# Hamlet and Othello Wandering in the Web

Inferences from Network Science on Cognition

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***Abstract*—Network theory was used to gain a deeper understanding of emotional cognition, pretending that Shakespearian tragedies of Othello and Hamlet were life-like linguistic contexts. A manual segmentation of both plays was carried out for defining a lexicon of emotional words represented by networks. Using ad hoc developed computational methods, further instances of the emotional lexicon networks were compared with WordNet's manually extracted data. The results revealed organizations of emotional terms' neighborhoods, evidencing the emergence of emotional patterns, with symmetries and breaches of symmetries, thus giving a strong support to comprehend the dynamics operating on speech production cognitive processes.**

***Keywords-language; Shakespeare; network; semantics.***

## I. INTRODUCTION

Network science considers the organizational principles of complex structures found in different fields of research, from physics to biology and social sciences. Its starting point is the graph, a mathematical structure made of nodes connected by links. Network science has recently contributed to the study of language as a real-life problem, by analyzing the statistical properties of words associations [1], thesauri [2], syntactic dependencies networks [3], modeling the properties of these structures [1] and proposing abstract models for increasing the general knowledge of language functions. Though networks were already associated to cognition using different methods [4][5], network science greatly expanded cognitive science domains, improving knowledge about brain connectivity [6], representing semantics in the human brain [7] and studying semantic organization of memory [1][8][9]. Despite the huge number of studies aiming at analyzing language networks, cognitive processes underlying these networks have only been studied at the phonological level [10], for spoken word recognition [11], or failed lexical retrieval [12], thus leaving away the study of lexical semantic organization. In this paper, network theory was used as an explanatory principle and a methodological tool to gain a deeper understanding of emotional cognition into the Shakespearian tragedies of Othello and Hamlet as the best exemplar of narrative text, pretending they were real life situations. We considered mental lexicon as the parameter space of cognitive processes related to speech production. We considered the mental lexicon as a small-world network, and lexical retrieval as a search through that network, similar to the PageRank algorithm [13] searches through the World-Wide Web. Our aim was to represent the organization of words in memory in order to develop a more comprehensive view of emotional cognition dynamics and to see how the emotional speech could be understood and represented as dynamical system by network theory. Data obtained through the manual method was subsequently compared and analyzed by computational systems searching through WordNet, to examine the growth of semantic networks with networks obtained by manually segmenting both plays. Networks organized in structures that span from simple to complex mathematical configurations were detected. They represented patterns of semantically similar neighborhoods of emotional words, showing symmetries and motifs [14]. The organization of these semantic networks has been considered as dynamical attractors that work on the connections of semantic similarity. If two nodes share many common properties then it will be very likely that these two nodes share several links. Their concepts are definitely connected. The attractors also showed different dynamical patterns, used as a representation of emotional dynamics in the plays' characters and of productive processes in the verbal production.

The paper is organized as follows. After a subsection on the theoretical approaches to cognitive processes involved in emotional speech and behavior, and basic notions about network science, the methods used to analyze text as real life situations are described in Section II, specifying the two different types of analysis: the manual and the computational one. Results on the main theme of this paper are then deeply discussed in Section III. Conclusions and further developments are presented in Section IV, closing the work.

### *A. Basic assumptions on emotions and network science*

Emotions as psychological occurrences have exclusive traits, they are embodied, displayed into stereotyped behavioral patterns of facial expressions and conduct, stimuli driven and related to all aspects of cognition. Besides, emotions are significantly connected to the social-cultural situations in which they occur [15][16]. According to many researches [17][18][19][20], a stimulus in the environment

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triggers a chain reaction in humans. According to Frijda [21], emotions trigger cognitive structures, which are characteristic of a given emotional experience, by a process known as cognitive tuning. Human language represents the means to reach a deep knowledge about emotions and body language allowing furthermore to understand the other participants cognitive mental processing of ideas and concepts [22]. Linguistic properties have often been analyzed through network science, interpreting language as a graph. A classic definition of network is a set of nodes connected by edges [23][24][25]. Considering G as an ordered set G = {N , E}, where $E = \{e_{ij} = (x_i, x_j) \mid x_i, x_j \in N\}$ is a set of paired elements of N, among which a relationship is established. The components belonging to N are called nodes, or vertices, while the components belonging to E are called edges. At the words level, the single term is considered a node, while the connections among words is the synonymic relation. Crucial features of semantic organization can be detected and explained with networks models. To analyze the size of a semantic network, the total number of nodes (n) and edges (m) is calculated. Size in terms of nodes may also be critical for the structure of word relationships. Another significant feature of semantic networks is the degree of a word (k), which identifies its number of links and highlights the weight that a single term has as a source of ties (possible connections and influences of a word with other words in the whole structure). For very large networks, the degree distribution deviates significantly from the Poisson distribution, as highlighted for the World Wide Web [24], for the Internet [26], and for metabolic networks [27]. The work of Barabási et al. [23] defines these networks as scale free. This structure includes few words which are highly interconnected nodes (hubs) participating to a large number of interactions and other terms connecting to the network by following a preferential attachment to these hubs. The mathematical approach based on network science's principles used in this experiment represented a useful tool to model and analyze cognition.

## II. METHODS

This Section describes the two different methods used.

### A. How to

In order to obtain a cognitive organization of emotional terms, these steps were followed: starting from a text a list of emotional terms was manually extracted; from this list several networks were built as described in the next subsection; finally a comparison between these networks with the network extracted from WordNet [28][29][44] was made to depict and analyze how the emotions are configured in the text.

