Text to multi-level MindMaps

A novel method for hierarchical visual abstraction of natural language text

Mohamed Elhoseiny · Ahmed Elgammal

Received: 20 July 2014 / Revised: 22 December 2014 / Accepted: 12 January 2015 / Published online: 21 April 2015 © Springer Science+Business Media New York 2015

Abstract MindMapping (Tony Buzan and Harrison, 2010) is a well-known technique for note-taking, which encourages learning and studying. MindMapping has been manually adopted to help present knowledge and concepts in a visual form. Unfortunately, there is no reliable automated approach to generate MindMaps from Natural Language text. This work firstly introduces the MindMap Multi-level Visualization concept that jointly visualize and summarize textual information. The visualization is achieved pictorially across multiple levels using semantic information (i.e. ontology), while the summarization is achieved by the information in the highest levels as they represent abstract information in the text. This work also presents the first automated approach that takes a text input and generates a MindMap visualization out of it. The approach could visualize text documents in multi-level MindMaps, in which a high-level MindMap node could be expanded into child MindMaps. The proposed method involves understanding of the input text and converting it into intermediate Detailed Meaning Representation (DMR). The DMR is then visualized with two modes; Single level or Multiple levels, which is convenient for larger text. The generated MindMaps from both approaches were evaluated based on human subject experiments performed on Amazon Mechanical Turk with various parameter settings.

Keywords Text visualization · Multi-level MindMap Automation · Text summarization · Text Abstraction · MindMapping
1 Introduction

MindMapping was introduced as a visual note-taking technique, developed by Tony Buzan in the 1960s [47]. It is a useful pictorial method for representing knowledge, concepts and ideas. Figure 1 shows a MindMap example that illustrates William Shakespeare’s biography. It is not hard to see that by just looking at this picture, it is easy to recall many aspects of Shakespeare’s life, which is one of the MindMap benefits. Creating MindMaps itself is also interesting compared to linear text. It also improves imagination and meanwhile it is fun.

“Linear note-taking has served as one of the greatest impediments to learning,” says Tony Buzan. However, he claimed that linear note-taking constraints the brain’s potentials by forcing it to use limited modes of expression and hence it fails to stimulate creativity [47]. According to Buzan, the main motivation behind MindMapping technique is that, unlike linear text, using pictorial representation of ideas stimulates both sides of the brain (left and right) [47]. However, there are scientific doubts about Buzan’s argument on the brain hemispheres. For example, a recent neurological study performed on 1000 subjects showed that the brain is more complex than this claim of left and right-sided brain [8]. They divided the brain into 7000 regions and they found no evidence that the human subjects had a stronger right or left-sided hemisphere network.¹ Despite that Buzan’s justification of MindMaps by brain hemispheres is mere popular psychology and not scientifically justified, there are a lot of studies that shows that the MindMapping is a powerful and effective technique to access information and to encourage learning, studying and reading (e.g. [14, 17]).

With today’s vast and rapid increase in the use of electronic document readers, smartphone, and tablets, there is an eminent need to develop methods for visualizing and summarizing textual contents. We argue that MindMapping is not only a note-taking tool, but also can be developed to serve as a powerful tool for joint text summarization and visualization. Converting a text paragraph to a MindMap would provide an easier way to visually access the knowledge and ideas in the text.

One of the reasons why many people may not create MindMaps is that it needs a huge mental effort and concentration, specially for MindMapping a big text. Besides, only few people are creative enough to draw good MindMaps. To the best of our knowledge, there is no existing method to build MindMaps from raw text according to the joint text summarization and visualization concept that we develop in this paper. The goal of this work is to develop a framework that takes a text input and generates a MindMap visualization out of it; a former version was presented in [16]. Our framework is constructed to visualize large text documents in the form of multi-level MindMap, in which a high-level MindMap node could be expanded into a child MindMap. Figure 2 shows a MindMap automatically generated by our framework for the Shakespeare example in a single level and multiple levels (his life and work information are expanded as two child MindMaps).

