Narrative Conflicts: A Tri-Modal Computational Analysis of Antagonism in Shakespeare's Julius Caesar

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Abstract

This study introduces a novel computational framework to analyze multi-modal antagonisms—semantic, emotional, and relational—in dramatic literature, specifically focusing on Shakespeare's *Julius Caesar*. Employing natural language processing (NLP) techniques, text embeddings, emotion classifiers, and network-based character analyses, we systematically extract and quantify antagonistic relationships within the play. Semantic antagonisms are identified through hierarchical clustering and dimensionality reduction of character embeddings, revealing rhetorical groupings aligned closely with narrative functions. Emotional antagonisms, captured via emotion distribution profiles and variance analysis, illuminate characters' affective dynamics and their alignment with dramatic roles. Relational antagonisms are explored through co-occurrence networks, highlighting unexpected centrality of minor characters as critical mediators of conflict. Integrating these modalities with Hegelian dialectics and Nietzschean interpretations, our tri-modal analysis provides fresh insights into ideological tensions, character motivations, and narrative structure. This interdisciplinary approach demonstrates the effectiveness of AI-driven tools in enriching literary criticism opening new avenues for exploring conflict dynamics in canonical texts.

Keywords

Artificial literature, Computational literary criticism, Semantic antagonism, Emotional antagonism, Relational antagonism

1. Introduction

How can computational methods uncover and analyze multi-modal antagonisms—semantic, emotional, and relational—in dramatic texts, and what does this reveal about the narrative structure and ideological tensions in canonical literature? This question anchors our study at the intersection of computational methods and literary criticism, where advanced methods probe the complexities of narrative conflict in dramatic texts [1, 2, 3, 4]. By focusing on antagonism, we employ natural language processing (NLP) and network-based techniques to extract and analyze semantic, emotional, and relational dimensions of conflict [5, 6, 7], offering fresh insights into narrative dynamics.

We apply these methods to Shakespeare's *Julius Caesar*, a text rich in antagonistic relationships [8]. The play's central conflict—between Caesar's autocratic ambition and the republican ideals of Brutus and the conspirators—drives a dialectical progression of political ideologies, making it an ideal case study for computational analysis of antagonisms.

As a philosophical analyses, from a Hegelian perspective, the clash between Caesar's power (thesis) and republican resistance (antithesis) resolves in the rise of Octavius and the Roman Empire (synthesis) [9]. Nietzschean lenses further illuminate the characters' actions as expressions of the will to power and a transvaluation of moral values, with Brutus's moral ambiguity challenging conventional notions of good and evil [10]. These philosophical frameworks, combined with computational methods, reveal how *Julius Caesar* navigates individual agency, societal norms, and historical transformation [11].

This study bridges computational techniques and literary analysis to uncover latent patterns in *Julius Caesar*, advancing our understanding of narrative structure and ideological tensions in canonical literature. Our main contributions are:

- **Tri-modal Framework**: We propose a novel framework to analyze literary antagonism through semantic, emotional, and relational dimensions, leveraging NLP and network-based techniques.
- **Computational Reading of *Julius Caesar***: We apply this framework to Shakespeare's play, revealing hidden patterns of conflict across characters, emotions, and ideologies.

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- **Cross-disciplinary Integration**: We demonstrate how AI-driven methods—text embeddings, emotion classifiers, and character graphs—enhance literary criticism by providing scalable, interpretable tools for narrative interpretation.

2. Related Works

We review key related works, organized by their methodological and thematic contributions to computational literary studies (CLS).

The conceptual foundation of our tri-modal antagonism framework draws directly from prior work that operationalized computational techniques to explore conflict in dramatic literature. Semantic antagonism originates [12], who applied statistical inference methods to reveal ideological and conceptual oppositions within literary texts, highlighting how contrasting thematic elements can be quantified. Emotional antagonism is rooted [13], where character emotions were analyzed using the EmoLex lexicon, enabling the detection of affective dissonance and mood-based tension across narrative arcs. Relational (or social) antagonism stems from the graph-based analysis of character interactions [14], in which social dynamics and conflict structures were mapped through co-occurrence networks, revealing underlying power struggles and interpersonal oppositions. These three modes—semantic, emotional, and relational—not only capture distinct facets of dramatic conflict but also provide complementary lenses through which narrative antagonism can be systematically modeled and interpreted.

Recent studies have applied Information Theory to characterize writing styles and compare authors quantitatively. For instance, Rosso et al. introduced complexity quantifiers combining Jensen-Shannon divergence with entropy variations computed from word frequency distributions [15]. Their analysis of 30 English Renaissance texts, including works attributed to Shakespeare, revealed distinct entropy clusters for Shakespeare's corpus, highlighting the homogeneity of his writing style compared to contemporaries. This approach informs our semantic analysis, as entropy-based methods could quantify stylistic markers of ideological conflict in *Julius Caesar*. However, their focus on stylometry lacks the multi-modal perspective of our framework, which integrates emotional and relational dimensions.

