre. This EDA shows unique patterns in the trajectories of different genres, which informed my selection of the five genres to focus on in this analysis.

For Action, there are noticeable fluctuations in scores, with higher ratings observed in earlier years but gradually declining over time. Initial peaks in scores give way to a general downward trend, especially in recent years, suggesting that Action films may be receiving lower critical acclaim as genre expectations evolve.

Adventure films show a gradual decrease in scores from the earlier years, particularly around the mid-century period, though this trend stabilizes in later years. A slight recovery is observed more recently, yet scores remain lower than those in the earliest years, indicating a more tempered reception for Adventure films in modern times.

The trend for Biography appears more stable, with moderate fluctuations but no strong upward or downward trajectory. Biography has a relatively stable trajectory, only with minor fluctuations and no clear upward or downward trend. Scores for this genre tend to stay within a narrow range, which suggests that critical reception has remained stable over the years.

Comedy shows a general downward trend over time. High scores in the earlier years gradually taper off due to an evident shift in the genre's reception, with Comedy films receiving lower scores in recent years. This decline may reflect changing audience expectations and the evolution of comedic styles.

Drama films show a downward trend but with more pronounced fluctuations than Comedy films. Drama scores are high in the early years but steadily decline over time, indicating that this traditionally well-regarded genre has shifted towards lower ratings in recent decades.

Based on these observations in Figure 1A, I selected Action, Adventure, Biography, Comedy, and Drama for more focused analysis in Figure 1B. This selection of genres lets me explore a range of patterns: Action and Adventure both show a downward trend over time, Drama has some noticeable fluctuations amid its decline, Comedy steadily drops, and Biography holds steady. Figure 2 shows the overall distribution of meta scores across the dataset, giving us a sense of general critical reception across all genres. Most scores cluster between 70 and 90, indicating that films are generally viewed in a favorable light.

Table 1 breaks down these meta scores by genre, with Drama leading at an average score of 79.4, followed by Comedy (78.6) and Adventure (78.4). Action, however, scores lower on average at 74.2, which may suggest critics' tendency to favor narrative-rich genres over those driven by spectacle.

This distribution helps frame the variations observed in the GAM results. Even though each genre has its own trajectory, the central clustering around moderate-to-high scores hints that, overall, critical reception tends to be positive.

Figure 3 shows the distribution of `Released\_Year` for the focused genres, with higher frequencies of releases in 1970 and after. This is aligned with the "New Hollywood" era, which saw significant growth in film production. Because of increased frequency in recent years, the data lends itself to a more detailed analysis of trends and cyclic patterns for later periods compared to earlier decades. Figure 4 displays the frequency of films across the five genres. There are greater frequencies of Drama and Action films and much lower frequencies of Biography and Adventure titles. This uneven genre distribution may result in observing less stable trends in less represented genres due to smaller sample sizes.

Approach

At first, I considered using a Generalized Linear Model (GLM) because of its simplicity, which I believed would help me generate a straightforward interpretation. However, I opted for a Generalized Additive Model (GAM) since I expected genre trends to be at least somewhat non-linear. GAMs offer greater flexibility in capturing the unique, genre-specific patterns in meta scores over time because they have the ability to fit several smooth functions to model gradual changes while retaining linearity in the parameters, improving upon my first draft using a GLM. I will use R's thin-plate spline basis (`bs = "tp"`) so that the model can adapt smoothly to variations in meta score trends without overfitting. Knot placement is controlled through the parameter `k`, set to 10 in my R code, which determines the number of 'bins' along the spline. This allows me to balance detailed trends while maintaining model interpretability, which is especially useful when observing gradual shifts in genre preferences over time.

To comprehensively address my research question regarding genre-based changes (which I predict to be non-linear) in meta scores and potential cyclic patterns, I will combine GAMs with Seasonal-Trend decomposition using LOESS (STL) and autocorrelation function (ACF) analysis.

STL decomposition on the time series data for each genre will allow me to isolate the data's trend, seasonal, and residual components for a clear view of both long-term and seasonal

patterns. By focusing on the seasonal component, STL reveals recurring patterns—or cyclical— in the meta score data, which may reflect influences from industry cycles, such as franchise trends or advancements in production technology, that shape critical reception, especially in genres like Action and Adventure, where industry cycles often have a strong influence on critical reception.

I will conduct an ACF analysis to complement the STL decomposition by examining correlations across different lags in the residuals, helping to validate any cyclic patterns independently of the seasonal analysis. If there are significant peaks in the ACF plot, it will confirm recurring cycles in critical reception, while a lack of peaks will suggest more linear trends or random fluctuations.

By combining these three approaches—GAMs for trend modeling, STL decomposition for seasonal analysis, and ACF for cycle validation—I can gain insight into genre-specific meta score dynamics over time and make informed conclusions about meta score changes over time and potential cyclical patterns in critical reception.

III. Results

In analyzing the temporal evolution of meta scores across selected genres (Action, Adventure, Biography, Comedy, and Drama), the results indicate genre-specific trends that underscore significant differences in how critical reception for each genre has evolved. Through my use of GAMs, Seasonal-Trend decomposition using LOESS (STL), and ACF analysis, the findings reveal both unique temporal trajectories for each genre and potential cyclic patterns within specific genres.

The GAM analysis of meta scores over time (Figure 5) reveals detailed, genre-specific trends, illustrating how critical reception has evolved for Action, Adventure, Biography, Comedy, and Drama films. For Action films, the model shows that meta scores generally remained high until the 1960s, at which point a noticeable decline began which lasted from the 1970s to the 1990s. It has stabilized in recent years, with average scores between 70 and 80. The trend line shows this mid-century drop and the later stable period, which can lead to an improved understanding of how the reception of Action films changed over the decades.