There are various potential applications for automatically created MindMaps using our framework. For example, audio recording of notes can be converted into text that is passed into our framework to generate a MindMap notes. A lecturer can utilize the framework to prepare presentations by converting text to MindMaps. Furthermore, the generated hierarchical MindMaps would help make MindMap presentations more common due to minor effort and time needed to create them. Finally, MindMaps visualization could help users of electronic book readers to better access information through them.

¹More discussion on this study is covered by the guardian http://www.theguardian.com/commentisfree/2013/nov/16/left-right-brain-distinction-myth
The contributions of this paper are:

1. We introduce MindMapping as an approach to jointly visualize and summarize textual information. Visualization is achieved pictorially across multiple levels using semantic information (i.e. ontology), while summarization is achieved by the information in the
highest levels. Our work could also be viewed as a method to visually abstract textual information in multiple levels.

2. We propose a novel approach to generate Single and Multi-level MindMaps from pure text and an input Ontology.

3. Two methods are proposed for retrieving relevant pictures from the web.

4. First comprehensive evaluation of an automated MindMap framework by human subjects.

The rest of this paper is organized as follows. Section 2 presents the related literature. Sections 3 to 7 describe the proposed framework and techniques. Section 8 describes the evaluation procedures and shows the results using different system parameters. Section 9 presents our conclusion and the future work.

2 Related work

Our formulation addresses the problem as a hybrid between text summarization and visualization. In the context of text summarization, the top-level MindMap serves as a summarized version/abstraction of the document. Meanwhile, the detailed information of textual content could be visually accessed through a hierarchy of MindMaps. This section presents related work in text summarization and visualization literature, as well as a connection to Concept/Topic Maps. We also review existing systems for MindMapping.

2.1 Text summarization

Several approaches have been proposed for text summarization [13]; key approaches follow. Conroy and O'leary [11] used Hidden Markov Models (HMMs) to model the problem by sentence extraction/selection from a document considering local dependencies between sentences. Later, Osborne [42] used log-linear models to obviate the feature independence assumption in previous models as he claimed and showed empirically that the system produced better extracts than a naive-Bayes model, with a prior appended to both models. Then, Kaikhah et al [24] trained a Neural Network model from the labels and the features for each sentence of an article, that could infer the proper ranking of sentences in a test document. Other approaches use deep Natural Language Processing (e.g. [34], where Marcu et al merged the discourse-based heuristics with traditional heuristics).

While, text summarization provides a reasonable resolution to the growing information overload, it does not provide an organized access to the document information. This limits its capability to structurally localize the information of user’s interest in a given document, which introduces a key motivation for our multi-level MindMap visualization concept.

2.2 Text visualization

Some of the state-of-the-art text visualization techniques build on tag clouds. Examples include work conducted by IBM in Wordle, which is a web-based text visualization method that creates a tag-cloud-like displays with careful attention to typography, color and decomposition [48]. The generated clouds give greater prominence to words that appear more frequently in the source text. Van Ham et al. [21] presented PhraseNet technique, which diagrams the relationships between different words in the text. It uses a simple form of pattern matching to provide multiple views of the concepts contained in a book, speech,
or poem. Recently, Afzal et al. [1] integrated spatial constraints to automatically visualize textual information on typographical maps. There are three significant differences differentiate our work from the aforementioned works. First, their algorithms do not involve deep understanding of the text. Second, each node is visualized with the word itself. However, in MindMaps, visual nodes could be mapped into pictures of a concept and its properties (e.g., car with red color attribute). Third, our approach can generate multi-level representation, which is not supported by Wordle, PhraseNet or Afzal’s method. Figure 3 shows the example visualizations for Wordle and PhraseNet models.