### B. Manual research method

Two different methods were used for analyzing emotional cognition. The first one employed a lexicon of about 2000 emotional words, drawn directly and manually from the tragedies of Hamlet and Othello, referring to the five basic emotions of 'anger', 'love', 'sadness', 'joy'/'enjoyment' and 'fear'. A first linguistic modeling was applied to this data, organizing them in tables divided by emotion and five grammatical categories: verbs, names, adjectives, adverbs and sentences (i.e., metaphors or idiomatic expressions). The annotation system that was used is showed in Figure 1.

From this first step, a second kind of modeling was built: the linguistic data was transformed in numerical data, where every element was associated to its synonyms, in order to create five separated undirected graphs, containing all the words selected for each emotion, with links to every synonym in the text. The next step was to complete the nodes in the networks, using different kinds of codes:

- a color code to indicate grammatical categories;
- a numerical code for the same purpose (i.e., Names 1, Adjectives 2): it allowed the extraction of quantitative information about the distribution of the nodes in the text;
- an alphabetical code of small letters to indicate acts and scenes (i.e., a=sc.1);
- an alphabetical code of capital letters indicating the character speaking.

### C. Computational Research Methods

In order to define a computational model inspired to biological cognition, the psychological resource WordNet was downloaded from Princeton University's website [44]. Developed by George Miller and collaborators [28][29], the resource is an attempt to capture psycholinguistic theory within a linguistic system, for defining and modeling the meaning of words and associations between meanings. The system was then transformed into a network, presenting 139,999 nodes (at the time the system has been downloaded for the present study). The following computational models, completely adherent with the WordNet system, were developed:

- R1_Antonyms collected words which stand in gradual opposition with a chosen term, have complementary meanings, or are the opposite, as different and symmetrical terms;
- R2_Hypernyms created the hierarchical structure of the words, taxonomically classifying them into types and subtypes;
- the function R3_Hyponyms collected terms correlated by the 'IT IS A' relationship;
- R4_Entailment identified all the terms that were in some way required, from a conceptual point of view, by the starting term;
- R5_Similar collected semantic resemblance between terms;
- R6_Synonyms searches for words with share partial sharing of semantic content, denotative and connotative meaning, are perfectly interchangeable;
- R7_Related identified the terms correlated to the one chosen for the study;
- R8_Overview identified a mix of all the above semantic dynamics for the term under study, for all syntactic categories.

The above detailed formal models were implemented in the software (SWAP), which performs search in the WordNet database, and then calculates a network in which nodes are connected by edges according to a chosen R.

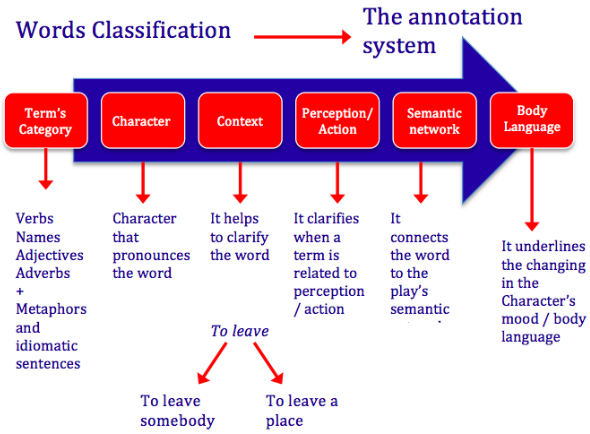


Figure 1. The annotation system used for creating the dictionary and the emotional words' classification system.

We thought of these computational models as 'emotional-terms-hunters bots', or search engines (software robots) of emotional terms, virtually able to 'hunt' all the semantic connections related to emotional lexicon. Investigating the system with different computational models allowed the detection of distinct characteristics due to the particular network topology: choosing to move only within paths of the network that converged to few nodes or a single node, the number of nodes visited decreases, as in the case of the computational model R3_Hyphonyms. But, if the paths diversified or specialized (as in the case of computational models such as R2_Hypernyms and R6_Synonyms), the number of visited nodes increased. This could suggest that the neighbors of synonyms and hypernyms are more densely populated while those of hyponyms are sparser. The total network held steady, while the visited part changed. But, if the visited nodes were considered as possible states of the system, with the computational models seeking synonyms and hypernyms, then the number of states eligible by the system was wider than in the case of the system using the computational model to search for hyponyms.

## III. RESULTS AND DISCUSSION

Section III highlights and discusses major results.

### A. *Manual Research Network Results*

The manual annotation method of emotional terms disclosed several features of emotional cognition for every character (see an example in Table I).

Considering parameters $\lambda$ and $\gamma$, where $\lambda$ is the ratio between the average path length (L) and the path length of the equivalent random network and $\gamma$ is the ratio between the network clustering coefficient and the random one clusterization, the small-world index $\sigma$ is then calculated as the ratio between the clustering coefficient and the path length ratios. If $\gamma >> 1$, $\lambda \approx 1$, $\sigma > 1$ [30], the network has a small-world structure. Statistical data reported in Table II shows such parameters for emotional terms in both tragedies: the emotional language in Hamlet follows a small-world structure and the same is for 'fear' and 'joy' in Othello. What emerged was that verbs related to the main emotions, for example 'to fear' in both tragedies, were generally pronounced by the main characters in every act. Positive emotion words were rare and they generally appeared only in negative contexts. The verb 'to love' and the substantives 'passion' and 'happiness' in the tragedy of Othello, were always related to the idea of 'hate', and to the character of Iago. The inner emerging dynamics are invisible to a classical approach, the association of the character of Iago to the idea of 'hate' and 'anger' could be rather predictable, but the semantic slip of the idea of 'hate' hiding in term such as 'passion' and 'love' are not completely detectable without considering different level of complexity and different computational models, such as the one proposed to the present study. In Hamlet, the main character, according to his dramatic role in the play, had never pronounced the most meaningful substantives of the network of the term 'enjoyment'. Later, the computational approach allowed to calculate and to visualize the networks dynamics in Othello and Hamlet, detecting the main organization involved in this process, compared to the growth model and the communities of the WordNet networks.