Adventure films, on the other hand, exhibit a more volatile pattern. The GAM shows that the Adventure genre had large peaks around the 1950s and again in the 1980s, followed by downturns. Meta scores for Adventure films oscillate between 60 and 90, suggesting cyclical popularity shifts within the genre. These oscillations are likely influenced by changing audience expectations or production trends.

Biography films, on the other hand, have a more stable trend that has a slight upward turn beginning in the 1970s. The gradual nature of the rise in meta scores shows that the genre's critical reception increases slowly but steadily over time, likely because of improved production quality or audiences taking a greater interest in biographical storytelling.

The GAM for biography films is smooth, effectively capturing this upward trend while avoiding excessive wiggleness, capturing the upward trend without overfitting minor fluctuations.

Comedy films, however, show a noticeable downward trend starting in the 1950s, steadily hovering, dropping from around 90 to meta scores in the 70s by the early 2000s. This consistent decrease might be due to evolving tastes in humor or standards by which Comedies are critically

evaluated. The GAM shows this long-term trend, with a smooth line to prevent overfitting due to minor fluctuations.

For Drama films, the GAM illustrates a consistent downward trajectory since the early 20th century. By the 2000s, meta scores are shown to have gradually decreased, starting at around 100 and dropping to the mid-70s. This suggests that there has been a long-term shift in the manner in which Drama films are evaluated.

My GAM models provide a detailed visualization of genre-based meta score trends. They help detect temporal patterns across genres, contributing to addressing the overarching research question. In allowing each genre to follow its own non-linear, smoothed trend, I can use the model's patterns to assess how critical reception for each genre has evolved over time.

Time Series Decomposition

The time series decomposition (Figures 6 to 10) breaks down the meta scores for each genre into three components: trend, seasonal, and remainder components, helping to visualize long-term shifts and residual variability. The trends show unique trajectories across all five genres, while the remainder components display varying degrees of randomness, implying minimal seasonal patterns.

Drama films have declined steadily since the early 1950s, but they have stabilized in recent years. The remaining popularity shows random changes each year without clear patterns. Action films rose in popularity initially, then sharply declined in the 1970s, leveling off around 2000. The remainder component for Action is initially stable but becomes increasingly variable post-1960, reflecting heightened fluctuations over time.

Comedy films show a gradual decline in meta scores from the 1950s to the 1980s, punctuated by a brief rise in the 1950s and a slight increase in recent years. The remainder component for Comedy is marked by frequent spikes, hinting at irregular changes in critical reception that might reflect shifts in what audiences find funny over the years. Biography films show a dip around 1965, then stabilize and gradually climb in recent years, with the remainder consistently spiking—suggesting that critics' views on biographical stories fluctuate quite a bit. Adventure films have a more complex trend, with alternating periods of rise and fall, likely indicating cyclical shifts in popularity. The remainder component here shows sporadic spikes starting in the 1950s, which could be tied to the impact of blockbuster releases on how Adventure films are received.

Overall, my analysis demonstrates how, despite each genre having its own long-term trends, none follow a consistent seasonal cycle. This indicates that the changes in meta scores are influenced by broader, genre-specific factors along with cultural or industry shifts rather than regular, predictable patterns. By breaking down each genre's scores into trend and random components, this time series decomposition offers a closer look at how genres have evolved over time, focusing on long-term changes rather than recurring cycles, and helps us get closer to answering the research question.

Autocorrelation Analysis

The ACF plots (Figures 11 to 15) for the remainder components of each genre indicate minimal autocorrelation beyond the initial lag, suggesting no significant cyclical patterns in meta score over time. In each genre, we observe a substantial spike at lag 1 that quickly dissipates, with autocorrelation values primarily within the confidence bounds at higher lags. This lack of consistent autocorrelation suggests that the residuals behave similarly to white noise, with random fluctuations around the trend as opposed to recurring seasonal cycles.

For Drama and Comedy, the weak autocorrelation beyond lag 1 implies that these genres do not exhibit time-based cycles. Instead, variations in meta scores are likely influenced by non-periodic factors, such as individual film quality or cultural changes. Similarly, Action and Adventure show a small initial spike in autocorrelation at lag 1, reflecting minor dependencies on immediate past values but with little evidence of sustained temporal structure. These genres experience more significant residual variability, likely due to irregular "blockbuster" releases, but these deviations do not follow predictable cycles. Biography shows almost no autocorrelation across all lags, indicating stable reception unaffected by seasonal or periodic trends, potentially reflecting a steady and gradually evolving audience interest.

The combined ACF plot (Figure 16) across all genres reinforces the findings, showing no strong cyclical structure in the residuals. While long-term trends in meta score may vary by genre, these changes are primarily driven by overarching trends and influenced by genre-specific factors and external industry shifts rather than regular cycles or inherent seasonality.

Overall, the ACF analysis indicates that fluctuations in meta score are primarily shaped by trends and random noise, suggesting that critical reception, while unique to each genre, does not follow a predictable cycle, making it difficult to predict year-to-year changes in meta score.

IV. Discussion

Findings and Implications

Meta score varies over time uniquely across genres, with each genre exhibiting distinct trend trajectories. GAMs provided details into these genre-specific trends by allowing flexible, non-linear modeling that captured gradual changes in critical reception over time. For example, Drama and Comedy showed early high trends followed by a decline, while Action and Adventure had more volatile trends, probably influenced by genre-specific industry factors like blockbuster releases. The Seasonal-Trend decomposition using LOESS (STL) further isolated these trends, revealing no significant seasonal component and thus no regular cyclic patterns in the meta scores across years for any genre. My ACF analysis of the remainder component confirmed this, as the residuals did not reveal significant autocorrelations beyond the immediate lag. This suggests that changes in the meta score for each genre are primarily trend-driven rather than cyclic.