Emotion and sentiment analysis have become central to CLS, offering insights into narrative emotional arcs and character dynamics. Kim and Klinger surveyed computational approaches to sentiment and emotion analysis, emphasizing their role in tracking plot development and modeling character relationships [16]. Their proposed task of emotion relationship classification aligns with our emotional analysis of antagonisms, particularly in capturing the moral ambiguities of Brutus and Caesar. Similarly, Makhdom et al. reviewed recent advances in sentiment analysis within digital humanities, highlighting its potential to uncover emotionality in texts [17].

Complementing these surveys, Schmidt et al. applied a fine-tuned BERT model to analyze emotional trajectories in German dramas from the 17th to 19th centuries [18, 19]. Their findings revealed genre-specific patterns, such as higher proportions of "suffering" and "abhorrence" in tragedies, which inform our emotion classification of *Julius Caesar* as a tragedy. Additionally, Christ et al. developed Transformer-based methods to model continuous valence and arousal in children's stories, creating a benchmark dataset for emotional trajectory analysis [20]. These methods inspire our use of emotion classifiers to track conflict-driven emotional shifts, though our focus on dramatic texts and ideological tensions extends beyond their scope.

Network science has emerged as a powerful tool for modeling narrative relationships and structures. Dexter et al. introduced "quantitative criticism," using stylometry and machine learning to analyze intertextuality in Latin literature, with Caesar's writings as a stylistic inflection point [21]. Their network-based mapping of stylistic relationships parallels our character graphs for relational antagonisms. Similarly, Perri et al. employed graph neural networks and character co-occurrence networks to analyze Tolkien's Legendarium, demonstrating how network science reveals narrative dynamics [22]. Their approach informs our relational analysis, though our focus on ideological conflicts in a dramatic text is distinct.

Hatzel et al. provided a comprehensive overview of machine learning in CLS, noting the persistence of feature-based methods alongside transformer-based models [23]. Their survey supports our integration of NLP and network-based techniques, particularly for scalable analysis of canonical texts. Furthermore, a computational analysis of fanfiction by Yin et al. used NLP to examine character focus, revealing shifts in narrative dynamics compared to canonical texts [24]. This work underscores the scalability of our methods, though our study emphasizes the ideological underpinnings of a single dramatic text.

The integration of computational and humanistic methods remains a challenge in CLS. A position paper by Eve et al. discussed transdisciplinary workflows, advocating for collaborative approaches to combine computational linguistics with hermeneutic traditions [25]. This perspective supports our cross-disciplinary framework, which bridges quantitative analysis with Hegelian and Nietzschean interpretations of *Julius Caesar*. Similarly,

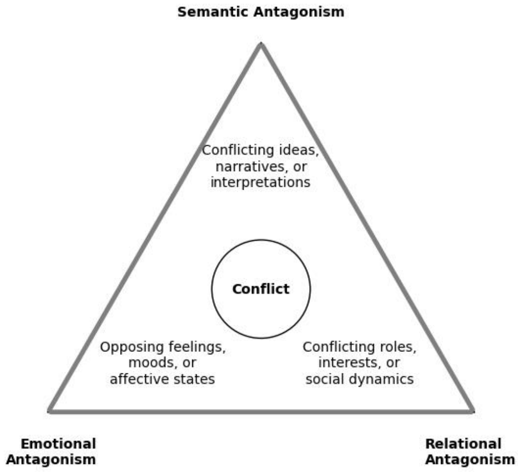

Figure 1: The figure illustrates the concept of conflict and the modalities of antagonisms.

Kestemont et al. used stylometry to authenticate Caesar's writings, providing historical context for our analysis of Shakespeare's portrayal [26]. However, few studies explicitly integrate philosophical frameworks with computational methods, positioning our tri-modal approach as a novel contribution.

While existing works have advanced CLS through Information Theory, emotion analysis, and network science, they rarely address multi-modal antagonisms in dramatic texts. Our study fills this gap by applying a tri-modal framework to *Julius Caesar*, combining NLP, emotion classifiers, and character graphs to uncover semantic, emotional, and relational conflicts. Unlike Rosso et al.'s stylistic focus or Schmidt et al.'s genre-based analysis, we emphasize ideological tensions, drawing on Hegelian dialectics and Nietzschean will to power. By integrating these philosophical lenses with scalable computational tools, our work offers fresh insights into narrative structure and moral complexities in canonical literature.

3. Modalities of Antagonism

Figure 1 conceptualizes antagonism in three complementary dimensions—semantic, emotional, and relational—each of which we operationalize in our computational analysis of *Julius Caesar*.