### B. *Computer Simulation Results: Network Statistics for Emotional Terms*

The statistical values for the analyzed sample of networks, for the 5 emotional terms, till 5 levels, together with the communities of each network, were calculated. As for Othello and Hamlet, such values revealed a small-world structure and a broad scale behavior (see as example Tables III and IV). It was observed that the relationship between nodes varies from one term to the next, with a number of similarities among terms. It should be noted that for certain terms the overall number of nodes and edges is very high, and the number of nodes and number of edges are correlated. It also stands out that the term 'fear' is the one with the absolute highest number of nodes and edges, at all the levels that were taken into consideration (Table V and Figures 2, 3 and 4).

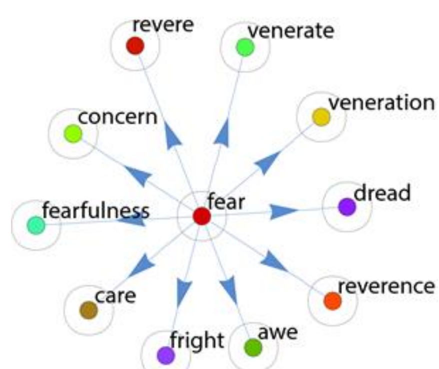


Figure 2. First level of the experimental run with the computational system R8_Overview.

TABLE I. STIMULUS-TRIGGER MODEL [20] APPLIED TO SOME CRUCIAL EVENTS OF THE TRAGEDIES (MANUAL ANNOTATION METHOD). MORE DATA IN APPENDIX A [43].

| Event | Stimulus Event: ‘threat’ | Cognition: ‘danger’ | Feeling State: ‘fear’ | Overt Behavior: ‘escape’ | Effect: ‘safety’ |
|---|---|---|---|---|---|
| Othello: ACT II SC III Othello is afraid of what Iago says about Desdemona and Cassio | Desdemona could betray him and fall in love with Cassio | Desdemona is unfaithful and Cassio is a betrayer | Fear of betrayal | He escapes the idea of a betrayal | Iago could be wrong and his love is not in danger |
| **Event:** | **Stimulus Event: ‘obstacle’** | **Cognition: ‘enemy’** | **Feeling State: ‘anger’** | **Overt Behavior: ‘attack’** | **Effect: ‘destroy obstacle’** |
| Hamlet: ACT II SC II Hamlet discovers the truth about the betrayal of his mother | The shame that the Queen threw upon Hamlet and his father must be revenged | Hamlet perceives his mother as an enemy: she is a betrayer | Disgusted by the Queen’s treachery, Hamlet is mad for anger | Hamlet prepares his revenge against the Queen | He is going to destroy his mother, revenging his father |

TABLE II. SMALL-WORLD PARAMETERS [30].

| Network | γ | λ | σ |
|---|---|---|---|
| **Hamlet** | | | |
| ‘fear’ | 2.32095 | 0.96244 | 2.41154 |
| ‘anger’ | 1.67713 | 0.99621 | 1.68352 |
| ‘joy’/’enjoyment’ | 2.00461 | 1.00792 | 1.98886 |
| ‘love’ | 1.70119 | 0.99388 | 1.71167 |
| ‘sadness’ | 1.96461 | 0.97257 | 2.02008 |
| **Othello** | | | |
| ‘fear’ | 1.54020 | 1.00695 | 1.52956 |
| ‘joy’/‘enjoyment’ | 1.42291 | 1.01292 | 1.40476 |

TABLE III. FIT RESULTS FOR THE DEGREE DISTRIBUTION OF THE NETWORK OF THE TERM ‘FEAR’, SUGGESTING A TRUNCATED POWER LAW.

| ‘fear’ | Truncated Power Law | | | | Power Law | | |
|---|---|---|---|---|---|---|---|
| | *a* | *b* | $k_c$ | $R^2_{adj}$ | *a* | *b* | $R^2_{adj}$ |
| in | 1.041 | -1.096 | 22.24 | 0.999 | 1.007 | -1.5 | 0.996 |
| out | 0.295 | 0.035 | 9.435 | 0.9994 | 0.355 | -0.675 | 0.804 |
| tot | 0.957 | -0.779 | 66.16 | 0.976 | 0.976 | -0.895 | 0.969 |

| ‘fear’ | Exponential Law | | |
|---|---|---|---|
| | a | $k_c$ | $R^2_{adj}$ |
| in | 1.652 | 1.783 | 0.962 |
| out | 0.3 | 9.956 | 0.9992 |
| tot | 0.817 | 5.64 | 0.83 |

TABLE IV. SMALL WORLD PARAMETERS FOR THE NETWORK OF THE TERM ‘FEAR’, WHICH IS A VERY MUCH CLUSTERED AND SMALL WORLD NETWORK.

| ‘fear’ | *n* | *γ* | *λ* | *σ* |
|---|---|---|---|---|
| | 8228 | 60.81 | 1.226 | 49.61 |

Results from the other experimental runs are presented in Appendix B [43]. The degree was also distributed among individual networks in accordance with the terms that presented a very high correlation between nodes and edges.

Networks clustering peaked in correspondence with ‘anger’ and ‘sadness’, reflecting high search levels in the WordNet repository. On the other hand, the networks’ efficiency seemed to follow a trend that was only marginally significant to increase in search levels. Another important element was represented by the network’s diameter, which grew in correspondence with the increase in size of the linguistic networks. A comparative analysis about simulated and inside the tragedies communities was made and it is reported in the following paragraph.

