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| **Theatrical Genre Prediction Using Social Network Metrics** |
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Abstract: Networks study connections within large groups of objects. The anlaysis of how vertices are linked by edges has revealed many unexpected features of large systems. In this paper we apply network theory in the field of literature and explore how well social network features perform in literary analysis of theatrical genres. (Enough???)

# 1 INTRODUCTION

In literary studies, the three key areas of research could be defined as philology (the study of words), bibliography (the study of books as objects), and criticism (the evaluation or interpretation of literary meaning). Particularly since the advent of New Criticism, "the basic task of literary scholarship has been close reading of texts" [Moretti], which builds textual interpretations from precise study of specific words. Computational approaches to literature offer an alternate methodology for the work of literary study without close reading. "Distant reading" takes many forms, but for it to produce new literary insights, it must provide information about literary texts which is not easily accessible by reading them, and must do so for more texts than it is feasible for a person to read. Our paper presents a distant reading method which may aid in the task of literary criticism: using network graph analysis on social networks generated from the scripts of plays.

Social network analysis is well-established as a way to study social groups. In most approaches, the relationships between social actors are modeled as a graph, allowing a variety of new and existing graph algorithms to be applied. Social network analysis has been less often applied to literary works, but some scholars have created networks of plays wherein nodes represent characters, and edges represent interaction between pairs of characters in the play. Because these plays graphs are handmade for a very small number of plays, however, almost no work has been done to study the ability of mathematical properties of network graphs to predict features of a play. We address this gap by exploring correlations between the mathematical properties of the networks and dramatic genre.

Properties of social graphs are described with respect to two levels: ‘global graph metrics’ and ‘local graph metrics’. Global graph metrics consider the characteristic of the graph as a whole e.g., its diameter, mean node distance, betweenness, size of the giant component, clusters, small-worldness [8], etc., whereas the ‘local metrics’ relate to the features native to individual nodes such as degree, neighborhood, etc. Focusing on global graph metrics, we argue that the basic graph of a play reveals a great deal of information about the play and that social network metrics are, in fact, able to predict a play’s genre.

In this paper, we study the social networks of Shakepeare’s plays. To do so, we build a weighted, undirected graph of each play, in which characters are nodes, communication between characters represents an edge, and the weights represent the sum of total number of words spoken by two characters in the scenes in which they appear together. We define three classes for Shakespeare’s plays, namely ‘comedy’, history’ and ‘tragedy’. Then, we study the plays from the three groups to identify which features of their social networks allow us to distinguish between the three classes. With the class definitions and features in hand, we train a Support Vector Machine (SVM) classifier on our three classes.  We then use One Vs One (OvO) classification  to identify the top matching class for each play in our test set. We used TEI encoded XML formatted plays which we downloaded from <http://showcases.exist-db.org/exist/apps/Showcases/index.html>. Once the SVM is trained, it is used to predict the genre of unseen plays.

In a nutshell, our contributions are as follows: (1) we offer a list of individual and social factors that may help in literary analysis; and (2) we create a classifier to find the genre of an Early Modern play using the above individual and social metrics.

The rest of the paper is organized as follows. In Section 2, we present the existing work on social network analysis in different use cases. Section 3 describes our system. Section 4 contains experimental results, and Section 5 summarizes our findings and offers suggestions for possible future improvements.

# 2 Related Work

## 2.1 Support Vector Machines

Support Vector Machines (SVMs) are a popular machine learning method for classification, regression, and other learning tasks. Since our classification problem had more than two classes, we combined SVM with one vs one classification. In this technique, we pick a pair of classes from a set of *n* classes and develop a binary classifier for each pair. So, given *n* classes, we can pick all possible combinations of pairs of classes from *n* and then for each pair we develop a binary SVM.

For combinations we have:

and for *k*=2 corresponding to two pairs we have

Therefore, we need C(*n*,2) SVM classifiers; with three classes, that is [X] SVM classifiers. These vote for each play’s class and the winning class gets picked as the play’s classification.

“This is much less sensitive to the problems of imbalanced datasets but is much more computationally expensive.”