Topic models and semantic representations have been adopted to help organize and visualize information. In this direction, Feng et al. [18] developed a model for multimodal meaning representation, based on linguistic and visual context. The approach exploits enormous resource of documents and associated images available on the web. A relevant application is the automatic conversion of text to 3D animation. Ma [32] proposed Lexical Visual Semantic Representation (LVSR) which connects linguistic semantics to the visual semantics and is suitable for action execution. This application involves deep analysis of the text converting it into user defined concepts by which it converts the text into actions to be performed on 3D graphically animated models. In addition, Coyne et al. [12] presented a method that incorporates lexical and real-world knowledge to depict scenes from language. However, these approaches are constrained to limited number of predesigned 3D-models and relations and are not hierarchical. Recently, Dou et al. [15] presented an approach to visualize text collections using topic hierarchies. While, their approach provides a reasonable access to visually explore text corpus, our approach addresses pictorial visualization and abstraction of a chosen textual document by the MindMap Visualization concept. In addition, the explored hierarchy in [15] are topic based, while the hierarchy provided by our visualization is based on semantic abstraction of the textual input content. As an illustration, our approach could be integrated with the approach [15] to visualize a document selected by exploring the topic hierarchies, organized by [15].

2.3 Topic maps and concept maps

Concept maps [40] have been used to express people’s understanding about a specific topic. For few decades, this tool has attracted people of all ages and different knowledge domains. They include concepts usually enclosed as boxes or circles and relationships between these concepts indicated by a connecting line. Topic maps [33, 43] are very similar to Concept

![Fig. 3 Wordle (left) [48] and PhraseNet (right) [21]. These examples from the web that are available at [28] and [49]](image_url)
Maps, however Topic Maps are standardized. It has been defined as a form of semantic web technology and significant work has been done to address interoperability between the W3C’s RDF/OWL/SPARQL [50]. The current standard is taking place under the umbrella of the W3C committee [50].

In contrast to Concept Maps and Topic Maps, MindMapping often includes, but is not limited to radial hierarchies (where central ideas is in the center, while connected to related entities around it) and tree structures. Another difference is that a MindMap reflects people’s thoughts about a single topic, while Concept Maps/Topic Maps can present a real or abstract system or a set of concepts, which is not restricted to specific topic.

The majority of the literature has focused on the representation of topic maps and concept maps to enhance some NLP tasks (e.g. parsing, Word Sense Disambiguation [38], etc). Rather, we would like to view these maps as a powerful tool that could be used to jointly visualize and summarize information. In particular, we present the concept of multi-level/hierarchical MindMaps as a notion of visualizing textual information in multiple levels. Higher levels reflect coarse information in the text document, while lower levels present the fine details. We chose to name it multi-level/hierarchical MindMaps because MindMaps are (1) less restrictive on the representation than Concept and Topic Maps, (2) topic-oriented, which is relevant in the setting we utilize (i.e. representing information from textual description), and (3) in our experiments, we focus on topics that could be presented as a single central idea, which is consistent with the MindMap notion. However, we argue that most of the text descriptions could be presented by a set of central ideas which could be visualized by MindMaps. Hence, we don’t restrict our definition of Hierarchical MindMaps to topics of a single central idea. We focus in this paper in the steps, we designed to generate the multi-level MindMap from a textual description.

2.4 Existing MindMapping systems

There are two ways for creating a MindMap. One way is manually, by using a paper, pens and colors, but this requires reading and understanding the text well beforehand to design a good MindMap. Another way is to use existing software that just serves as an editing canvas, where a user can insert pictures and create relations between them (i.e., manually). Examples include “I Mind” [41], “Nova Mind” [46].

Finally, the most relevant work was conducted by Hamdy et al. [22]. They presented a prototype for the MindMap Automation, however, it was just a demonstration on few examples of few sentences and then it was applied in a mobile application in [26]. There are two critical drawbacks in this work. (1) It is almost an unevaluated demo. (2) It supports only single-level MindMaps. This limitation makes the approach incapable of representing information of a larger text. Hence, it can not support our concept of simultaneously visualizing and summarizing textual information.

3 Proposed framework

Our objective is to develop a method to jointly visualize and summarize textual information (we call multi-level MindMap visualization). We begin by presenting the outline of the approach through the data flow diagram in Fig. 4; we will present the details in later sections.

