Title

Centrality measures as a signature of roles in Rousseau's *Les Confessions*

Authors

Rochat, Yannick, Frédéric Kaplan

DHLab, EPFL, Lausanne, Switzerland

Abstract

We investigate how a selection of centrality measures can be used to differentiate roles of characters in Jean-Jacques Rousseau's autobiography *Les Confessions*. We define methods to build automatically a network of characters, based on their co-occurrences. In the resulting network, each character of the novel is a node connected to other nodes representing other characters. We rank these with four centrality measures and find different ordering depending on the measures. We highlight how characters with high betweenness centrality tend to play positive role in the narration as they act as important mediators and facilitators of Rousseau's social life. On the contrary, we show that characters with high eigenvector centrality form a cluster of interchangeable figures, acting in practice like a "meta-character", a crowd that conspires against Rousseau. Although we cannot yet generalise these findings to other work, we argue that these preliminary results motivate further research based on well-chosen centrality measures in digital literary studies.

Introduction

In digital literary studies, applying network analysis to literature usually consists in studying the influence of given novels or authors on other works, over time (Jockers, 2013; So and Long, 2013). Network analysis is also sometimes used within a single novel to understand, for instance, the evolution of the relationships between the different characters (Agarwal 2010; Mac Carron and Kenna, 2012; Moretti, 2011). In this work, we use networks to model the structure of relations between the characters of the autobiographical novel *Les Confessions*. This approach lets us analyse the proximity and influence of the characters among them, and identify the roles played throughout the narrative and the various story arcs. We build the network from an index of characters compiled by scholars (Rousseau, 2012). Using the index allows to bypass the text mining problematic of linking words in the text to the corresponding named entity (Elsner, 2012; Elson, 2012), to address a different research objective: understanding how network analysis measures allows to characterize narrative roles in a novel.

This article begins with a preliminary investigation on centrality measures for the study of character networks. Centrality is a family of indices defined on networks that measure forms of importance based on properties of the network structure (Koschützki et al., 2005). This concept comes from social network analysis (Bavelas, 1948), which studies the application of graph theory to relational data in social groups (Wasserman and Faust 1994). Various centrality measures exist. *Degree centrality i*s based on the number of connections of each node. *Betweenness centrality* measures the role of a node in terms of global connectivity in a network (Freeman, 1978). *Eigenvector* and *harmonic centralities* compute centrality on the basis of the centrality of neighboring nodes (Bonacich, 1987; Rochat, 2009).

The core contribution of this paper is to discuss how these measures rely to narrative roles. We show how in *Les Confessions*, characters with high betweenness centrality differ from characters with high eigenvector centrality, the first ones playing a positive role as intermediaries in Rousseau's early life, the latter being perceived as a cluster of negative characters, conspiring against him in the second part.

In the following sections, we describe in detail the method we use to construct the co-occurrence network based on indices and discuss the robustness of our approach. We first discuss the network general properties, then we focus more specifically on ranking characters using centrality. We conclude on the literary interpretation of these findings and the motivation for applying these measures beyond the particular case of Rousseau's *Les Confessions*.

Method: From an index of characters to a network

An index of characters is composed of at least two entries: one with the name of a character, the other with all the pages on which its name occurs. The index is expected to include all existing transcriptions of the said character (for example *M. Dupont* and *Jean Dupont* if they are the same character). *Les Confessions* is made of twelve chapters, written in two periods (one to six, then seven to twelve), that spans fifty years of Rousseau's life. Its index contains 543 entities and 1932 occurrences (see Fig. 1).[1]

[1] In order to transform this index into a network, we present the index as a table with, on each row, a single name and a single corresponding page number on which the name occurs. For each character, we create as many rows as pages on which that character is mentioned at least once. More than one occurrence on a page does not induce rows other than the one previously created.