## 2.2 Social Network Analysis

As [SOURCE] notes, “Social network analysis (SNA) is not a formal theory, but rather a wide strategy for investigating social structures,” which “borrows most of its core concepts from sociometry, group dynamics, and graph theory” [CITE]. In social network analysis of human activities, the nodes can be connected by many kinds of ties, such as “shared values, visions, and ideas; social contacts; kinship; conflict; financial exchanges; trade; joint membership in organizations; and group participation in events, among numerous other aspects of human relationships” [CITE]. Regardless of the nature of the connection, “[t]he defining feature of social network analysis is its focus on the structure of relationships” [5]. SNA methodologies assume that relationships between nodes are of central importance. Social network analysis has been used in a wide variety of applications, with applications as diverse as disintegration models based on social network analysis of terrorist organizations [19], collaboration of scholars in graduate education, football team performance based on social network analysis of relaionships between football players [21], money laundering detection [22], and stress disorder symptoms and correlations in U.S. military veterans [23].

**2.3 Literary Analysis using SNA**

Because dramatic performances enact social encounters, social network analysis translates surprisingly well to fictional societies. Stiller et al. have shown that social networks in Shakespeare’s plays mirror those of real human interactions, particularly in size, clustering, and maximum degrees of separation (2003). Moretti uses social networks to examine the plots of three Shakespearean tragedies, and to contrast a few chapters in English and Chinese novels (2011). Surveying the field of literary analysis using SNA, Moretti categorizes several types of analyses: “an empirical, quantitative and hierarchical description of literary characters [31], corpus-based analyses exploring options for historical periodisation of literature [32] and types of aesthetic modelling of social formations in and by literary texts [33,34,35].” Work following Moretti has focused on historical periodization, as in Algee-Hewitt’s examination of 3,439 plays looking only at the Gini Coefficient of each play’s eigenvector centrality to track changes in ensemble casts from 1500 to 1920 (2017). Our project focuses on a novel application, the classification of literary genre. When scaled up to a corpus covering a wider historical time span, our approach to genre could also provide insight on the historic periodization of literature. Moretti also identifies that, in the application of SNA to literature, “[m]ethods for the automated extraction of network data … and their evaluation are of particular importance [25, 26,27,28, 30, 31],” which we accomplish. [Moretti].

**2.4 Gephi Toolkit**

Gephi is an open source software for graph and network analysis, which allows for fast visualization and manipulation of large networks. As a generalist tool, “[i]t provides easy and broad access to network data and allows for spatializing, filtering, navigating, manipulating and clustering.” [Gephi Paper] Gephi also calculates a wide range of mathematical features for each graph, which we use as the basis for our mathematical analysis (as discuss in more detail in 3.3)

# 3 OuR Design

Our system for identifying genre consists of three building blocks: the Play Parser, the Social Network Generator and the Genre Predictor. Figure 1 diagrams the main components of the system architecture, which are discussed in more detail in the following subsections.

Play Parser

Social Network Generator

Genre Predictor

Figure 1: Block diagram of our system.

## 3.1 Play Parser

The main purpose of this module is to parse each play for the basic information which will be the buildging blocks for the graph of the play. The information extracted includes the total number of characters in the play, the name and role of each character, the total number of acts and scenes, who was present in each scene (using stage directions to account for entrances and exits within scenes), who spoke, and how many lines and words are spoken. Table 2 shows some details.

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| **XML Tag** | **Information contained** | **Example** |
| <casteItem> | Character Name and role in the play | <castItem type="role">  <role xml:id="Pedro"> Don Pedro</role> <roleDesc> prince of Arragon</roleDesc>  </castItem> |
| <div> | Act | <div xml:id="sha-man1">  <head>Act 1</head> |
| <div> | Scene | <div xml:id="sha-man101">  <head>Act 1, Scene 1</head> |
| <speaker> | Current Speaker | <speaker>Beatrice</speaker> |
| <l>, <ab> | Line | <l xml:id="sha-man101299" n="299">  And tell fair Hero I am Claudio,</l>  <ab xml:id="sha-man201311" n="311"> born to speak all mirth and no matter.</ab> |

Table 2: TEI encoded XML files information

Our parser also correlated some of these extracted features with each other, in order to determine, for each line spoken, which characters were on stage to hear it. We assume that all characters on stage are able to hear all speech

Our primary source of data is <http://showcases.exist-db.org/exist/apps/Showcases/index.html>, a digital library which contains xml format of 37 plays Shakespeare’s plays in TEI encoding format. We downoaded the xml files and labeled each one with their genre.

## 3.2 Social Network Generator

This module builds play graphs using the information generated by the play parser in the previous section. In order to generate files which can be used to create graphs for plays, we used gephi api to generate gexf files. Each gexf file will map character to a node and communication between characters as an edge. Each character will store as an attribute, total number of lines and words spoken in the play. After this mapping, each edge is weighted with the sum of total number of words spoken by the two characters in the shared scenes. These are respresented as extracted features in Table 3. Once the basic structure is ready, using inbuilt functions of gephi api we calculated various metrics on the graph. Those are represented as network features in Table 3.