We first extract what we call Semantically Enriched Parse Trees (SEPTs) from the input text through a Text Semantic Preprocessing step that we implemented. The SEPTs consist of the parse trees for each sentence augmented with disambiguated senses at each terminal
node in the parse tree. Furthermore, for each anaphor node (e.g. pronouns), a pointer, to what it refers to, is stored. These SEPTs are then converted into a Detailed Meaning Representation (DMR) that represents all the information in the text as a graph. Then, the DMR is converted to a Multi-Level Meaning Representation (MLMR), which is a tree of meaning representations. Each node in the MLMR tree stores a Meaning Representation (MR) starting from the root node where its MR holds the most abstract information in the text to the leaves where details are presented. The final step in our framework is the MindMap Generation, which converts an input MR into its pictorial representation and dynamically allocate it on the screen. Hence, the MLMR could be visualized as a multi-level MindMap by traversing the MLMR tree and visualizing the MR of each node. It is worth mentioning that a single-level MindMap could be generated by running the MindMap Generation step directly on the DMR instead of Generating a MindMap for each node in the MLMR. However, if the input text is of a big size, the single-level MindMap would be quite unclear and unorganized. Figure 5 (middle part) shows an example, where single level Mindmap visualization hinders comprehension speed, simplicity and clarity. However, multi-level MindMap visualization is much clearer (see Fig. 5 bottom part).

An ontology is needed for both DMR Generation, to understand attributes of objects/subjects while creating the DMR, and for MLMR generation, to semantically group related entities in MLMR. Ontology is also used in the MindMap Generation step to determine whether a concepts needs to be pictorially represented; see Fig. 4. The details of the outlined approach is presented as follows. Section 4 details the Text Semantic Preprocessing (TSP) step. Section 5 presents the DMR generation approach. Section 6 presents the MLMR Generation. Finally, Section 7 presents the MindMap Generation step.

4 Text semantic preprocessing (TSP)

In this step, we extract sentence-wise information from plain text, which we call Semantically Enriched Parse Tree (SEPT). As aforementioned, each SEPT consists of a parse tree,
anaphora resolution (discourse analysis) results, and the intended sense for each word in the sentence. In order to compute the SEPTs, four main tasks are performed: (1) morphological analysis [51], (2) parsing [4, 10, 35] and syntactic structural analysis [27, 31], which produces a single parse tree that respects the structure of given sentence. (3) discourse analysis [29, 44] outputs anaphora resolution results (4) Finally, Word Sense Disambiguation (WSD) [2, 5, 38] determines the intended sense for each word in the sentence based on WordNet [37]. Having augmented the parse trees with the senses produced by WSD and the anaphora resolution results, the generation of a SEPT for each sentence in the text is concluded. In this work, we utilized recent approaches for such a well-studied phase in Natural Language Processing, as detailed in [22]. Other methods could be applied as long as they produce the SEPTs.

Figure 6 shows TSP output of the Shakespeare’s example. The bottom left part shows the generated parse trees as the output of the parsing and syntactic structural analysis. The bottom left part shows the discourse analysis output, which is anaphora resolution. “HE(2,1)” means the “HE” word that occurs as the first word of the second statement. The listing in the figure indicates that “Shakespeare (1,1)”, that occurred in the first word of the first statement, is referenced in the succeeding pronouns (i.e. “He(2,1)”, “His(4,4)”, etc).
top right part of the figure shows the meaning/sense of each word that occurs in the sentences, while grouped in the data structure for each statement. Augmenting the parse trees with the discourse information and senses directly produces the SEPTs. We denote the set of SEPTs extracted from the text by $P = \{p_i, i = 1 \rightarrow N\}$. We define $n$ to be a node in any of the SEPTs, we define $n.r$ as the node that $n$ points to in case it points to a previously declared noun/noun phrase, $n.r = NULL$ otherwise. $n.r$ could point to a node in a possibly different SEPT. We also define $n.s$ as the sense that $n$ means in case it is a terminal node, $n.s = NULL$ otherwise.