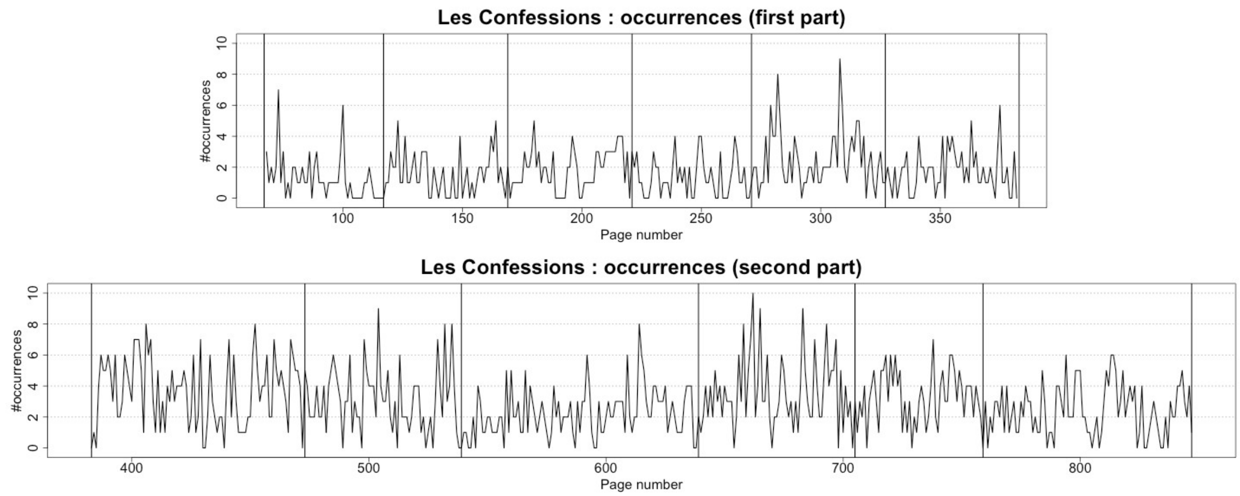

Fig. 1 Occurrences of characters in *Les Confessions*. First part is composed of books 1 to 6, second part of books 7 to 12. Vertical lines delimit books. Characters apparitions are sparser in the first part.

In this edition (Rousseau, 2012), 774 pages contain text, and among them 102 pages contain no name[2].

Our method is based on co-occurrences of characters on same page and consecutive pages. The fact that two names appear on the same page does not necessarily imply that they are linked in any manner, but recurring co-occurrences imply a narrative bond between them. This is why we combine for this method a rather flexible co-occurrence strategy (considering the co-occurrences spanning on consecutive pages) with a threshold allowing to discern recurring association from random ones.

In other words, we define (1) a system that takes into account co-occurrences on consecutive pages in order to create links. The domain is not the set of pages, but a set of overlapping couple of pages. We weigh the links by counting the co-occurrences. (2) Then, we define a

[2] It implies that there are gaps when studying trajectories of characters on story arcs via a temporal scale based on the page unit. These pages are considered as well.

method that requires two characters to appear at least two times together, closely or not, in order to infer the link in the network. This minimum intensity condition implies the definition of a threshold to determine if a link is to be created. We define more formally these two steps below.

(1) The set of occurrences for any given character is defined on couples of pages instead of single pages. Let A be the name of a character. If A appears on page i, we consider that A occurs on both couples of pages {i −1,i} and {i,i +1}. We build for each character a set of occurrences. The intersection of two such sets determines the number of co-occurrences between the concerned characters. The cardinality of the intersection is an attribute that estimates the intensity of the link. Thus, the relation between two co-occurrent characters on the same page is incremented by two. Overlapping co-occurrences allow considering proximity as smooth and distributed. For the sake of comparison, the application of this method on the index generates 4286 edges instead of 2118, for 543 nodes[3].

(2) We select a threshold value of 3 to distinguish relevant associations from noisy ones. Here are examples of the three possible cases with intensity equal to three: (a) when two characters are once co-occurrent on the same page and once on a disjoint couple of consecutive pages, (b) when they are both co-occurrent on two consecutive pages, (c) when two characters are three times co-occurrent, never on the same page. In our corpus, we recorder these cases among the links with intensity equal to three: (c1) there are 75 all successive, (c2) 109 mixed, and (c3) 6 all disjoint. We give examples for each case.

[3] We have gathered much of the information but have generated noise at the same time. For example, on the first pages of chapter IV, *Venture de Villeneuve*, an adventurer, appears on page 221, and *Jean-François de Dortan*, a cantor, appears on page 222. They are mentioned in other places of the book, both before and after, but this is the only time they appear close one with the other. From reading the text, we can assert that they do not meet, or play a role in a common scene. Such a weak relation does not need to remain present in the final network, as many such others scattered throughout the book.