TABLE V. NETWORK STATISTICS (n=NUMBER OF NODES, m=NUMBER OF EDGES, <k>=AVERAGE DEGREE, C=CLUSTERING COEFFICIENT, E=EFFICIENCY, <L>=AVERAGE PATH LENGTH, d=DIAMETER, δ=DENSITY) FOR THE TERM ‘FEAR’ FOR FIVE EXPERIMENTAL RUNS.

| Net | n | m | <k> | C | E | <L> | d | δ |
|---|---|---|---|---|---|---|---|---|
| Fear1 | 11 | 10 | 1.82 | 0 | 0.09 | 0.48 | 1 | 0.09 |
| Fear2 | 72 | 98 | 2.72 | 0.08 | 0.07 | 2.3 | 3 | 0.02 |
| Fear3 | 393 | 769 | 3.91 | 0.16 | 0.05 | 3.66 | 5 | 0.005 |
| Fear4 | 2178 | 4778 | 4.39 | 0.17 | 0.04 | 4.73 | 7 | 0.001 |
| Fear5 | 8228 | 23521 | 5.72 | 0.23 | // | 5.41 | 13 | 0.0004 |

### C. Analysis of both Computational and Manual Networks

The various search algorithms that were developed contributed to the creation of completely different networks, identifying the relationships within WordNet’s deep structure. In order to collect all of the experimental data, the search algorithm $R_8$*_Overview* was used. For each emotional term, the search variable ALL was applied (thus the algorithm searched for and inserted in the network all the grammatical categories for the studied term, only varying in the depth level – in this case, from level 1 to level 5). For each search level, the relationships established between terminal nodes were not taken into account.

### D. Computer Simulation Results: Emerging Cognitive Attractors

The term ‘love’ was used as an example. Two fundamental dynamics showed noticeable phenomena, both quantitative and qualitative.

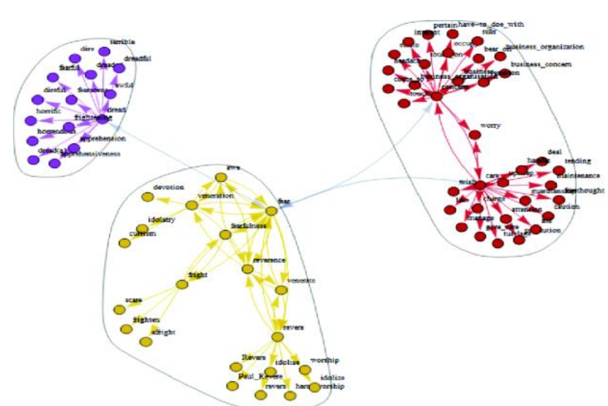

Figure 3. Second level using the function R8_Overview, for the term ‘fear’. It shows a significant network’s growth and three communities.

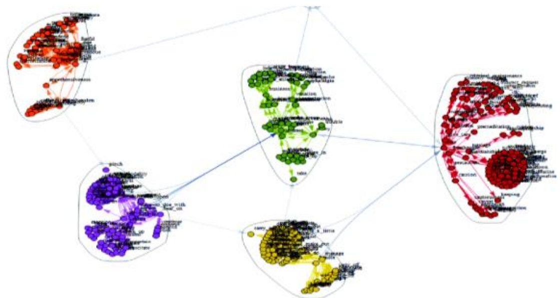

Figure 4. Third level using the function R8_Overview, for the term 'fear', with a greater growth rate of both the network and the communities.

*1) The Growth of the Network Structure Through the Function R8_Overview*

Networks analysis was carried out using the software Mathematica. The program to achieve communities of networks with this software is given in the Appendix C of supplementary materials [43]. This network is composed by a mix of names and verbs, related to the term 'love' in all its varieties of manifestation and behavior.

The first levels of the system and the communities of the network (Figure 5) showed strongly connected terms, sharing mutual meaning relationships: links are bidirectional. In fact, there is a clustering of terms based on the communities to which they belong. The verbs of the first experimental run for the word 'love' have reciprocal links, which create an emerging structure with terms very close from the semantic point of view. The emerging structure is a complete graph (see following paragraphs for details). The second community presented different relationships, less dense and more distant, and moreover, with a different spatial organization. From a cognitive perspective, these differences in topology may imply a greater clustering of terms (denser neighborhoods [10]), resulting in a higher availability of the terms of one community compared to another.

In the second level of the network, the number of communities arose from 2 to 4 and, as before, the dynamical reorganization of meanings was complex. The denser community didn't change throughout the growth processes, while the other community acquired new terms. These additions let the three new communities emerge, i.e., three new network topologies. A growth that was significantly different from Barabási and Albert's preferential attachment [23] was observed in this case, given that each node had the possibility to develop in multiple dimensions of the semantic space.

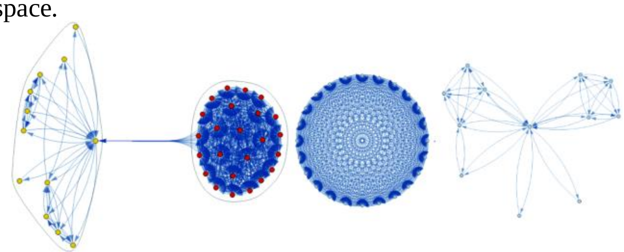

Figure 5. Communities of the first growth level of the term 'love'. The whole network is showed on the left, and the communities on the right.

At level 4, this phenomenon kept getting more and more complex: here, the computational system collected a network composed by 290 nodes and 2546 edges, structured over the 13 communities.

Many of the communities among the 13 formed in this level, though still belonging to the term 'love', created in turn second level structures, which reproduced the structures observed at the first depth level of search algorithm. Topologically, similar structures emerged in this network, with the same spatial organization, but with different terms.

These structures started to grow in neighborhoods characterized by highly connected terms, or in neighborhoods, which were globally poorly dense, but locally dense. From this analysis, generative growth models were detected: they worked combining their own growth mechanism to other existing ones, thus realizing creative cognitive processes of terms association.