5 DMR generation

Designing a meaning representation for Natural Language Text implies understanding its content and representing it in a semantically accessible way. During DMR Generation, $P$ is converted to a further meaningful representation, which consists of conceptual frames and relations between them. There are two types of frames in our framework (entity frames and action frames). Entity frames represent entities mentioned in the text (persons, objects etc), while action frames represent activities in the text (i.e. verbs). Possible relations between the frames are case-role, domain and temporal relations. A Case-Role relation represents semantic role of an entity frame in a particular action. For instance, in “john plays football” sentence, the subject “john” has an “agent” case-role in the “play” action, and the object “football” frame has a “theme” case role in the same action. Temporal relations are interpropositional relations that communicates the simultaneity or ordering in time of events or states. Domain relations encode logical connection between action frames (i.e. verbs). Figure 7 illustrates different types of case-roles, domain relations and temporal relations that are designed in our framework. Having detected the frames and the relations, the final output of the DMR generation became a graph, whose nodes are the frames (action or entity...
Formally, we assume that DMR is a graph $G_d = (\mathcal{V}, \mathcal{E})$, where $\mathcal{E}$ is the set of entity and action frames (i.e. the nodes) and $\mathcal{E}$ is the set of relations including case-role, domain, and temporal relations (i.e. the edges).

**Algorithm 1** DMRGen

*Input:* $\mathcal{P} = \{p_i, i = 1 \rightarrow N\}$, Ontology $\mathcal{O}$, Parser CFG Dictionary $\mathcal{H}$

*Output:* $G_d = (\mathcal{V}, \mathcal{E})$ is a graph of entity and/or action frames as vertices, where related frames are connected by edges

*Initialization:* $\mathcal{V} = \emptyset, \mathcal{E} = \emptyset$

for all $p_i$ in $\mathcal{P}$ do

Initialize $\mathcal{E}^i = \emptyset$ and $\mathcal{A}^i = \emptyset$, where $\mathcal{E}^i$ and $\mathcal{A}^i$ are the entity and the action frames to be detected in $p_i$.

Initialize $\mathcal{R}_C^i = \emptyset$, $\mathcal{R}_D^i = \emptyset$, and $\mathcal{R}_T^i = \emptyset$, where $\mathcal{R}_C^i$, $\mathcal{R}_D^i$, and $\mathcal{R}_T^i$ are the case-role, domain, and temporal relations to be detected in $p_i$.

FillFramesAndRelations($p_i$, $\mathcal{E}^i$, $\mathcal{A}^i$, $\mathcal{R}_C^i$, $\mathcal{R}_D^i$, $\mathcal{R}_T^i$, $\mathcal{O}$, $\mathcal{H}$)

end for

return $G_d$

function FillFramesAndRelation $p$, $\mathcal{E}$, $\mathcal{A}$, $\mathcal{R}_C$, $\mathcal{R}_D$, $\mathcal{R}_T$, $\mathcal{O}$, $\mathcal{H}$

if $f_n$ is not NULL then

$fn(p, \mathcal{E}, \mathcal{A}, \mathcal{R}_C, \mathcal{R}_D, \mathcal{R}_T, \text{Ontology})$

else

for all $ch$ in $p$.children do

FillFramesAndRelations($ch$, $\mathcal{E}$, $\mathcal{A}$, $\mathcal{R}_C$, $\mathcal{R}_D$, $\mathcal{R}_T$, $\text{Ontology}$)

end for

end if

end function

The DMR generation procedure is illustrated in algorithm 1. The set of frames $\mathcal{V}$ and relations $\mathcal{E}$ are initialized to empty sets. In order to generate the DMR, each $p_i \in \mathcal{P}$ is traversed and the grammatical structure is followed to define subjects, objects, and verbs. Entity frames are created for objects and subjects. While action frames are created for verbs. We denote the set of entity frames in the $i^{th}$ sentence by $\mathcal{E}^i = \{e^i_1, e^i_2, \ldots e^i_{enq}\}$, and the set of action frames in the same sentence as $\mathcal{A}^i = \{a^i_1, a^i_2, \ldots a^i_{end}\}$. Each frame is augmented with its intended sense from the node information stored in the SEPTs (i.e. $n.s$). This step also includes adding attributes of each frame if any. For example, “small red ball”, a “ball” entity frame is generated with attributes “small” and “red”. The attributes were detected using the parse tree structure. In this case, “small” and “red” are adjectives of “ball”. In addition, the type of the attributes is determined by the ontology (e.g. red is a color attribute). Simultaneously, the relations (see Fig. 7) were created following the syntactic structure of the sentences to connect the generated frames. No new frames are created for anaphors, they are linked to the frames they refer exploiting n.r. The newly generated frames for each statement are added to $\mathcal{V}$ and they are connected by case-role, domain, and temporal relations following the parse tree structure. These relations are then added to the edges $\mathcal{E}$.