Case (c1). This is the most compact case, meaning that at least one of the two characters' names is positioned between occurrences of the other name. The probability that they belong to the same narrative event and have physically met, is high. For example, *Françoise-Louise de Warens* and the *abbé Blanchard* respectively appear, among others, on pages 304 and 306, and pages 305 and 306. *Blanchard* is someone recommended to Rousseau for music lessons. He has to ask the permission to leave the house to Mme de Warens, and she helps him financially on this occasion.

Case (c2). There is a strong connection and a weak one, and they are spread on close or distant pages. We interpret that last fact as a high probability that they significantly play a role in the same narrative event. For example, Jacques-Armand Dupin de Chenonceaux and Louise-Marie-Madeleine Dupin (also known as Mme Dupin) respectively appear, among others, on pages 404 and 491, and on pages 404 and 490. Jacques-Armand Dupin de Chenonceaux is the son of Mme Dupin. The strong co-occurrence on page 404 happens when Rousseau is hired as a tutor. The weaker co-occurrence on pages 490 and 491 happens in a context of large footnotes covering respectively about 40% and 75% of these pages, which means that this weak co-occurrence is potentially present in another edition. In this example, Rousseau is leaving his job as secretary of M. de Francueil, a close friend of Mme Dupin, who then hires him to tutor Mme Dupin's son and work as a secretary.

Case (c3). Here, two characters share three weak co-occurrences. They meet three times, never on the same. For example, Jean Le Rond d'Alembert and Mme d'Épinay respectively appear, among others, on pages 536, 645 and 785, and on pages 535, 646, 784. It is important to notice that these co-occurrences happen on three couples of pages, each time distant of more than hundred pages. These characters are not explicitly cited together, but are mentioned in similar situations. In the first case, Mme d'Épinay is mentioned because she offers to

Rousseau to retreat in a house she possesses in the countryside. Before leaving, Rousseau is told, as well as d'Alembert, that an author is being excluded from the Academy in which he is. This is definitely a very weak link. The second one concerns the article *Genève* that d'Alembert is writing for the *Encyclopaedia* while willing to use it to highlight the lack of theatres and cultural life in Geneva. That fact annoys Rousseau, who answers by the *Lettre à d'Alembert sur les Spectacles*, in which he depicts some people of his time, including Mme d'Épinay. A stronger link, but with characters acting on various levels: one is active and one only mentioned. In the last case, Rousseau realises that some of the letters he conserves have disappeared, and among them some from Mme d'Épinay. He ends up suspecting d'Alembert. We can hardly infer the existence of a relation between those two characters. However, we observe that they have had importance in a few common events. Nonetheless, such cases of relations where intensity is equal to three are difficult to interpret.