Semantic Antagonism: This modality addresses the linguistic and conceptual dimensions of conflict. It encompasses opposing ideas, contradictory statements, or conflicting narratives, where clashes arise from differences in meaning, interpretation, or framing.

Emotional Antagonism: This modality highlights the affective dimension of conflict. It involves incompatible feelings, clashing moods, or opposing emotional states, often manifesting in interpersonal disputes as individuals experience and express contrasting affects.

Relational Antagonism: This modality concerns the social and interpersonal facets of conflict. It encompasses conflicting roles, incompatible interests, or adversarial relationship dynamics. Examples include workplace rivalries, family disputes, or political power struggles.

Figure 1 effectively illustrates how these three modalities intersect at the core of the play's conflicts. By adopting this multi-faceted framework, we gain a nuanced lens for examining the complex character relationships and motivations that drive the tragedy's plot.

Shakespeare weaves these modalities together masterfully, creating a rich tapestry of conflict that encompasses ideological differences, emotional turmoil, and power dynamics. This interplay of semantic, emotional, and relational antagonisms propels the narrative and contributes to the enduring depth of Julius Caesar.

Together, these three modalities—conflicting ideas (semantic), clashing affects (emotional), and competitive social positions (relational)—form an integrated lens through which the tragedy's narrative momentum can be understood.

4. Methodology

This study employs an algorithmic approach to analyze character relationships in Shakespeare's *Julius Caesar*, integrating semantic, emotional, and relational information derived from character dialogueß. Let $\mathcal{S} = \{s_1, \ldots, s_N\}$ denote the set of all speeches and let M denote the total number of distinct characters.

4.1. Semantic Embedding Algorithm

Given a textual encoder ϕ : Text $\to \mathbb{R}^d$, the semantic embedding for each character i is computed as

$$\mathbf{e}_i = \frac{1}{|S_i|} \sum_{s \in S_i} \phi(s) \in \mathbb{R}^d,$$

where $S_i \subseteq \mathcal{S}$ denotes the speech set for character i. Pairwise semantic similarity between characters i and j is determined using cosine similarity:

$$C_{ij} = \frac{\mathbf{e}_i^\top \mathbf{e}_j}{\|\mathbf{e}_i\| \|\mathbf{e}_j\|}, \qquad D_{ij} = 1 - C_{ij}.$$

Hierarchical clustering (Ward linkage) is then applied on the distance matrix D to form semantic clusters $\{\mathcal{C}_k\}$. Dimensionality reduction via t-SNE is performed by minimizing

$$\mathrm{KL}(P \| Q), \qquad P_{ij} \propto \exp\left(-\frac{\|\mathbf{e}_i - \mathbf{e}_j\|^2}{2\sigma^2}\right).$$

4.2. Emotion Distribution Algorithm

Each speech s is segmented into overlapping textual chunks $\{c_{s,1}, \ldots, c_{s,K_s}\}$. An emotion classifier f_{emo} : Text $\to \Delta^{C-1}$ assigns a probability distribution $p_{s,k} \in \mathbb{R}^C$ over C emotional categories for each chunk. The aggregate emotional representation for character i is computed as

$$\bar{\mathbf{p}}_i = \frac{1}{\sum_s K_s} \sum_{s \in S_i} \sum_{k=1}^{K_s} p_{s,k},$$

with corresponding emotion covariance

$$\Sigma_i = \frac{1}{\sum_s K_s} \sum_{s \in S_i} \sum_{k=1}^{K_s} (p_{s,k} - \bar{\mathbf{p}}_i)(p_{s,k} - \bar{\mathbf{p}}_i)^\top.$$

The emotional distance between characters is defined as

$$E_{ij} = \|\bar{\mathbf{p}}_i - \bar{\mathbf{p}}_j\|_2,$$

and hierarchical clustering is applied on E to generate emotion-based character groupings. Emotion volatility for each character is analyzed through $\mathrm{diag}(\Sigma_i)$.

4.3. Graph-Based Relational Algorithm

An undirected weighted graph $G = (V, E, W)$ is constructed with vertices $V = \{1, \ldots, M\}$ representing characters. Edge weights represent co-occurrence in scenes:

$$W_{ij} = \sum_{\ell=1}^{T} \mathbf{1}\{i, j \text{ co-occur in scene } \ell\},$$

where T is the total number of scenes. The following metrics are computed:

- **Degree centrality:** $d_i = \sum_j A_{ij}$.
- **Betweenness centrality:** $b_i = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}}$, where σ_{st} is the number of shortest paths from s to t.
- **Community detection:** Communities $\mathcal{C}_i^{(R)}$ are obtained by maximizing modularity:

$$Q = \frac{1}{2m} \sum_{i,j} \left(A_{ij} - \frac{d_i d_j}{2m} \right) \delta(\mathcal{C}_i^{(R)}, \mathcal{C}_j^{(R)}),$$

  via the Louvain algorithm.