We name the function that fills all the frames and relation as “FillFramesAndRelation”, see algorithm 1.

Practically, we implemented the function “FillFramesAndRelations” by recursively traversing the given SEPT $p_i$ starting from the root node. Each node is processed according to the grammar rule that corresponds to it; this could be possibly any rule
that our parser allows. Each rule could be processed differently depending on how it produces frames and/or relations. For instance, entity frames are added to $E$ while processing a “Noun Phrase” (NP) node (see Fig. 6 Syntactic Analyzer Output). Another example is that domain relations are added to $R_D$ while processing a rule like $S = DS(“because”, “So that”—“So”) DS$, where there are two simpler statements ($DS$) separated by a preposition that indicates a reason or a result (e.g. “because”, “So that”, and “So”). Following the same idea, it is not hard to build a function for the rules of interest in order to fill the frames and the relations in each statement.$^2$ A hash table $H$ helps retrieve each of these functions based on the rule as a key. GetMatchingRuleFunction$(p, H)$ simply returns the function that processes $p$’s rule if one exist in $H$, and NULL otherwise. Having traversed all $p_i \in P$ by “FillFramesAndRelations”, a complete graph of all the information in text is created, which is the DMR (i.e. $G_d = (V, E)$). Figure 8 shows an example meaning representation for the statement “Ali ate the sandwich because he was hungry”.

6 MLMR generation

Figure 9 shows our MLMR recursive generation step. Initially $G_d$ meaning representation is passed to Meaning Representation Summarization Algorithm (MRSA) algorithm, detailed later in this section. Specifically, MRSA generates the most abstracted version of $G_d$, denoted as parent MR $G_p$, and it connects the abstract nodes in $G_p$ to regions in the $G_d$ that details such abstract nodes. We denote those regions by DMR Regions. Then each of the DMR Regions are processed recursively by the MLMR process if there are still big to fit in the screen. This termination criterion could be defined by the number of nodes for instance. In our case, we simply stop if the MR did not change from the previous iteration. The remaining part of this section details the MRSA algorithm, the role of the ontology in the algorithm, and how to make the MLMR Generation process interactive.

$^2$we will put the code of the framework online
6.1 Ontology

We assume that the ontology has the property that semantically related concepts have short paths in its hierarchy. We also assume that the concepts in the ontology could be mapped to the senses of the frames stored in the DMR. We opt to study our framework in one domain to prove that this concept works. Another reason is that natural language research is still progressing towards generalized ontologies so that it covers any arbitrary text. The ontology, utilized in this work, consists of 1300 concepts that we created according to the taxonomy of the historical figures topics. The ontology consists of three root nodes of “Work”, “Personal......
Life”, “Political Life”; the ontology is attached in the supplementary materials. Concepts presented in the textual information are assumed to be found as sub-nodes under one of these four root nodes. The main reason behind designing our custom ontology is to focus on the evaluation of our main contribution, Multi-level MindMap visualization, rather than addressing ambiguity problems that exist in the available ontologies (e.g. WordNet [37], SUMO [39], and CYC [30]), which are out of the scope of our work.

It is important to note that, for each concept in the ontology, we added a field called “MAP-LEX”. This field basically contains all the senses that matches these concepts. The purpose of this field is to easily map frames in a meaning representation to its corresponding concept. Hence, after the DMR is generated, we augmented each frame in the DMR with the corresponding concept in the ontology by finding the concept, whose “MAP-LEX” field contains its stored sense. Finally, each concept also contains “Is-Visual” flag which indicates whether the concept could be presented as a picture.