*2) The Associative Dynamics Obtained through the Functions R2_Hypernyms, R3_Hyponyms and R6_Synonyms*

The simulations with the functions R2_Hypernyms, R3_Hyponyms and R6_Synonyms revealed interesting behaviors of terms organizations. Again, using 'love' as an example, simulations were run for the three functions at level 4, in order to understand the general dynamics of aggregation and the related network topologies that sustained such functions.

For the function R2_Hypernyms, the computational simulations gave the network (Figure 6) showing behaviors of terms aggregation, which were similar to the synonyms.

As for the function *$R_3$_Hyponyms*, instead, the topological organizations of the emerging communities were different. The relationship between nodes and edges had the same nature for synonyms and hypernyms, changing for the hyponyms network.

As regards the function *$R_2$_Hypernyms*, it showed behaviors of terms aggregation that are similar to the synonyms, as can be seen in Figure 7.

As for the function *$R_3$_Hyponyms*, instead, the topological organizations of the emerging communities are different, as showed in Figure 8. In this last network, communities were not linked: hypernyms network showed a greater amount of communities as for the other two functions, but these communities were composed by terms settled in non-densely populated neighborhoods, which somehow linked themselves to the key terms of every detected sub- community.

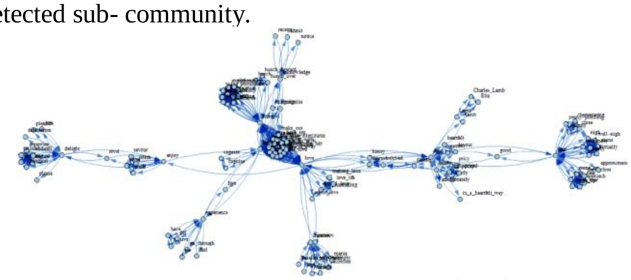

Figure 6. Network obtained by R2_Hypernyms starting from the term 'love', and realizing a structure composed by 125 nodes and 1142 edges.

Figure 7. Communities of the hypernyms network of ‘love’. The structure had 168 nodes and 1480 edges.

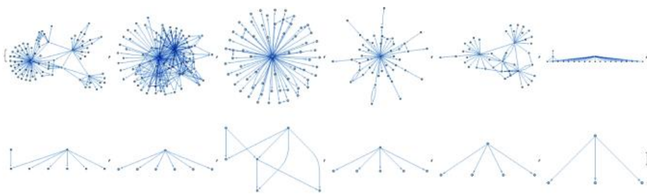

Figure 8. Hyponyms network, presenting 370 nodes and 758 edges. The aggregational structures are limited to few terms, often not interconnected.

What emerged were structured dynamics hiding in both computational and cognitive modeling, similar to a mental lexicon organization, shaped by the processes of clusterization according to semantic fields and grammatical categories or according to a set of stimulus-reaction families, which activated different cognitive spreading activation dynamics of meaning.

The clusterization of emotional terms at the first level appeared as a structured set of three main collections linked to the central term love. The emerging idea is that terms clustered according to grammatical categories, where verbs topologically and quantitatively represented the main nucleus and two outlying clusters composed by adjectives and substantives fork, changing the main geometry. At the second level of growth, the communities arose with the grammatical clusterization of substantives and related hypernyms, hyponyms and synonyms. The third level totally broke the initial topology of the network, creating new ramifications, which semantically blended. The term love reached its whole geometry covering with brand-new meanings. The emerging grammatical phenomenon is the absence of relevant new verbs, in fact, newly appeared categories were substantives, adjectives and adverbs. The existing set of adjectives near the meaning of ‘dear’ increased its cluster, strengthened its connotation and mixed grammatical categories. At this level, emerging phenomena focused on specific growing principle and structured dynamics hiding in computational modeling and similar to a mental lexicon organization.

### *E. The Resulting Dynamics for Othello and Hamlet*

The emergence of communities was analyzed in the five networks related to the five basic emotions in Hamlet and Othello as well (Figure 9).

#### *1) ‘anger’*

Starting with Othello (Figures 10 and 11), the first level of connection of the central term was related to the concept of ‘evil’. The growing process of the synonym network proceeded in a shading semantic path, sliding from the notion of ‘fury’ and ‘rage’, to the conceptualization of ‘bad’ and ‘evil’. First high degree nodes arose as central architecture of meaning where the emotional lexicon was shaped. At an advanced growth level ‘foul’ created a new geometry, connecting the meaning of ‘evil’ and ‘bad’ to the concept of ‘madness’ with the term ‘foul’. The creative process seemed to model the shade of meaning according to the cognitive dynamics involved in the play. There were different levels of synonymy, which modeled the topology of the network.

The second major clustering of the network reorganized the semantic space, moving from the concept of ‘madness’ to the cluster with the highest degree node ‘caitiff’. The new shade of meaning shuttled to another dimension and affected the initial denotation of ‘anger’, according to the well-known plot of Othello, where the idea of ‘evil’ and ‘anger’ was strictly related to ‘dreadful traitors’. The term ‘anger’ was analyzed in detail in Hamlet too, through the visualization of three time steps of its network evolution, from a single node to a small synonymic network.

At time step 1 (see Figure 12), ‘anger’ linked itself to other key terms such as ‘rage’, ‘choler’ or ‘wrath’, reproducing results that were similar to WordNet networks, where they were considered pure synonyms of ‘anger’. Due to diachronic mutations of semantic areas of the terms, in this step other words were included as synonyms, such as ‘gall’, ‘distemper’ or ‘venom. These elements gave remarkable hints about the author perception of the emotion ‘anger’, always focused on poisonous and contagious elements. Unsurprisingly, at the second level of the network (Figure 13) terms as ‘poison’ and ‘contagion’ appeared, progressively expanding the semantic area covered by the initial node ‘anger’. It is interesting to note the immediate presence of the term ‘madness’ in the network, already at level 1 of its evolution and growing at level 2, linking to other existent nodes such as ‘choler’, Furthermore, ‘lunacy’ was added as node to the network configuration. ‘madness’ and ‘poison’ (which are the two leitmotifs in Hamlet’s plot) were well-represented concepts in Shakespearian language production networks.