The genre-specific trends in meta scores contribute valuable insights into how genres evolve in public and critical perception for the film industry, streaming platforms, and distributors, with applications in areas such as forecasting, resource allocation, and content strategy development. For example, because there are no consistent seasonal cycles in meta scores, it indicates that genre popularity and critical reception are primarily driven by overarching cultural and industry shifts rather than predictable, recurring cycles. The notion that critical reception varies uniquely by genre, often with minimal seasonal trends, could help industry stakeholders improve predictions of genre trends and tailor their marketing and production strategies accordingly.

These genre-based insights also have practical applications. For example, streaming platforms can focus resources on genres with recent upward trends in meta scores, such as Biography, or strategically schedule releases during periods of stable critical reception, as seen with Drama. Because Comedy and Adventure possess fluctuating scores driven by cultural and industry shifts, this revealed sensitivity to broader cultural changes that could help stakeholders target their promotional efforts to maintain audience interest accordingly. For genres with historical peaks (e.g., Action), platforms could align their release dates to match predicted increases in audience interest, thereby enabling them to optimize audience engagement and better adapt to changes in evolving public taste.

Limitations and Roadblocks

One of the main challenges I faced during this assignment was handling data entries with inconsistent formatting. I had to do some data cleaning, such as normalizing the 'Released_Year' variable, which had many missing and improperly formatted values. This required me to filter out incomplete entries and/or reformat text-based entries to a usable numeric format.

For simplicity purposes, I decided to focus my analysis on five genres: Drama, Comedy, Action, Biography, and Adventure. This helped me draw comparisons between genres with different narrative styles and characteristics, but it also introduced some selection bias since I left out other genres that might show different trends.

Additionally, the dataset only includes the top 1000 films, which may have skewed my findings toward highly-rated films that do not necessarily represent broader genre trends across all movies. As a result, the insights from these trends are more applicable to the film industry as a whole rather than specific genres.

Additionally, many films were listed with multiple genres, so I categorized each title by 'Primary_Genre' based on the first genre listed. While this simplification made it easier for me to categorize and interpret trends for each genre, it could have skewed my results, overlooking films that belonged to multiple genres. For example, the multi-genre nature of common combinations such as Action-Adventure or Drama-Biography may influence critical reception differently from single-genre films. If I redid the assignment, I could use multi-genre classifications to capture these interactions for a more detailed view of genre dynamics and to reduce potential biases from single-genre categorization to better understand genre-based trends.

Lastly, while GAMs are a strong choice for modeling non-linear trends while retaining linearity in the parameters, their flexibility introduces a risk of overfitting, especially for this dataset's limited size. By using a moderate number of basis functions ($k = 10$), I aimed to mitigate the risk of overfitting by avoiding minor fluctuations and focusing on broader trends over time. Future exploration with larger datasets could optimize model complexity further using cross-validation or criteria such as AIC or BIC. This adjustment would allow the model to balance trend fidelity and overfitting more effectively, accurately representing each genre's long-term trends.

Causal Inference Discussion

In this assignment, my meta score trend analysis is limited to observational insights, which inherently restricts causal inference. While the observed trends in meta scores over time indicate

associations between genre and critical reception, these findings cannot establish *causation* because of the confounding factors inherent to the data.

The Directed Acyclic Graph (DAG) in Figure 17 visually represents probable relationships between confounding variables (e.g., cultural shifts, industry trends, and technological advancements) and genre and meta score. These confounders likely influence both genre popularity and critical reception, obscuring any direct causal link between genre type and meta score trends. As a result, changes observed in meta scores by genre reflect associative patterns influenced by unmeasured factors rather than direct causal effects of genre on critical reception.

Without experimental or quasi-experimental approaches, such as randomized controlled trials or natural experiments, the analysis remains limited to correlational interpretations. For instance, a more controlled setting that isolates variables influencing both genre and score would be needed to determine if a genre shift directly impacts critical reception. Experimental setups or advanced causal models could provide this level of control, though they remain challenging in dynamic, real-world contexts like film reception.

If causal interpretation is desired in future studies, Bayesian Structural Time Series (BSTS) models or other advanced causal inference techniques could be explored. These models could help account for time-related confounders and further the insights derived from cultural and industry shifts. Nevertheless, true causality in this area remains complex, as genre perception and critical reception have a complicated relationship that changes with new societal trends and technological innovations.

This analysis, therefore, does not infer causation but rather provides associative insights into how genre-specific trends in critical reception have evolved over time. It is evident from this analysis that while descriptive patterns are valuable for understanding genre dynamics, they require careful interpretation when discussing industry implications or genre impacts.

Improvements if I Redid the Assignment

If I redid the assignment, I could utilize techniques that address these limitations by broadening the dataset to include a more comprehensive range of films and genres beyond the top 1000, potentially reducing selection bias and capturing genre trends more representatively. Additionally, I could incorporate multi-genre classifications to solidify the validity and robustness of my findings by accounting for films with overlapping genres. I could also implement SARIMA (Seasonal Autoregressive Integrated Moving Average) models to help manage the effects of autocorrelation over time, which would complement the GAM and STL decomposition findings by capturing any residual dependencies that may exist.