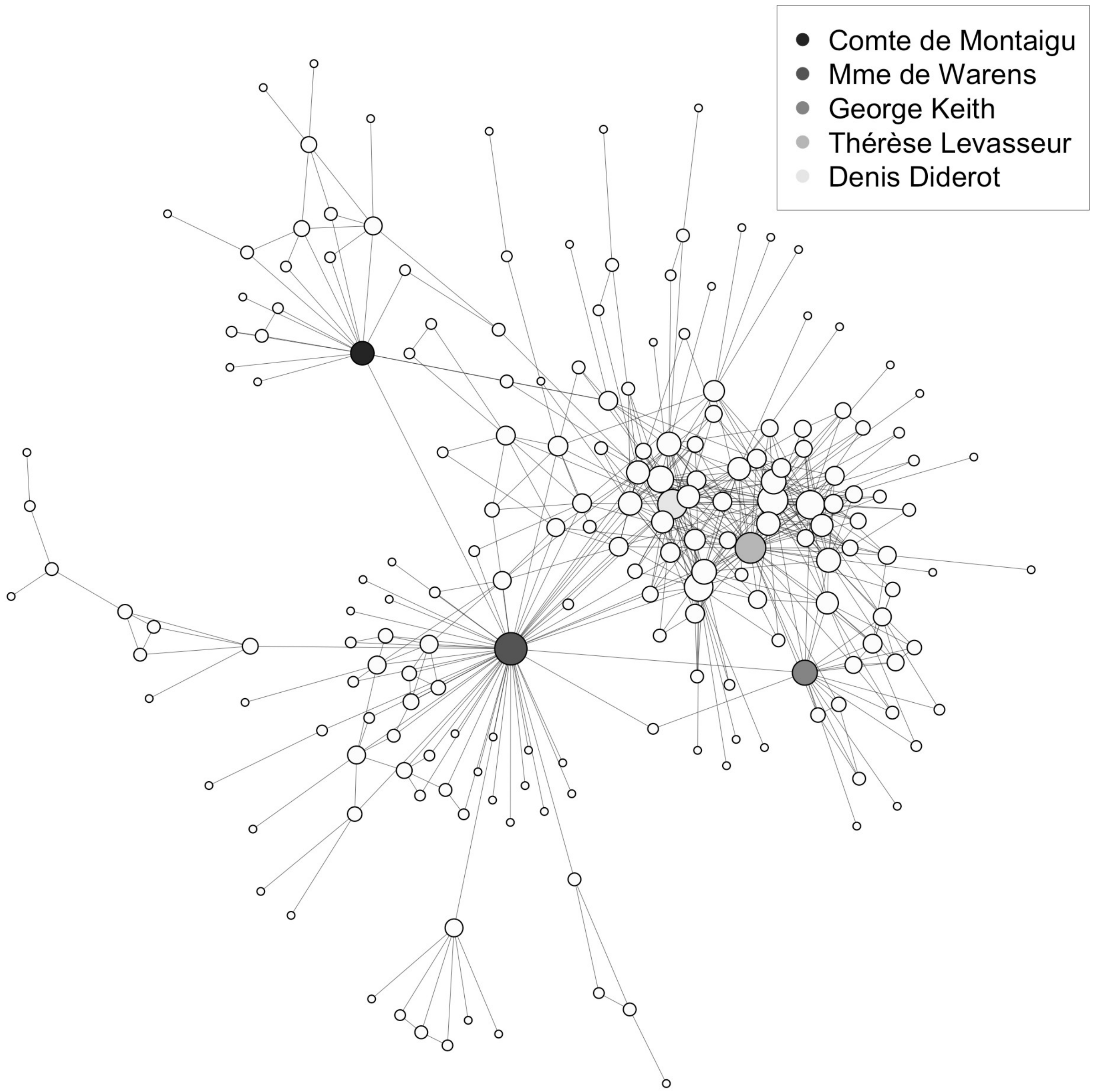

Fig. 2 A visualisation of the network. Five nodes are highlighted, which correspond to characters with central roles in this model. For example, *Comte de Montaigu* and *Mme de Warens* act as intermediaries, since there are situated on paths relying disjoint clusters.

The resulting network is given in Fig. 2. Before the analysis, we make two cautionary remarks:

1) The "network" is the mathematical object made of nodes, edges and attributes, and not the visualization proposed in Fig. 2. In such a case of a non-regular network, we use, in order to determine the positions of nodes, an algorithm that stochastically minimizes given conditions and, after a given number of iterations, produces a suitable layout (Fruchterman and Reingold, 1991). The analysis must not be based on the visualization alone.

2) Despite the fact that we are working on his autobiography, this network is not “Rousseau’s social network”. It is a computational model derived from *Les Confessions* (Moretti, 2011). In the following section, we use it to make a literary analysis, independently of any historical reality.

Results

General characteristics of the network

The network is undirected. It has 205 vertices and 533 non-directed edges. This is 38% of the total number of characters at the beginning of the study: since our model is concerned only by relational data and main narrative, characters appearing in too coarse zones of pages are not retained by our method of building the network. To deal with the whole network, we need measures that go along with weights. At this step, the network is disconnected: the giant component[4] is composed of 194 nodes out of 205. We focus on the analysis of the 194 nodes and 527 edges composing the giant component. This is a critical step that allows us to use measures that are more efficient in connected cases, like betweenness centrality. From now on, we define the giant component as the character network of *Les Confessions*.

Centrality measures

[4]A subset of nodes where, for each couple of them, there exists a path, comprised of edges and nodes alternately, linking them.

Centrality is a concept from social network analysis. Most of the time, it is expressed by a mathematical index, or a family of indices, measuring “structural advantage, importance or dominance” (Hennig et al., 2012). Among the numerous choices, classic ones are degree, betweenness, closeness and eigenvector indices. In this work, we use harmonic centrality instead of closeness. Its results are correlated to closeness, but it has higher variance due to the decreasing importance given to vertices as they are situated far from the vertex under study.