4.4. Integration Algorithm

Semantic clusters, emotional clusters, and graph-based communities are integrated to identify and analyze characters' thematic, affective, and structural roles within the dramatic narrative, highlighting both convergent and divergent patterns.

5. Implementation Details

This section details all engineering choices, hyperparameters, and software dependencies necessary to reproduce our multi-perspective analysis. All relevant code is accessible in the companion repository[1].

Data Pre-processing. XML parsing of the Shakespeare corpus for *Julius Caesar* was performed using *xml.etree.ElementTree* [2], extracting speech nodes and discarding stage directions. Speaker aliases were standardized using a predefined lookup table. Speeches were tokenized and segmented into overlapping chunks of 200 tokens with a 50-token stride using SpaCy 3.7.

Semantic Embedding Pipeline. Semantic embeddings were generated using *Qwen1.5–Embedding–0.6B* (2,048-dimensional output) as the state-of-the-art and most comprehensive comprehensive data embedding model, accessed via *sentence-transformers*. Speech embeddings exceeding 8,096 tokens were truncated. Mean embeddings per speaker were calculated and cosine similarity was used to create a distance matrix. Ward linkage hierarchical clustering was applied, and embeddings were visualized using t-SNE with perplexity 30, learning rate 200, and 1,000 iterations.

Emotion Distribution Pipeline. Emotional analysis utilized the *j-hartmann/emotion-english-distilroberta-base* classifier, predicting probabilities for Ekman's 6 basic emotions, plus a neutral class. Inference was performed in batches of 32 chunks per GPU pass with gradients disabled via *torch.no_grad()*. Mean emotion vectors and covariance matrices were computed per speaker. Hierarchical clustering was conducted separately on mean emotion vectors and emotion variance vectors.

Relational Graph Pipeline. A co-occurrence graph was constructed by connecting characters appearing together within each scene. Edge weights represented shared scenes. Degree and betweenness centralities were computed using NetworkX's parallel brandes algorithm. Louvain community detection identified stable relational communities (resolution parameter 1.0), and a Fruchterman-Reingold layout (with default parameters) was cached for reproducible visualization.

[1] https://github.com/convergedmachine/narrative-conflicts

[2] The XML-encoded version of *Julius Caesar* used in this study is derived from the public domain edition prepared by Jon Bosak as part of the Moby Lexical Tools project, with SGML and XML markup dating from 1992–1998. The full text is freely available and widely used for computational literary studies. https://www.ibiblio.org/xml/examples/shakespeare/j_caesar.xml

Cross-View Integration. Semantic, emotional, and relational cluster assignments were integrated into a combined character-by-view matrix. Adjusted Rand Index (ARI) and Normalized Mutual Information (NMI) metrics were calculated pairwise to quantify alignment.

5.1. Semantic Antagonisms

To uncover latent rhetorical patterns among characters in *Julius Caesar*, we extracted sentence embeddings for each speaker and performed unsupervised clustering based on pairwise cosine distances. The resulting groups were visualized using both a two-dimensional t-SNE projection and a hierarchical dendrogram (see Figures 2 and 3).

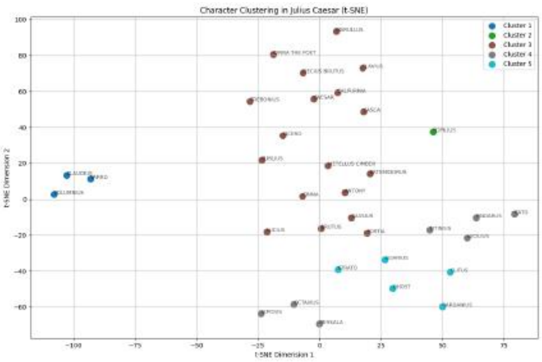

Figure 2: t-SNE projection of character embeddings from *Julius Caesar*, clustered into five semantic groups. Each point represents a speaker, colored by their assigned cluster. Cluster 3 (brown) contains the political core of the play, including Caesar, Brutus, and Antony. Cluster 1 (blue) consists of Brutus' servants, isolated in their functional dialogue. Cluster 4 (grey) and Cluster 5 (cyan) represent battlefield and fatalistic roles, while Cluster 2 (green) isolates Popilius Lena for his distinctive lexical footprint. The spatial arrangement reveals meaningful discourse-based stratification across dramatic roles.