Our social network generator successfully and rapidly produces sophisticated social network graphs of marked up plays. We have used these networks as a supplement to close-reading Shakespeare’s oeuvre, and as a tool to explore complex relationships between Early Modern theatrical genres.

**3.3 Feature Set**

**3.3.1 Extracted Features**

As extracted features, we chose to use the most popular and easily quantifiable metrics for the play, such as total number of characters in the play, who was present in the scene, total number of lines spoken by each character in each scene. Our results will demonstrate that, number of edges in the graph and number of words spoken by the character play a crucial role in determining the genre.

**3.3.2 Network Features**

We compute the network features of a play solely from the generated graph. One obvious feature is degree count, or the number of immediate connected nodes to a particular character. Crititcality, desnity and diameter also play a crucial role in determining the genre.

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| **Extracted Features** |
| ***Features*** |
| **1. tot\_characters** = *total number of characters of* ***n*** |
| **2. tot\_edges** *= total number of edges of* ***n*** |
| **3. tot\_lines** = total number of lines spoken by **c** in play **n** |
| **4. tot\_words** = total number of words spoken by **c** in play **n** |
| **Network Features** |
| **5. Degree** *= set of adjacent nodes of* **c** *in the graph* |
| **6. Criticality** = *A****k-critical graph****is a critical graph with chromatic number k; a graph G with chromatic number k is****k-vertex-critical****if each of its vertices is a critical element.* |
| **7. EigenVector** *= A measure of node importance in a network based on a node's connections.* |
| **8. Eccentricity** *= The****eccentricity of a graph****vertex in a connected****graph****is the maximum****graph****distance between and any other vertex of.* |
| **9. Closeness** **Centrality** *= The average distance from a given node to all other nodes in the network.* |
| **10. Harmonic** **Centrality** = *In a (not necessarily connected) graph, the****harmonic centrality****reverses the sum and reciprocal operations in the definition of closeness centrality*. |
| **11. Betweeness** **Centrality** *= Node Betweenness Centrality measures how often a node appears on shortest paths between nodes in the network.* |
| **12. Clustering Coefficient** = *The clustering coefficient (Watts-Strogatz), when applied to a single node, is a measure of how complete the neighborhood of a node is. When applied to an entire network, it is the average clustering coefficient over all of the nodes in the network.* |
| **13. Density** *= Measures how close the network is to complete. A complete graph has all possible edges and density equal to 1.* |
| **14. Diameter** = *The maximal distance between all pairs of nodes.* |
| **15. Path Length** = *The average graph-distance between all pairs of nodes.* |
| **16. Connected Components** = *A****connected component****of an undirected graph is a maximal set of nodes such that each pair of nodes is connected by a path.* |
| **17. Modularity** *= Measures how well a network decomposes into modular communities.* |

Table 3: Features Extracted from Shakespeare plays. Here n represents a play in graph, c character node in a graph, e edge in graph.

## 3.4 Genre Predictor

The genre predictor is a Support Vector Machine binary classifier which uses one vs one technique for classification. It takes in the features mentioned in Table 3 and trains the model. We compared results with [????]

**4 Experiment**

## 4.1 Dataset

Our dataset consisted of 37 Shakespeare plays. We used TEI encoded xml format of the plays. XML format was chosen as it was much easier to fetch the information required from the play along with maintaining accuracy in the extraction. The dataset was downloaded from exit-db.org which contained above mentioned digital format of the orginal Shakespeare Plays.

For our dataset, we used 31 plays as a training set, and remaining 6 as a test set. The test set conatined two plays from each genre. For 5 fold cross-validation we used all 37 plays. For validation set, we downloaded six plays other than Shakespeare’s to validate how well our model performed in general.

## 4.2 Experimental Setup (Rephrase)

We then use our generated network graphs to test our central question: whether the social network enacted by a play’s characters can be used as a proxy for features of the play’s narrative content. More specifically, we ask whether social networks can be used to distinguish between the dramatic genres of tragedy, comedy, and history. Using a support vector machine with five-fold cross-validation, we tested 17 different mathematical features of the networks. We tested with how well individual features were able to distinguish between different genres. Second test comprised of various combinations of pair of features and third combination was combination of three features at a time to predict genre. Upcoming section discusses the findings.