Degree centrality is a measure originated in graph theory (Berge, 1958). It is the sum of incident edges to a given node, thus it is also the count of its neighbors. The more a node is connected, the bigger the size of its direct neighborhood, the higher its measure of degree centrality. It measures popularity: a high value of degree centrality implies that the character appears on pages on which occur many other different characters in total. It is not influenced by the structure of the network at a distance further than one.

Betweenness centrality measures the control an actor has on the information flowing in the network. Mathematically, it is the sum on each couple of nodes of the proportion of shortest paths starting from and ending on the two nodes on which the node under study appears. If the node is in a very dense cluster, most of the flow will be distributed inside of it, and the node will get low betweenness centrality, since it doesn’t appear directly on shortest paths. It is considered as a measure of medial centrality. In the case where a node is situated between two such clusters, then it will appear as having high betweenness centrality. In the context of narrative, this concept means for example appearing in disjoint events, not necessarily consecutive, while other characters don’t occur in these. In such a case, the author uses that character in order to accompany the narrative while it takes a turn into another direction.

Eigenvector centrality is computed by solving a system of linear equations based on the adjacency matrix of the network. The eigenvector centrality of a node is a function of the neighboring nodes own centrality values. If the node under study is connected to a highly central node, this will influence it. Nodes at a higher distance also influence the measure, which is inversely proportional to their proximity to the node. The computation of a node's measure is based on its neighbors'[5]. Practically, eigenvector centrality index is defined as the eigenvalues of the adjacency matrix.

Harmonic centrality computes the harmonic mean of all the inverted distances from a given node to all the others in the network. Like eigenvector centrality, it is based on local information, reaching elements further in the network than what degree centrality does, without attaching too much importance to nodes situated on the longer shortest paths, as it is the case with betweenness and closeness centralities. Harmonic centrality appears to be a robust index (Bold and Vigna, 2013). It measures the importance of a node's neighborhood in terms of proximity and of size.

Ranking based on centrality

In this section, we present the results of computing the four previously detailed centrality indices. In each case, we show the ten most central characters in tables 1-4. A comparative ranking is also given in table 5, with non-normalised measures.

[5]Measures of that kind are called feedback centralities.

Name	Degree
Mme de Warens	56
Thérèse Levasseur	44
Duchesse de Luxembourg	41
Denis Diderot	38
Mme d'Épinay	33
Montmorency-Luxembourg	32
Mme Dupin	24
George Keith	20
Comtesse d'Houdetot	19
Jean Le Rond d'Alembert	19

Table 1 The 10 characters with highest degree centrality.

Degree centrality (table 1) shows that Mme de Warens is the most connected character, followed by Thérèse Levasseur. They are the two main female characters in Rousseau's life: Mme de Warens is mostly cited from the second to the seventh books, while Thérèse Levasseur appears in that last book, and stays with him until the end at chapter twelve. This explains why they both are co-occurrent with many other characters. We remark that characters from the Parisian society are also well connected, such as Denis Diderot, Mme d'Épinay, Mme Dupin.

Name	Betweenness
Mme de Warens	11636.44
Comte de Montaigu	2875.58
Duchesse de Luxembourg	2786.58
Denis Diderot	2127.68
Charles Emmanuel della Rocca d'Arazzo	1487.00
George Keith	1409.40
Suzanne-Françoise de Larnage	1134.00
Mme Dupin	1122.52
Mme d'Épinay	1102.92
Voltaire	1084.01

Table 2 The 10 characters with highest betweenness centrality.

Name	Harmonic
Mme de Warens	0.160
Duchesse de Luxembourg	0.139
Denis Diderot	0.131
Mme Dupin	0.127
Voltaire	0.126
Comtesse d'Houdetot	0.123
Thérèse Levasseur	0.122
George Keith	0.121
Alexandre-Jean-Joseph Le Riche La Poplinière	0.120
Mme d'Épinay	0.119

Table 3 The 10 characters with highest harmonic centrality.

Betweenness and harmonic centralities (see table 2-3) show the overwhelming role of intermediary and local influence Mme de Warens has played for Rousseau, hosting him after he left Geneva, and then regularly sending him to diverse places in France or Italy. That role of *hub* is visible in figure 2, where the node representing her radiates in the many directions being linked to various nodes and clusters. The Comte de Montaigu, ambassador of France in Venice, appears in the betweenness ranking but not in the harmonic one, thanks to a role of intermediary he plays between the French society and the Venetian one, where Rousseau worked for him as his secretary.