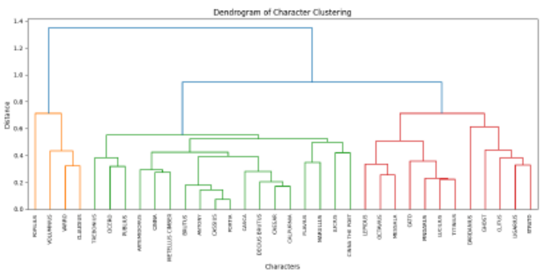

Figure 3: Hierarchical clustering dendrogram of characters in *Julius Caesar*, based on pairwise cosine distances between their sentence embeddings. The Ward linkage method was used to recursively group semantically similar characters. The dendrogram reveals a sharp early separation of servant characters (*Varro*, *Claudius*, *Volumnius*) from the rest, while the main political figures and battlefield voices form distinct subtrees. This hierarchical structure supports the semantic roles uncovered in the t-SNE visualization, confirming both tight intra-cluster coherence and inter-group rhetorical divergence.

The t-SNE plot reveals five coherent clusters:

- **Cluster 1** (blue): This small, isolated group includes *Varro*, *Claudius*, and *Volumnius*, all servants of Brutus. Their compact position in the lower-left quadrant suggests a tightly constrained lexical field, largely limited to practical and obedient speech.
- **Cluster 2** (green): *Popilius Lena* appears as a lone semantic outlier. His brief but thematically loaded line foreshadowing the assassination gives him a unique lexical profile, detached from any dominant rhetorical faction.
- **Cluster 3** (brown): This dominant cluster encompasses nearly all central political actors—*Caesar*, *Brutus*, *Cassius*, *Antony*, and others. Their discursive similarity stems from shared themes of persuasion, honour, and betrayal. Sub-clusters within this group reflect localized interactions, such as the conspirators' planning or Caesar's dialogue with Calpurnia and Decius.
- **Cluster 4** (grey): Characters appearing primarily in Acts IV–V, such as *Octavius*, *Lepidus*, and *Lucilius*, group together due to their military and strategic vocabulary. Their speeches diverge semantically from the courtroom rhetoric of earlier acts.
- **Cluster 5** (cyan): This group includes *Strato*, *Clitus*, *Dardanius*, and *Ghost*, unified by themes of death, loyalty, and moral hesitation—especially in the context of Brutus' final scene.

The dendrogram complements these findings by revealing the relative semantic distances between speakers. The early separation of the servant characters (Cluster 1) from the rest confirms their rhetorical distinctiveness. The clustering of the battlefield and ghostly figures (Clusters 4 and 5) at greater hierarchical distances further illustrates their deviation from the political core.

Overall, these unsupervised methods yield a linguistically grounded stratification of Shakespeare's dramatis personae, aligning semantic similarity with dramatic function and narrative arc.

5.2. Emotional Antagonisms

To explore the emotional landscape of *Julius Caesar*, we conducted hierarchical clustering of the main characters using two complementary feature sets: (i) mean scores for seven canonical emotions (fear, anger, sadness, disgust, surprise, joy, and neutrality), and (ii) the variance of each emotion across all speeches. The resulting dendrogram-heatmaps reveal distinct patterns of both affective tone and emotional dynamism, enabling nuanced insights into dramatic function (see Figures 4 and 5).

Clustering by Mean Emotion Profile. The first analysis clusters characters according to their average emotional scores, producing interpretable groupings that mirror narrative roles:

- **Fear-Dominant Cluster**: Calpurnia, Cinna, Cicero, and Trebonius display uniformly high fear and minimal joy or anger. These characters voice premonition, anxiety, and the foreboding atmosphere that precedes the play's central conspiracy.
- **Anger-Dominant Cluster**: Artemidorus, Cato, and Clitus are marked by extreme anger and negligible fear, representing moral outrage and rhetorical resistance within the narrative.
- **Political-Conspirator Cluster**: Central figures such as Caesar, Cassius, Decius Brutus, Marullus, Casca, and Octavius exhibit a balance of moderate fear and anger, with sporadic elevations in disgust. Their emotional complexity aligns with their roles as plotters and statesmen, navigating both ambition and trepidation.
- **Peripheral and Tragic Clusters**: Secondary characters are divided into subgroups reflecting neutrality, disgust, or sadness. For instance, Brutus, Titinius, and the Ghost cluster on high sadness and disgust, encapsulating the play's tragic undercurrents.

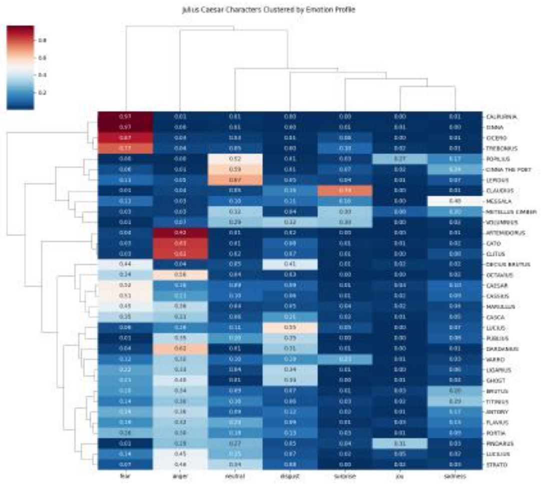

Figure 4: Hierarchical dendrogram-heatmap of Julius Caesar characters by seven-emotion mean scores (fear, anger, neutral, disgust, surprise, joy, sadness), showing clusters such as fear-dominant (Calpurnia, Cinna), anger-dominant (Cato, Artemidorus), neutral messengers, conspirators, and servants.