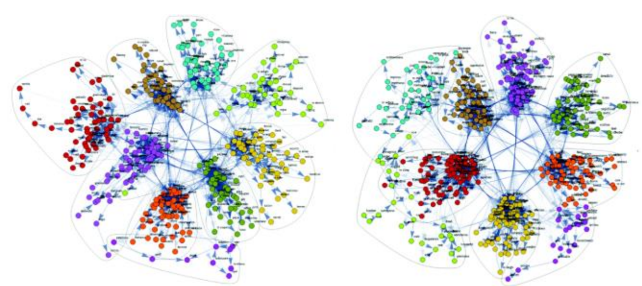

Figure 9. Communities of emotional words in Othello (left) and Hamlet (right).

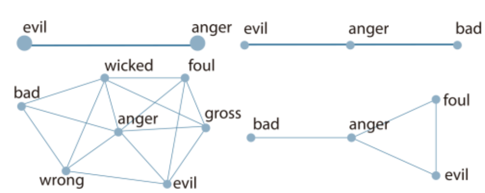


Figure 10. The network of emotion ‘anger’ in Othello at levels 1, 2, 3 and 5, clockwise.

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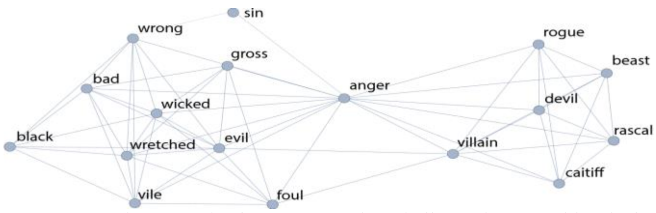


Figure 11. The network of term ‘anger’ in Othello, at the second level of clustering on the left.

*1) ‘fear’ and ‘joy’*

‘fear’ and ‘joy’ were analyzed as well. Two levels of growth were found by using both methods: the computational and the manual one showed few similar results. The term ‘joy’ reflected the same dynamics of growth. In the computational model, the starting point was a first setting of direct synonyms, which clearly belonged to the semantic field of ‘joyfulness’. As seen in Figure 14, the manual model, at the first level, reproduced a structure of cognitive organization similar to WordNet communities, connecting the word ‘joy’ with a specific set of word (‘delight’ and ‘pleasure’).

The second level detached from the probability rules of the computational model, clustering the terms according to different cognitive processes, used in the creation of the tragedy’s plot. Then, the term ‘joy’ acquired a different shade, growing in a non-linear sense, towards the semantic field of ‘satisfaction’ and ‘bliss’ with a hidden idea of ‘revenge’. This outcome was due to the differences in the structural properties of the two networks: the computational one grew by searching into a bigger database (WordNet) and looking for various kind of connections, while the manual one focused on the search of strong (mainly synonymic) links inside the pool of words used by Shakespeare in Hamlet. It is noticeable that while the first network allowed a general exploration of the semantic space of the ideal term ‘fear’, the second network was strictly indicative of Shakespearean lexical choices. The relationship between the same term in the two networks reflected the relationship of a ‘type’ with its ‘token’, where a ‘type’ represents a prototypical concept, and the token represents one of its possible real occurrences (in this case, the one chosen by the author of the tragedy).

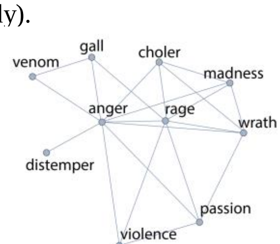


Figure 12. The network of the term ‘anger’ in Hamlet, at level 1.

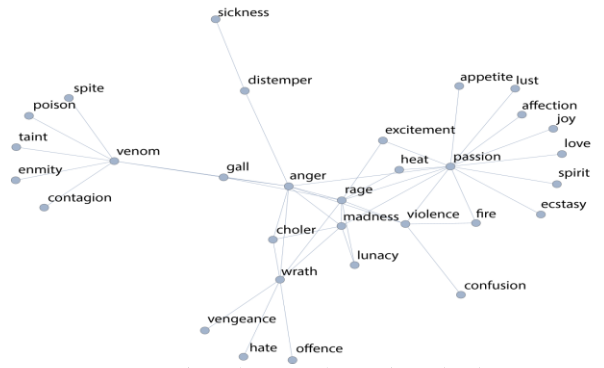


Figure 13. The node ‘anger’ in Hamlet, at level 2.

*2) Body and Emotions Dynamics in Othello and Hamlet*

Physiological changes due to specific emotions represent reparatory reactions to specific events [31]. Most of these modifications are highly visible, such as increase/decrease in heart rate, changes in skin complexion, etc. A deep analysis of the metaphors and images consciously or unconsciously associated to emotional states helped clarifying the way emotions are perceived. In the networks, we found a good example for this phenomenon, useful to discover how the characters of the plays sensed emotions. In Figure 15, the cluster in the network revealed how ‘mourning’ and ‘sorrow’ were expressed through a group of interconnected verbs. Sorrow expression was linked to hearing and voice. Thanks to clusters visualization, it was easy to study verbs such as: ‘to mourn’, ‘to weep’, ‘to grieve’, and ‘to lament’. They shared different auditory variations of the same sense, through which ‘sorrow’ became concrete and audible. Tables opened the possibility to enter in the character’s inner sensing and understand how an emotion shaped its body and mind.