Moreover, contextualizing meta score changes with external data on cultural or industry events could allow for a deeper interpretation of genre trends. Advanced causal inference techniques, such as Bayesian Structural Time Series (BSTS) models, could help control for some cultural shifts and industry developments over time. However, true causal inference remains challenging due to the dynamic and interconnected nature of these influences. An expanded dataset that tracks specific events or shifts in film production (e.g., the introduction of streaming platforms or advancements in special effects) might enable me to evaluate how such factors impact genre reception. Establishing causal relationships between genre trends and meta scores could significantly benefit the film industry, providing insights into critical reception shifts and enabling content producers to align strategies with evolving market dynamics.

Summary

In summary, my analysis emphasizes the unique trends in meta scores for various film genres over time, with no evidence of cyclic patterns. Although I encountered limitations such as selection bias and confounding variables, my analysis provides valuable insights for key stakeholders into the non-cyclic nature of trends in critical reception. I could redo this assignment with broader datasets, multi-genre classifications, and advanced causal inference techniques, which could help me better understand the underlying drivers of these trends and offer practical applications for industry stakeholders.

Figure 1A

Meta Score Trends by All Main Genres Over Time

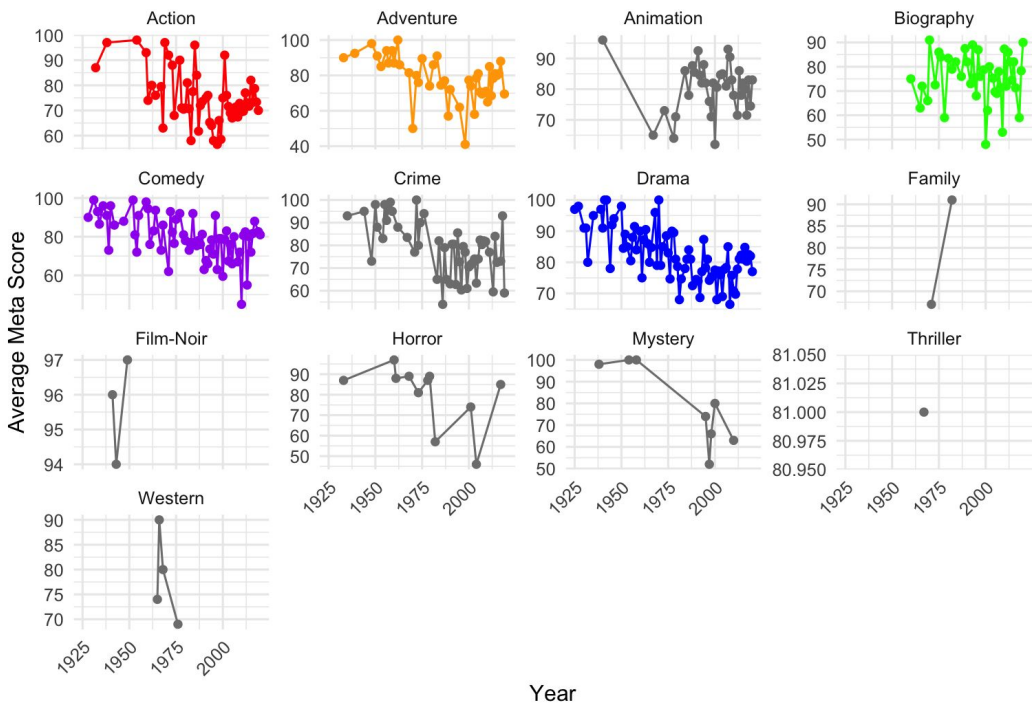


Figure 1B

Meta Score Trends by Main Genre Over Time

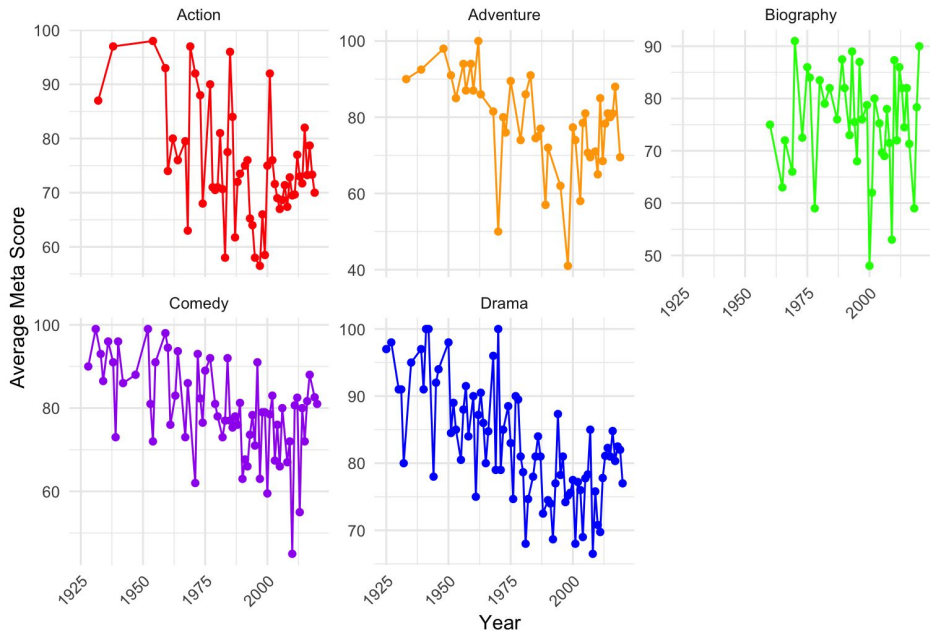


Figure 2

Distribution of Meta Scores

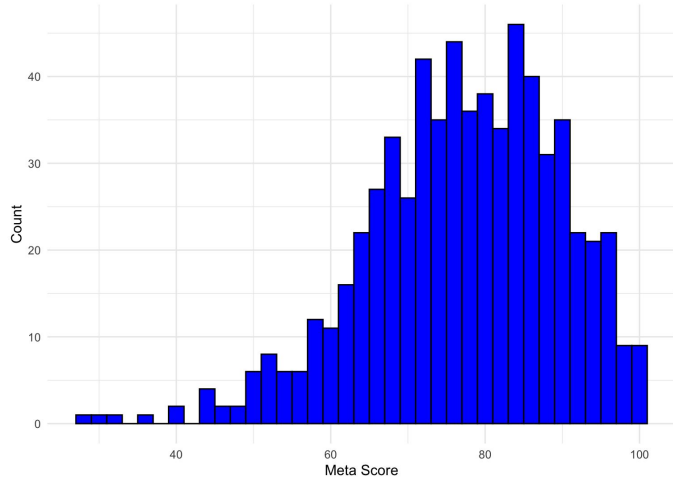


Figure 3

Distribution of Released Year

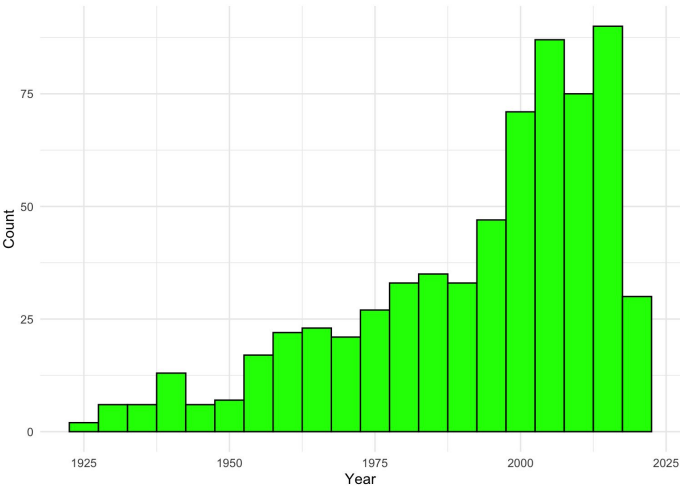


Figure 4

Number of Movies per Genre

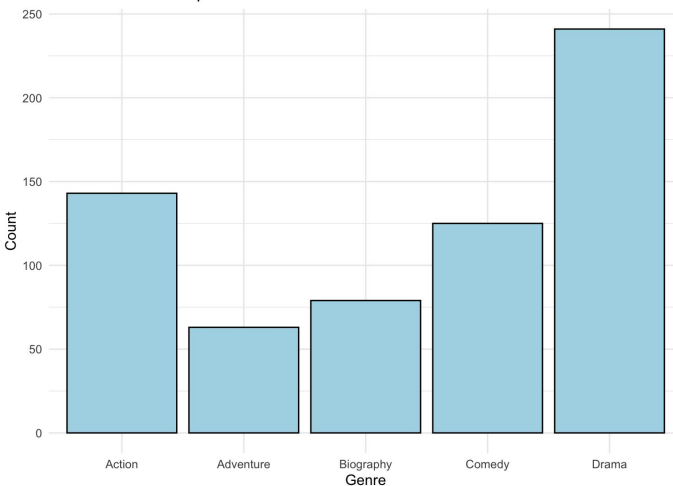


Figure 5

GAM Smoothing of Meta Score Over Time by Genre