Name	Eigenvector
Mme d'Épinay	1.000
Denis Diderot	0.961
Thérèse Levasseur	0.926
Montmorency-Luxembourg	0.709
Duchesse de Luxembourg	0.706
Comtesse d'Houdetot	0.672
François et Marie Levasseur	0.519
Saint-Lambert	0.397
Baron d'Holbach	0.397
Comtesse de Boufflers-Rouverel	0.356

Table 4 The 10 characters with highest eigenvector centrality.

Eigenvector centrality (see table 4) is the only measure for which Mme de Warens is not the most highly placed. Characters from the second part of *Les Confessions* occupy the top of this ranking: thanks to their proximity, they reinforce one each other's centrality. We discuss the important difference between this centrality index and the others in the following section.

	degree	betweenness	harmonic	eigenvector
Mme de Warens (ou Maman)	1	1	1	15
Thérèse Levasseur	2	11	7	3
Duchesse de Luxembourg	3	3	2	5
Denis Diderot	4	4	3	2
Mme d'Épinay	5	9	10	1
Montmorency-Luxembourg	6	30	35	4
Mme Dupin	7	8	4	11
George Keith	8	6	8	25
Comtesse d'Houdetot	10	12	6	6
Jean Le Rond d'Alembert	10	31	22	12
Comte de Montaigu	14	2	19	110
Charles Emmanuel della Rocca d'Arazzo	62	5	24	132
Suzanne-Françoise de Larnage	42	7	144	96
Voltaire	16	10	5	24
François et Marie Levasseur	12	13	27	7
Saint-Lambert	32	86	110	8
Baron d'Holbach, et Mme	22	73	84	9
Comtesse de Boufflers-Rouverel	12	60	37	10
Alexandre-Jean-Joseph Le Riche La Poplinière	32	55	9	40

Table 5 Ranking of the characters with highest centrality measures (characters appearing in tables 1-4).

Table 5 summarizes the different measures of centrality computed on this network. In this case where a novel is written in two times[6] and describes two different types of life courses, we can see that the centrality indices are sensitive to that aspect. Measuring Spearman correlations between these indices shows variations: in particular, eigenvector and betweenness centrality do not behave as closely as the other couples of indices (see table 6).

[6]Part 1: chapters 1-6. Part 2: chapters 7-12.

	betweenness	harmonic	eigenvector
degree	0.78	0.64	0.73
betweenness		0.56	0.49
harmonic			0.73

Table 6 Correlations between centrality indices.

Discussion

We have seen from the different ranking systems that at least two groups of measures give rather different ordering. Betweenness and harmonic centrality show the importance of a character like *Mme de Warens*: she plays a role of intermediary between many characters in the novel. She is the person who introduces him to many different societies. In the first part of Rousseau's life (which corresponds to the first book), she definitely is a positive character, being the "red line" that weaves Rousseau's pieces of network together. She literally has a central role in the sense that if she were not there, most of Rousseau's encounters would not have happened. She is one of the main driving forces of the story, acting like some sort of orchestrator.

On the contrary, if we consider the eigenvector centrality ranking, there are other characters to play the more central roles. They are a group of interconnected persons, situated in Paris. In the second part of Rousseau's life, these persons tend to play a negative collective role. Rousseau suspects them of leading a conspiracy against him. Whether these threats are real or just the results of Rousseau's paranoia is beyond our discussion. We can nevertheless spot that this group of highly interconnected characters play in fact the role of a kind of "meta-character", a cluster of persons, where the clusters count more than each individual entities. This is precisely the meaning of a high eigenvector centrality. Characters recurrently associated with one another are in practice interchangeable from a narrative point of view. They act like a crowd. Despite their high eigenvalue centrality, none of them is really “central” in the sense that the cluster would still play its narrative role if that person were to be removed. This lack of individuality is correlated with fear and suspicion, as Rousseau associates most of the members of this group as faceless enemies.