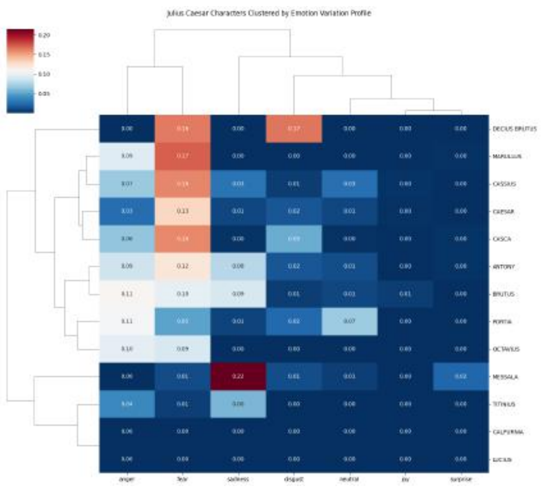

Figure 5: Hierarchical dendrogram-heatmap of Julius Caesar characters by seven-emotion variations scores (fear, anger, neutral, disgust, surprise, joy, sadness), showing clusters such as fear-dominant (Calpurnia, Cinna), anger-dominant (Cato, Artemidorus), neutral messengers, conspirators, and servants.

Clustering by Emotion Variation Profile. The second analysis leverages the variance (rather than the mean) of each emotional score to capture the dynamic range of affect displayed by each character:

- **High-Variance Oscillators**: Decius Brutus and Marullus show pronounced swings in fear and disgust, indicating characters who are especially reactive to dramatic shifts and moments of crisis.
- **Steady Strategists**: The principal conspirators and leaders (Cassius, Caesar, Casca, Antony, Brutus, Portia, Octavius) exhibit moderate, balanced variance—demonstrating emotional adaptability but avoiding extremes.
- **Volatile Grievers**: Messala and Titinius are distinguished by their high variation in sadness, reflecting the erratic and volatile mourning present in the aftermath of Caesar's death.
- **Emotionally Static Roles**: Calpurnia and Lucius exhibit near-zero variance across all emotions, reflecting their dramatically narrow and functionally consistent roles.

Interpretation. While mean-based clustering segments characters by their dominant affective signature (e.g., anxious, angry, or mournful), variance-based clustering reveals how emotionally dynamic or static each character is throughout the play. Together, these analyses provide a layered map of affective structure: highlighting both the tonal "centers" of each character and the degree of their emotional mobility. This dual approach uncovers not only who is most fearful or angry, but also who remains steadfast, who wavers, and who undergoes the most dramatic emotional transformations on stage.

5.3. Relational Antagonisms

Relational antagonism emerges from our co-occurrence network analysis (Fig. 6), which models characters as nodes and shared scene adjacency as edges. Node size reflects degree (number of unique co-occurrences), and spatial proximity indicates stronger relational ties. Two unexpected hubs—the Servant and Lucius—play outsized roles in mediating conflicts across social strata.

The Servant, located at the network's geometric center, links the citizen-cluster (First–Fourth Citizens, All, Cinna the Poet) to private councils (Calpurnia, Artemidorus, Decius Brutus). This bridging function highlights how subordinate figures sustain information flow between public assemblies and clandestine plots, driving antagonism through mediated exchanges rather than direct confrontation. Lucius, with high betweenness, connects Portia, Ligarius, and the core conspirators. His intermediary position underscores familial and servant-master dynamics that both facilitate and fracture alliances.

Distinct clusters reveal competitive factions:

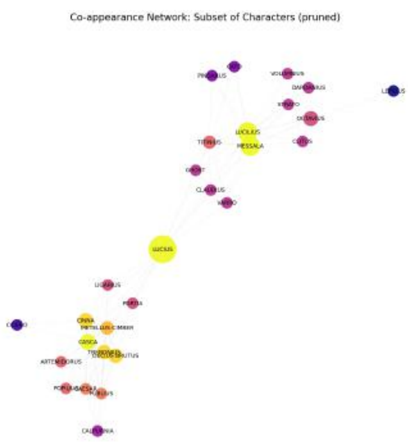

Figure 6: Force-directed co-occurrence network of *Julius Caesar* characters (pruned subset). Node size reflects scene-adjacency degree; edges indicate shared scenes. The Servant serves as the central mediator linking the citizenry clique to conspirators, while Lucius and Messala act as secondary hubs. Distinct clusters correspond to citizens, the conspiratorial circle, a military-political faction, and peripheral actors.