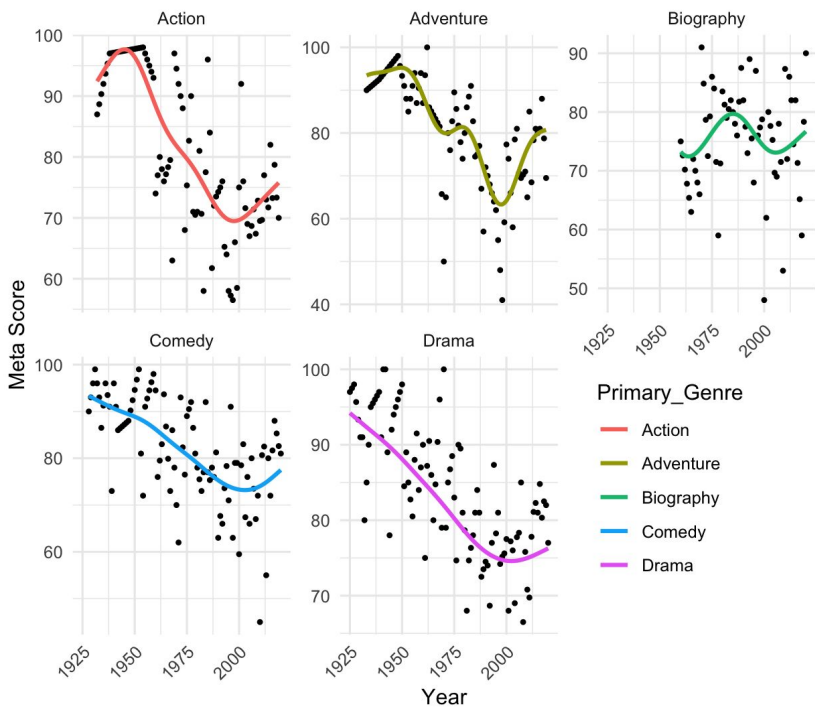


Figure 6

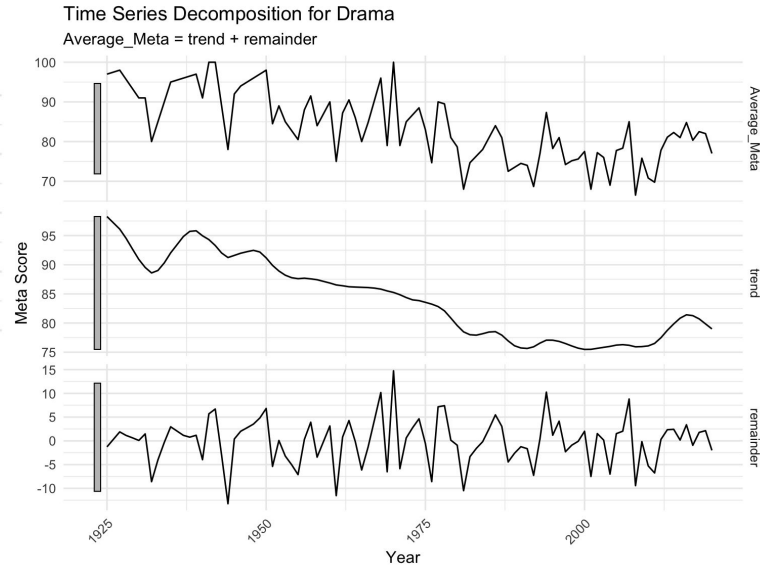


Figure 7

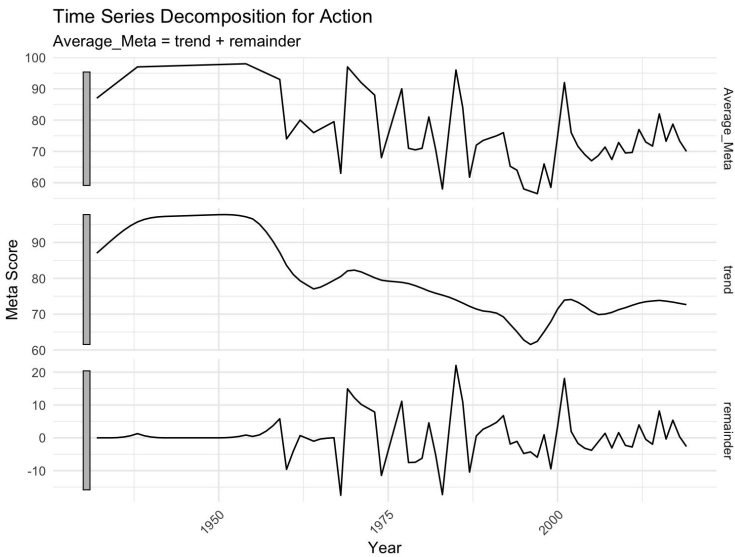


Figure 8

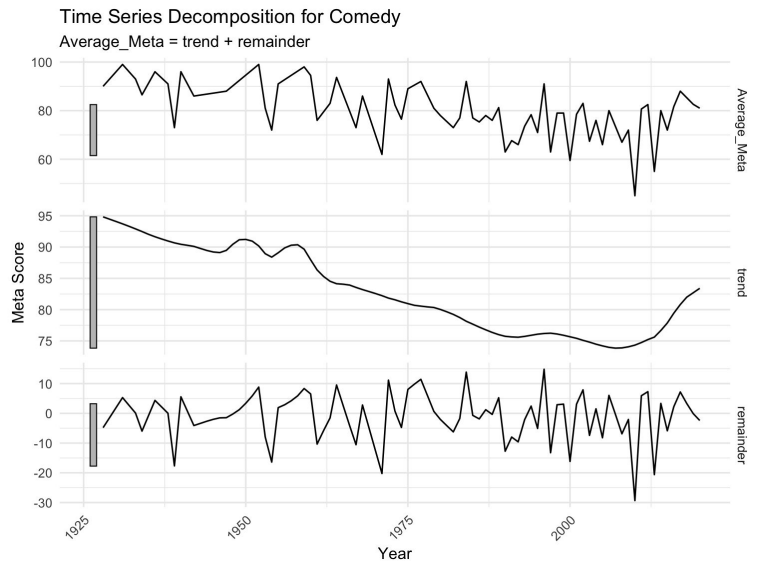


Figure 9

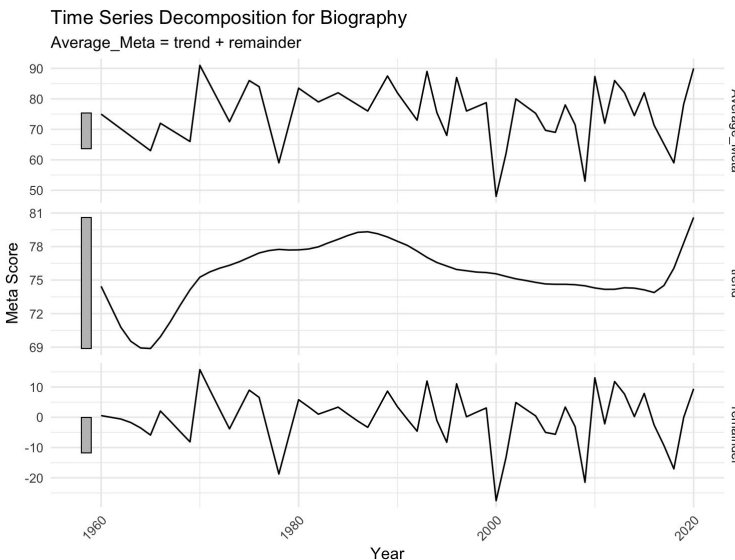


Figure 10

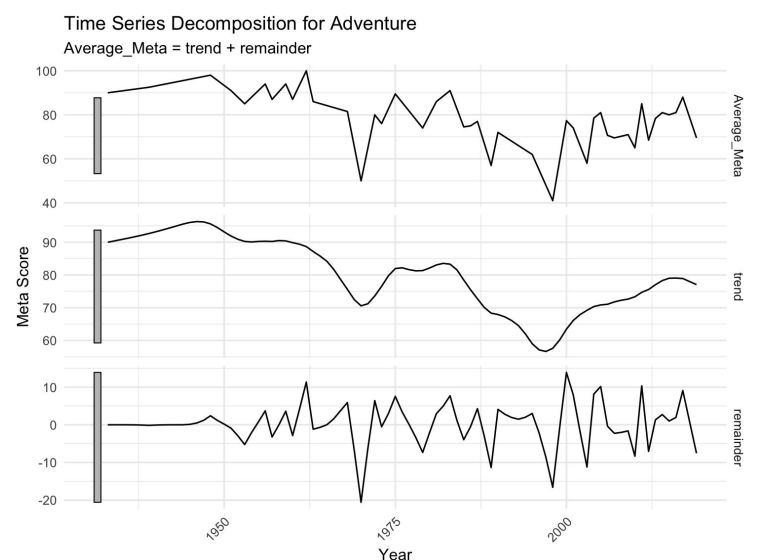


Figure 11

ACF of Remainder for Drama (Cyclic Pattern Check)

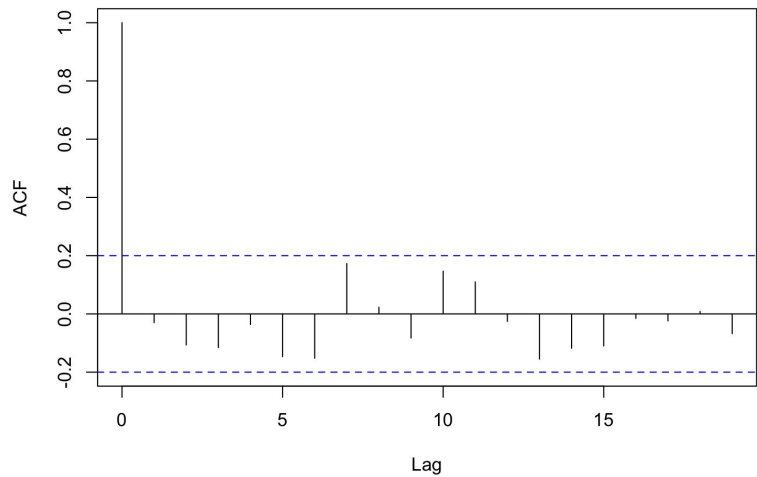


Figure 12

ACF of Remainder for Comedy (Cyclic Pattern Check)

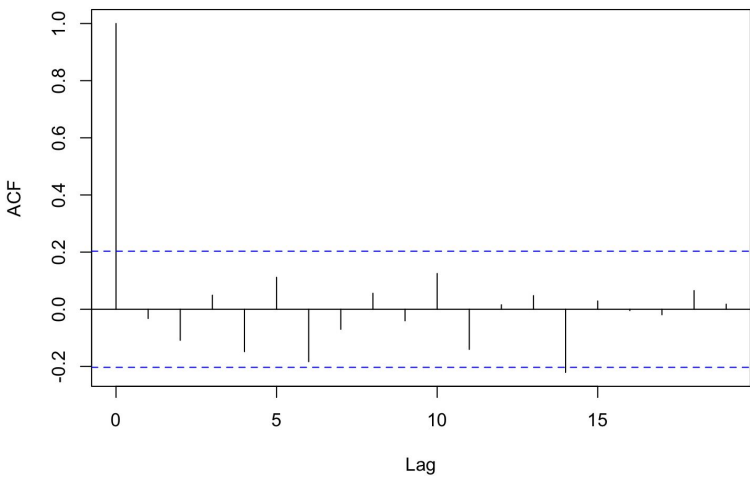


Figure 13

ACF of Remainder for Action (Cyclic Pattern Check)

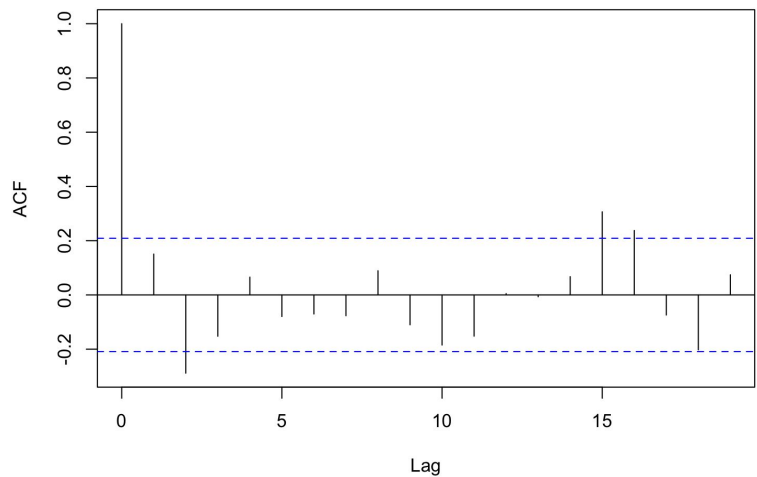


Figure 14

ACF of Remainder for Biography (Cyclic Pattern Check)