## 4.3 Results

**4.3.1 Single Feature Accuracy**

First test was based on identifying genre using only single feature at a time. No single feature was independently sufficient to identify the genre. Graph density provided maximum accuracy for genre identification using single feature.

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| **Feature** | **Accuracy** |
| Total No. of Characters | 66.67 |
| Total No. of Edges | 50 |
| Total No. of Words | 50 |
| Total No. of Lines | 66.67 |
| Average Criticality | 50 |
| Average Eigenvector Centrality | 33.33 |
| Average Eccentricity | 50 |
| Average Closeness Centrality | 50 |
| Average Harmonic Centrality | 33.33 |
| Average Betweenness Centrality | 33.33 |
| Average Clustering Coefficient | 50 |
| Graph Density | 83.33 |
| Diameter | 33.33 |
| Path Length | 66.67 |
| Connected Components | 66.67 |
| Average Degree | 66.67 |
| Modularity | 50 |

Table 4. Gernre Prediction Accuracy using Single Feature

**4.3.2 Pair of Features Accuracy**

However, if features are used in pairs, the network graphs can achieve full accuracy. Table 5 shows combination of pairs which were able to identify genre with 100% accuracy on our test set.

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| --- | --- |
| **Feature 1** | **Feature 2** |
| Edges | Connected Components |
| Lines | Eccentricity |
| Eccentricity | Connected Components |
| Density | Connected Components |
| Modularity | Connected Components |

Table 5. Pair of features which provided 100% accuracy in genre predection.

**4.3.3 Three Features Accuracy**

If we combine three features, the network graphs again achieve full accuracy. Table 6 shows combination of triads which were able to identify genre with 100% accuracy on our test set.

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| **Feature 1, Feature 2, Feature 3** |
| Characters, Edges, Connected Components |
| Characters, Lines, Eigenvector |
| Characters, Eccentricity, Path Length |
| Characters , Density, Path Length |
| Characters, Connected Components, Degree |

Table 6. Set of three features which provided 100% accuracy in genre predection

**4.3.4 Discussion**

The potential utility of graph density in distinguishing genres is visually obvious when individual comedy and history networks are compared. Histories feature highly dispersed networks, with large numbers of very minor characters, such as “First,” “Second,” and “Third” members of groups like soldiers and ambassadors. Connections form chains of acquaintance with little overlap, so even the monarchs have low eigenvector centrality.

Comedies, in contrast, feature networks with far fewer characters, in which nearly everybody speaks to nearly everybody else at some point. Although comedies often have multiple subplots, these separate stories do not result in highly-separated networks. We theorize that comedic networks are strongly shaped by the plays’ final “resolution” scenes, which bring together the full cast. The average eigenvector centrality of the characters in comedies is much higher than in tragedies or histories; this suggests that many more of the characters in a comedy are “important,” reflecting a focus on ensemble stories.

Graph density is insufficient, however, to fully distinguish the tragedies, which feature networks somewhere between history and comedy in their density. They often have a dense core with a secondary ring of more peripheral characters. What seems to distinguish them is the existence of the central tragic hero, whose influence directly touches more of the network than the protagonists of histories, but whose connections are less interconnected than the ensembles of comedies. These subtleties are better captured, it seems, by the combined metric rather than a single metric alone.

Table 5, shows that certain pair of metrics are successful in capturing the diffrences completely for different genres. Table 6, shows that each metric captures a specific information about the play and hence, the set of three pairs which provide 100 percent accuracy do not necessarily always include table 5 pairs.

[I’d like to include more discussion of these groups of metrics here.]

**5 Conclusion (Rephrase)**

In this paper, we successfully classify plays based on their genre without using words of the plays. Our parser successfully and rapidly produces sophisticated social network graphs of TEI plays that can be used to computationally identify theatrical genre in Shakespeare’s plays. 37 plays is a small scale for this approach: since the parser is highly extensible and can be used with any plays encoded in TEI, future work need not be restricted to the Early Modern period. It need not even be restricted to works written in English. Our networks of the well-studied works of Shakespeare can provide a baseline against which to contextualize analysis of these elements in works for which there is far less critical consensus. Social Network analysis provides a detailed insight about plays in a very reduced amount of time with greater accuracy.

**6 Future Work**

Lot of literary analysis can be perfomed using social network metrics. Our work can be further extended to find plot analysis over time, gender portrayal in plays over time, cross cultural gender representation over time in plays, cross cultural writing over .

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