- **Citizenry Clique**: A tight public-voice community expressing collective opinion.
- **Conspiratorial Circle**: An insular revolutionary faction (Brutus, Cassius, Decius Brutus, Casca, Trebonius, Metellus Cimber) united by shared secrecy and action.
- **Military-Political Group**: A post-assassination alliance (Cato, Strato, Octavius, Clitus, Pindarus, Titinius) reflecting battlefield loyalties and emerging power structures.
- **Peripheral Actors**: Figures such as Lepidus and Cicero occupy network fringes, marking episodic involvement and rhetorical interventions.

These relational patterns mirror the play's thematic tensions—populism versus aristocracy, secrecy versus spectacle—and demonstrate that antagonism in *Julius Caesar* is as much a product of mediated interactions among minor characters as it is of head-on clashes between leading figures.

6. Discussion

The tri-modal analysis sheds light on the multifaceted nature of antagonism in *Julius Caesar*. Semantic clustering (Experiment 1) aligned tightly with dramatic function: central conspirators and statesmen coalesced into a cohesive cluster, while servants and battlefield figures formed distinct outliers. This stratification confirms that lexical choices map onto ideological and role-based divisions within the play. Moreover, Popilius Lena's isolation underscores how brief but thematically charged utterances can create semantic singularities (Figure 2).

Emotional antagonism (Experiments 2 and 3) further nuances these patterns. Mean-based clustering distinguished affective archetypes—fearful, angry, or neutral—consistent with character motivations and plot turns. Variance-based clustering, by contrast, captured dynamic emotional trajectories: Decius Brutus and Marullus emerged as high-variance oscillators, reflecting their reactive roles during crisis moments, whereas figures like Calpurnia exhibited emotionally static profiles. Taken together, these two views reveal not only "what" emotions characters express but also "how" flexibly they traverse affective states, deepening our understanding of dramatic tension.

Relational network analysis uncovered hidden mediators of conflict. Contrary to expectations that leading figures dominate network centrality, minor characters such as the Servant and Lucius emerged as high-betweenness hubs (Figure 6), facilitating information flow between political and popular spheres. This finding highlights the importance of subordinate roles in sustaining narrative antagonism and suggests that relational antagonism often operates through mediated interactions rather than direct confrontations.

Across modalities, we observe significant intersections. Characters central in the relational graph also tend to occupy semantically intermediate positions and exhibit moderate emotional variance, indicating a balance of discourse, affect, and connectivity. This interplay suggests that multi-modal antagonism is not merely the sum of its parts but a synergistic network of linguistic, affective, and social forces.

Limitations Our emotion classifier relies on modern lexica and may not fully capture Early Modern English affective nuance. Minor characters with limited lines also pose challenges for embedding stability.

7. Conclusion

We have presented a comprehensive computational study of antagonism in Shakespeare's *Julius Caesar*, introducing a tri-modal framework that unites semantic, emotional, and relational analyses. Key contributions include:

- A systematic methodology for extracting and clustering semantic embeddings, emotion profiles, and co-occurrence networks.
- Empirical demonstrations of how each modality illuminates distinct facets of narrative conflict.
- Theoretical integration with Hegelian dialectics and Nietzschean will-to-power, enriching interpretive claims about ideological tensions.

Our findings underscore the potential of AI-driven tools to augment literary criticism by revealing latent structures of conflict.

Future Directions Extensions of this work could explore temporal dynamics of antagonism (e.g., sliding-window embeddings across acts), cross-play comparisons to identify genre-specific conflict patterns.

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A. Why Julius Cesar?

A comprehensive discussion of Julius Caesar through Hegelian and Nietzschean philosophical lenses reveals several key insights into the play's exploration of power dynamics, morality, and historical progress.

From a Hegelian perspective, Julius Caesar can be interpreted as a dialectical progression of political ideologies. The initial thesis of Caesar's growing autocratic power is met with the antithesis of republican ideals embodied by Brutus and the conspirators. Their conflict ultimately results in a synthesis - the rise of Octavius and the establishment of the Roman Empire. This dialectical movement aligns with Hegel's view of history as a process of continual development through conflict and resolution.

The characters' internal struggles, particularly Brutus's moral dilemma, exemplify Hegel's concept of ethical life (Sittlichkeit). Brutus grapples with conflicting loyalties to his friend Caesar and to the Roman Republic, illustrating the tension between individual morality and societal norms. This internal conflict drives the plot forward and contributes to the overall dialectical progression.