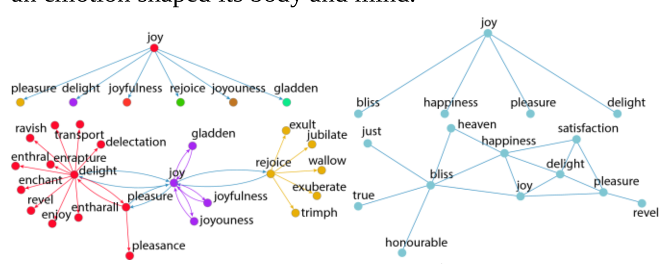


Figure 14. Growth levels Comparative analysis (first top and second level bottom) of the term ‘joy’: manual (right) and computational (left) methods.

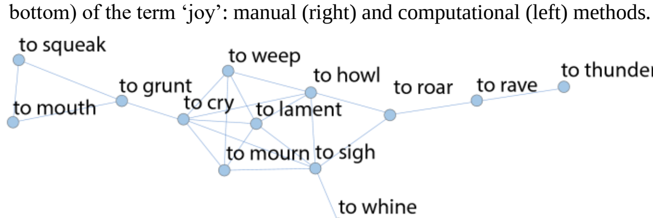


Figure 15. ‘sadness’ (Hamlet). Focus on the cluster of verbs representing pain and its expressions.

*3) The Emotional Continuum in Cognitive Phenomena: Dynamical Transitions*

Generally, emotions are described as a discrete phenomenon [32][33]. In real situations, subjects experiment a continuous passage from one emotion to another, giving the change of the variables (internal and external factors) that influence cognitive behavior [34].

We use networks and communities of emotional words as indicators of these complex changes in Shakespearean characters. In fact, networks visualizations made visible the intersection points between different emotional words. It allowed us to identify those terms recurring in every (or almost every) emotional phenomenon, as can be seen in Table VI for Hamlet and Othello.

TABLE VI. CROSS-EMOTIONAL TERMS IN HAMLET AND OTHELLO

| Hamlet | 'fear' | 'anger' | 'sadness' | 'love' | 'joy' |
|---|---|---|---|---|---|
| 'blood' | + | + | + | + | - |
| 'soul' | - | + | + | + | - |
| 'heart' | - | + | + | + | + |
| 'passsion' | - | + | + | + | - |
| 'madness' | + | + | + | + | - |
| 'fire' | + | + | + | + | - |
| 'bosom' | - | + | + | + | - |
| 'heat' | - | + | + | + | - |
| **Othello** | | | | | |
| 'blood' | - | + | + | - | - |
| 'soul' | - | + | + | + | + |
| 'heart' | + | + | + | + | + |
| 'love' | - | + | + | + | - |
| 'happiness' | - | + | + | + | + |

### F. *Emerging Motifs as Cognitive Attractors*

After this initial work, we found that cognitive networks, not only created structured connections between terms, but such terms, far from being arranged randomly, had an organization. We assisted to the emergence of self-organizing structures [35][36]. In discrete dynamic systems, such as Cellular Automata, said motifs are known as gliders [37], and are responsible for the stowing and transportation of information [38][39]. Similarly, the growth of linguistic networks produced increasingly complex structures, showing that there existed many modalities of network growth: at the global level, within the social/cultural expression of emotions, and at the community of words level, within the large domain of the characters dialogue. Well organized patterns were observed, recalling platonic solids and other multidimensional geometric figures. Each motif was preceded by the starting emotional noun and followed by a number. The latter defined the order of appearance of the motif within the growth of the emotional linguistic network. An iconographic apparatus was associated to each motif: two images that present the constitutive elements of the motif itself in two dimensions, one with linguistic tags and one without, and one three-dimensional image. Some explanatory examples are provided below.

### G. *Complete Graphs, Symmetries and Breaches of Symmetries*

Complete graphs were composed of n nodes, each of which was connected to all of the other ones. These motifs possessed both reflective and translational symmetries. Since the detailed study of said symmetries went beyond this article's objectives, for further details please see [40]. For explanatory purposes, it must be pointed out that polygons have two dimensions, prisms are three-dimensional objects (whose volume is composed of a finite number of planar polygons), and polytopes have various dimensions (4, 5 . . . n . . .), known as polychorons. The concept of polytopes extends that of prism to various dimensions. Some of the emerging motifs that were found belonged to the prism category and others to the polytopes category.

A second category of motifs was similar to the previous one, although some of the edges were removed: this resulted in the loss of some symmetries, also known as breach of symmetries. The latter had a very complex organizational nature; for example, the breach of two symmetries, if appropriately situated, could restore symmetry [41]. This category of motifs highlighted the presence of non-conventional symmetries of great interest to the previously presented cases. Many of these motifs presented a pair of elements joined by a double bond that pointed to other nodes situated in a plane orthogonal to the pair's axis. For example, AngerEP_C1 presented a pentagonal structure orthogonal to the pair's axis. The most outstanding symmetry in this structure was the 72° rotation, as in the traditional pentagon. Similarly, AngerEP_C3 presented an octagon on the plane orthogonal to the pair's axis, with a rotational symmetry of 42°. Examples of said motifs are presented in Figure 16 with the labels on the left, the link directions in the middle, and 3D structure on the right. AngerEP_B1 (containing the term ira, synonym of anger and degenerated to other meanings) and DisgustEP_B1 underwent a break of symmetry.

### H. *Motif Composition*

The emergence and breach of symmetries provided information regarding the extraordinary compositional abilities of the organizational and semantic structure of language. The sequence of motifs and patterns highlighted the typical nature of a generative grammar, significantly recalling the language of chemistry and the formation of biological macromolecules. Figure 17 shows some examples of the motifs AngerEP_D1 and AngerEP_D2, which identify attractors of emotional terms.