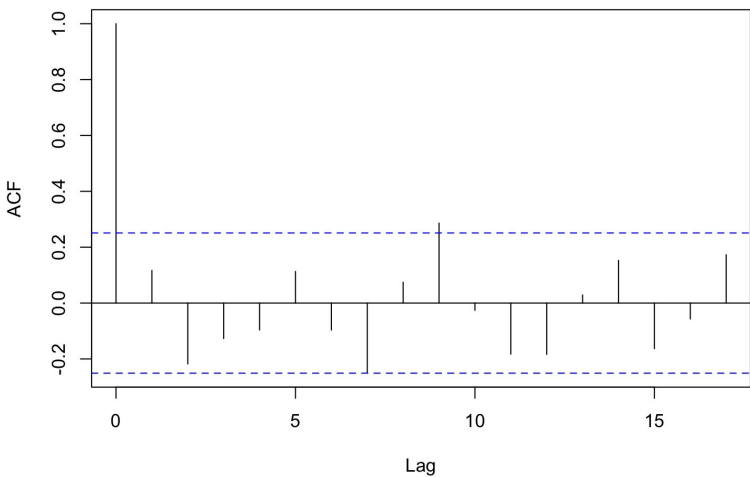


Figure 15

ACF of Remainder for Adventure (Cyclic Pattern Check)

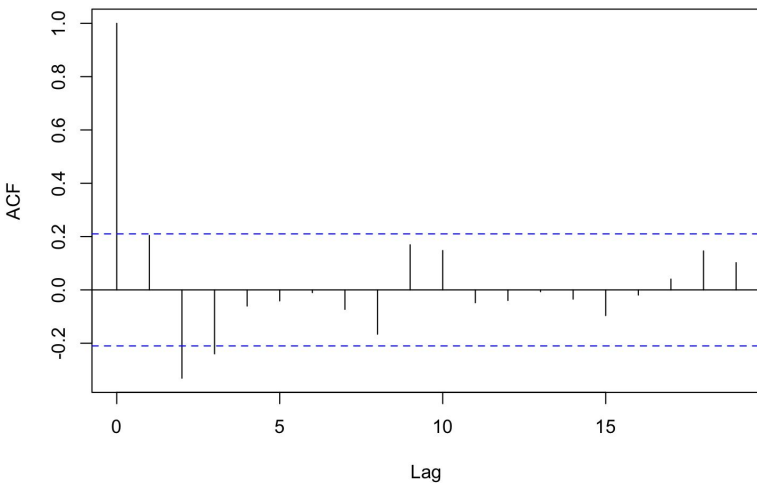


Figure 16

ACF of Remainder (Cyclic Pattern Check)

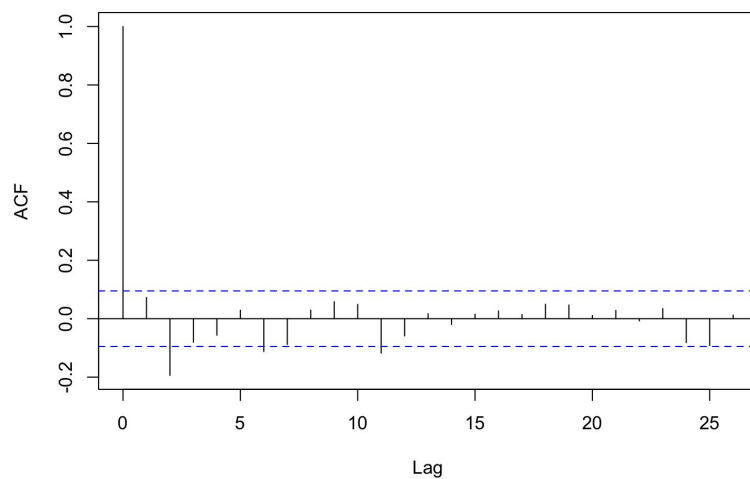


Figure 17

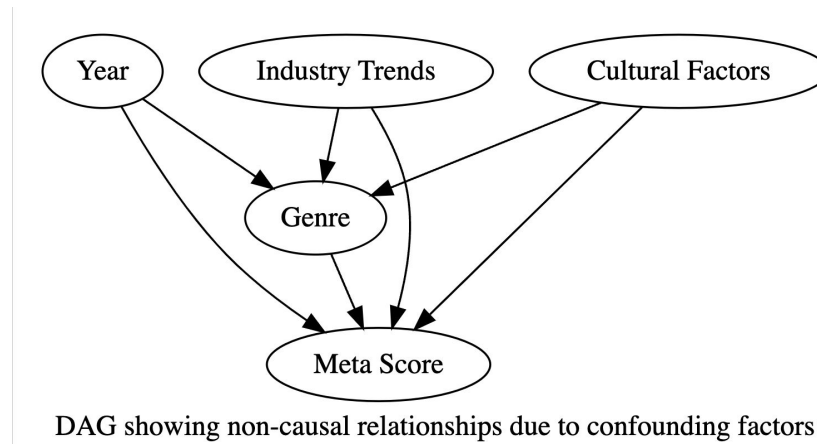


Table 1

Summary Statistics of Meta Scores by Genre

main_genre	mean_meta_score	sd_meta_score	count
Action	74.2	11.4	172
Adventure	78.4	11.7	71
Biography	76.4	10.5	88
Comedy	78.6	10.6	155
Drama	79.4	11.7	289

Table 2

GAM Smooth Terms Summary by Genre

Genre	Effective Degrees of Freedom (edf)	F-value	p-value
Action	5.025	26.38	$< 2e - 16$
Adventure	6.778	20.93	$< 2e - 16$
Biography	4.700	6.77	$2.67e - 06$
Comedy	3.626	17.33	$< 2e - 16$
Drama	2.990	20.73	$< 2e - 16$