Nietzsche's philosophical concepts, particularly his critique of morality and the will to power, offer another valuable lens for analyzing Julius Caesar. The characters' actions can be seen as manifestations of the will to power, with each faction striving for dominance and control. Caesar's ambition, Brutus's sense of duty, and Antony's cunning manipulation all reflect different expressions of this fundamental drive.

The play's treatment of morality aligns with Nietzsche's rejection of absolute moral values. The ambiguity surrounding the righteousness of the conspirators' actions challenges traditional notions of good and evil. This moral complexity is particularly evident in Brutus, whose noble intentions lead to disastrous consequences, echoing Nietzsche's skepticism towards conventional morality.

Furthermore, the transformation of Rome from a republic to an empire, as depicted in the play, can be viewed through Nietzsche's concept of the transvaluation of values. The shift in power structures and moral paradigms reflects a broader cultural change, akin to the historical transitions Nietzsche explored in his genealogy of morals.

In conclusion, analyzing Julius Caesar through Hegelian and Nietzschean perspectives enhances our understanding of the play's thematic depth and philosophical resonance. It illuminates the complex interplay between individual agency, societal forces, and historical progress, while challenging readers to critically examine their own assumptions about power, morality, and the nature of political change.

Appendix: Character Roles Table

Table 1 provides a structured summary of the principal characters in Shakespeare's *Julius Caesar*, annotated with their primary narrative roles. The categorization is based on their function within the play's central conflict and their relationship to the main ideological and emotional currents.

Table 1
Dramatis Personae in *Julius Caesar*

Character	Role	Description
Brutus	**Protagonist (Lead Conspirator)**	Often considered the tragic hero, Brutus struggles with loyalty to Caesar and duty to Rome.
Cassius	**Protagonist (Lead Conspirator)**	The key instigator who persuades Brutus to join the conspiracy against Caesar.
Casca	**Conspirator**	The first to strike Caesar; a conspirator against him.
Decius Brutus	**Conspirator**	Conspirator who persuades Caesar to ignore omens and attend the Senate.
Cinna	**Conspirator**	A conspirator against Caesar.
Metellus Cimber	**Conspirator**	One of the conspirators against Caesar.
Trebonius	**Conspirator**	A conspirator against Caesar.
Ligarius	**Conspirator**	A conspirator who joins late due to his admiration for Brutus.
Caesar	**Antagonist (The Target)**	Assassinated early, but his ambition and legacy drive the play's events.
Antony	**Antagonist (The Triumvirate)**	Loyal to Caesar, he becomes the primary antagonist to the conspirators after the assassination.
Octavius	**Antagonist (The Triumvirate)**	Caesar's adopted son and heir; member of the Second Triumvirate who wages war on the conspirators.
Lepidus	**Antagonist (The Triumvirate)**	Member of the Second Triumvirate with Antony and Octavius.
Portia	**Supporting Role (Family)**	Brutus's wife.
Calpurnia	**Supporting Role (Family)**	Caesar's wife, who warns him against going to the Senate.
Lucilius	**Supporting Role (Brutus's Army)**	Friend and soldier in Brutus's army.
Titinius	**Supporting Role (Brutus's Army)**	Friend of Cassius and soldier in the conspirators' army.
Messala	**Supporting Role (Brutus's Army)**	Soldier in Brutus's army.
Cato	**Supporting Role (Brutus's Army)**	Soldier in Brutus's army.
Strato	**Supporting Role (Aide/Servant)**	Soldier who assists in Brutus's suicide.
Lucius	**Supporting Role (Aide/Servant)**	Brutus's young servant.
Pindarus	**Supporting Role (Aide/Servant)**	Servant of Cassius who assists in his suicide.
Clitus, Dardanius, Volumnius, Varro, Claudius	**Supporting Role (Aide/Servant)**	Servants and soldiers of Brutus.
Citizens / Commoners	**Neutral (The Populace)**	Represent the Roman populace, easily swayed by the rhetoric of both Brutus and Antony.
Soothsayer	**Neutral (Warning Figure)**	Warns Caesar to "beware the Ides of March".
Artemidorus	**Neutral (Warning Figure)**	Tries to give Caesar a letter warning him of the conspiracy.
Flavius & Marullus	**Neutral (Tribunes)**	Tribunes punished for removing decorations from Caesar's statues.
Cicero	**Neutral (Senator)**	A respected senator who is not part of the conspiracy and is later killed by the Triumvirate.
Popilius	**Neutral (Senator)**	A senator who frightens the conspirators by wishing them well just before the assassination.
Cinna the Poet	**Neutral (Victim of Circumstance)**	Mistaken for Cinna the conspirator and killed by the angry mob.
Ghost	**Supernatural**	The Ghost of Caesar, who appears to Brutus as a manifestation of his guilt.