A variant of this structure was found in DisgustEP_D3, where a 3-simplex and a triangle related to the pair's axis. This case also presented a double breach in symmetry that reproduced another symmetry. Motif DisgustEP_D4 was more complex and difficult to visualize (and represent). Parallel to a plane containing a triangle, a square developed on a plane to one side, and a triangle to the other side, resulting in a breach of symmetry. The motif DisgustEP_D5 highlighted the emergence of a complex structure, starting from a complex 3-motif graph, from which several bonds with other motifs unraveled, situating themselves in a variety of manners across space. The motif ExpectationEP_D1 was particularly interesting: two

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complete graphs composed of a 9-simplex and a 3-node motif, joined around the axis of a node pair. The two nodes connected, one opposite the other, to the central pair and to one of the motifs, respectively.

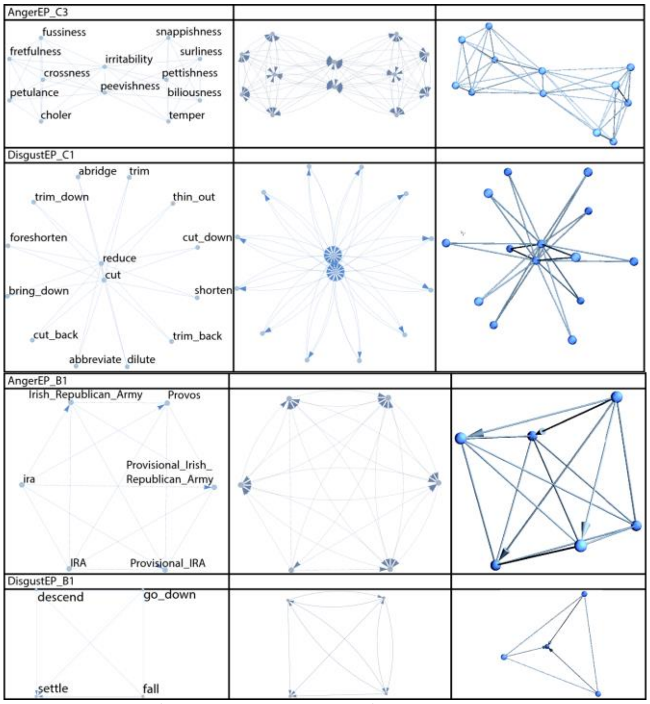

Figure 16. The figure shows examples of symmetries that intercept the semantic organization of two emotional terms.

This kind of visualization highlighted a typical feature of emotions: they tend to blend and mix in a sort of continuum [42], with no clear borders.

## IV. CONCLUSIONS

This analysis was a non-conventional study of texts full of emotional cognition: Hamlet and Othello, the two well-known Shakespeare's tragedies. The aim was to convert these masterpieces in a multi- dimensional field of exploration in order to understand how the creative processes in the Shakespeare mind modeled an emotion, how the emotional words semantic network was involved in the process, and how a character, like any other person, felt and expressed an emotion inside communicative contexts.

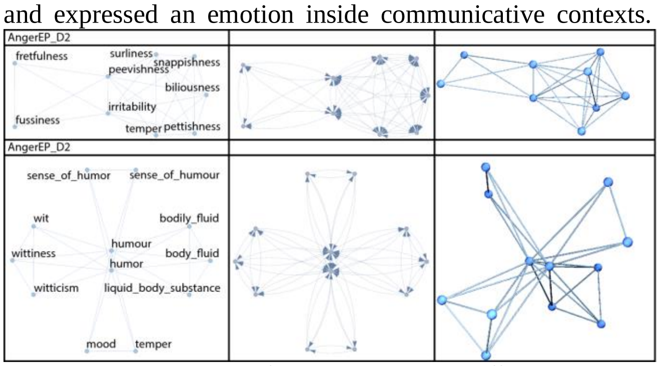

Figure 17. This collection of images represents two different semantic organizations for the emotional term 'anger'.

The first step was the creation of a list of names, verbs, adjectives, adverbs and sentences for five specific emotions, manually segmented from both plays. Terms referred to 'anger', 'love', 'sadness', 'joy' and 'fear' and their related semantic fields were selected. The list included specific characteristics for each term, such as who pronounced it, when it appeared in the plays, its context and the perceptual modality by which it was expressed. Then, complex systems theory was applied to the analysis of emotional cognition and these words were transformed into networks. The investigation was further explored by interconnecting the first skeleton of words with WordNet, thus allowing the flourishing of emotional words organization patterns, emerged from the interaction of many basic components at several levels of complexity.

The investigation highlighted the following issues:

- emotional states represented dynamical conditions explained through linguistic and behavioral complex configurations;
- transitions existed at different emotional states;
- linguistic and behavioral attractors were detected as stable configurations or related words patterns, which demonstrated complex organization, with symmetries and breaches;
- such attractors were identified by a set of variables describing environmental, cognitive and physical features of the main characters of both plays;
- patterns variations demonstrated the same features of chaotic systems: small changes in variables' values involved abrupt qualitative behavioral changes (both in corporeal and cognitive states changes). The transition from one attractor to another could represent phase transitions from an emotional state to another;
- complex organization motifs can be found in both the plays and in the WordNet search networks, that not only highlighted the complexity of the neighborhoods of each emotional term, but that such neighborhoods came with special organized structures, with different geometrical features, which arose during linguistic production.

The emotional terms networks' growth showed a different level of complexity for the various terms, which far from being strictly ordered, created many cognitive organization patterns. Results showed the evolution of the story plot connected to the growth of the emotional cognition networks, at the single character, and at the global level, particularly represented by transitions among different kinds of emotions, that demonstrated the complexity of the emotional dynamics in the characters of both plays.

The innovative contribution of this paper was to highlight how these elements are brought together in an extraordinary variety of patterns and dynamics, which according to us can represent an expression of cognitive organization of emotion.

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