In relation with these two opposite narrative roles, it is interesting to study the case of Denis Diderot, as he is one of the rare characters that globally score high in both betweenness and eigenvector rankings. This can be explained by considering the temporal unfolding of Rousseau’s autobiography. Indeed, Diderot is first perceived as a connector, like Mme de Warens, someone who opens door for Rousseau. However, he is later linked with the Parisian crowd, when Rousseau decides to leave this society and starts to consider his enemy as a group of interchangeable figures.

In summary, this first study shows on these particular cases that various centrality measures can be associated with different narrative roles. We cannot yet argue for the generality of such a finding beyond the particular case we study here, but we believe that these encouraging results should motivate further study in this direction. As the method we described is simply based on an index and is not relying on specific text mining techniques, it is extremely simple to deploy it on any book that comes associated with such information.

In addition, these preliminary results obtained globally on a novel should encourage results that investigate in more details the evolution of such measures inside a novel. In many cases, characters evolve as the novel unfolds, and it is likely that the different centrality measures we consider in this article could capture potential changes in narrative roles if such situations would occur.

Eventually, it is interesting to remark that in a work like this one, it is not only various development in mathematics and graph theory that have offered interesting new tools of studying literature but that, conversely, the particular case of the digital literary study we have considered allows to give constructed and illustrative examples about the important differences that characterise these various centrality measures. Indeed, characters in Rousseau's *Les Confessions* offer us a clear example where these "centrality" measures are not correlated and associated with opposite valence.

References

Agarwal, A., Corvalan, A., Jensen, J. and Rambow, O. (2010). Social Network Analysis of Alice in Wonderland, Proceedings of Empirical Methods in Natural Language Processing, Cambridge, Massachusetts.

Bavelas, A. (1948). *A mathematical model for group structures.* Applied Anthropology, **7**(3): 16–30.

Berge, C. (1958). *Théorie des graphes et ses applications*. Paris: Dunod.

Boldi, P., Vigna, S. (2013). Axioms for Centrality. arXiv:1308.2140v1 [cs.SI] (to appear in Internet Mathematics)

Bonacich, P. (1987). Power and Centrality: A Family of Measures. American Journal of Sociology, 92, 1170-1182.

Elsner, M. (2012). *Character-based Kernels for Novelistic Plot Structure, Proceedings of the 13th Conference of the European Chapter of the Association for Computational Linguistics*, Avignon, France, April 2012, 634 - 644.

Elson, D. K. (2012). *Modeling Narrative Discourse*. Ph.D. thesis, Columbia University.

Freeman, L. C. (1978) Centrality in Social Networks: Conceptual Clarification. *Social Networks*, **1**(3): 215 - 239.

Fruchterman, T.M.J. and Reingold, E.M. (1991). Graph Drawing by Force-directed Placement. *Software - Practice and Experience*, **21**(11): 1129-1164.

Hennig M., Brandes U., Pfeffer, J. and Mengel I. (2012). *Studying Social Networks: A Guide to Empirical Research*. Frankfurt-on-Main: Campus Verlag.

Koschützki, D., Lehmann, K. A., Tenfelde-Podehl, D., and Zlotowski, O. (2005). Centrality Indices. In Brandes, U. and Erlebach, T. (eds), *Network Analysis*, Lecture Notes in Computer Science, 3418. Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 16 - 61.

Jockers, M. L. (2013)**.** *Macroanalysis: Digital Methods and Literary History*. Urbana, Chicago and Springfield: University of Illinois Press.

Mac Carron, P., Kenna, R. (2012). Universal Properties of Mythological Networks. Europhysics Letters, **99**(2).

Moretti, F. (2011). Network Theory, Plot Analysis. *New Left Review*, 68. http://newleftreview.org/II/68/franco-moretti-network-theory-plot-analysis (accessed 14 november 2013).

Rochat, Y. (2009). Closeness Centrality Extended to Unconnected Graphs: the Harmonic Centrality Index. Applied Social Network Analysis, Zürich, Switzerland, August 2009.

Rousseau, J.-J. (2012). *Oeuvres complètes en 24 volumes*. Trousson, R. and Eigeldinger, F. S. (eds.). Genève, Paris: Slatkine.

So, R. J. and Long H. (2013). Network Analysis and the Sociology of Modernism. *Boundary 2*, **40**(2), 147 - 182.

Wasserman, S. and Faust, K. (1994). *Social Network Analysis: Methods and Applications*. Cambridge: Cambridge University Press.