6.2 Meaning Representation Summarization Algorithm (MRSA)

The objective of MRSA is to summarize a meaning representation (MR), based on the ontology and the important frames in the MR. Each frame of the summarized MR is connected to regions (i.e., a set of frames $V_c \subseteq V$ and relations $E_c \subseteq E$) in the input MR that are related to that frame. Frames in the summarized MR/parent MR that map to more than one frame in the input MR are denoted by group frames. Figure 10 shows the block diagram of MRSA algorithm. The rationale behind MRSA is to measure the significance of MR frames by a weight assignment phase. It then selects the most important frames (we call them main frames) by clustering, based on the assigned weights. Then, the main frames persist at the top level, with surrounding actions, conceptually grouped according to a conceptual metric (i.e., distance between the concepts inside the ontology hierarchy). This is achieved by a conceptual based partitioning step.

\footnote{All senses are identified by wordNet sense index}
6.2.1 Weight assignment

In this step, a weight for each frame \( f \in V \) of \( G_d \) graph is assigned to indicate its level of significance; the higher the weight, the more significant the frame is. Each of the case-roles, domain relations, and temporal relations is assigned a constant weight depending on its type (see Fig. 7; for example Agent may have a score different from Location or Reason). We observed that important entity frames have many important relationships to the other frames. Based on this observation, we model the weight per entity frame as the sum of the weights of its surrounding relations (see (1)).

\[
W_{EF}^k = \sum_i N_{CR_i}^k w_{CR_i} + \sum_i N_{DR_i}^k w_{DR_i} + \sum_i N_{TR_i}^k w_{TR_i},
\]

where \( W_{EF}^k \) is the weight of the \( k \)th entity frame \( (V) \) and \( N_{CR_i}^k \) is the number of case-role relations of type \( i \) in of the \( k \)th entity frame. Similarly, \( N_{DR_i}^k \) and \( N_{TR_i}^k \) are the number of domain relations, temporal relations of type \( i \) in \( f_k \) respectively. \( w_{CR_i} \), \( w_{DR_i} \) and \( w_{TR_i} \) are the constant weights assigned to case-role, domain and temporal relations of type \( i \) (Fig. 7).

On the other hand, we assume that an action frame is important if its is connected to important frames. Hence, the weight of each action frame updated by its neighbors (see (2)).

\[
W_{AF}^k = \sum_i \left( R_{CR_i} \sum_j w(F_{CR_ij}^k) \right) + \sum_i \left( R_{DR_i} \sum_j w(F_{DR_ij}^k) \right) + \sum_i \left( R_{TR_i} \sum_j w(F_{TR_ij}^k) \right),
\]

where \( W_{AF}^k \) is the weight of action frame \( k \), \( R_{CR_i} \) defines the weight of the case-role of type \( i \) (Fig. 7). \( w(F_{CR_ij}^k) \) is the weight of the \( j \)th frame connected to frame \( k \) with case-role of type \( i \). Similarly, \( R_{TR_i} \) and \( R_{DR_i} \) are the corresponding ratios for temporal and domain relations while \( w(F_{DR_ij}^k) \) and \( w(F_{TR_ij}^k) \) are the corresponding weights of frames related to frame \( k \) with temporal and domain relations respectively.

6.2.2 Weight-based partitioning

The entity frame weights, obtained from the weight assignment, are partitioned into clusters using K–Means++ [3], which has an advantage of the initial seeding of the cluster centers. K–Means++ provides a way to avoid producing poor clustering that is more likely to happen by the standard K-Means algorithm. The first cluster center is chosen uniformly at random as one of the data points, then each subsequent cluster center is chosen from the remaining data points with a probability proportional to its squared distance from the point’s closest existing cluster center. We used the method in [45] to select the best \( K \) with maximum ratio between the intra-cluster distance measure (\textit{intra}) and is the inter-cluster distance measure (\textit{inter}), as illustrated in (3).

\[
\text{intra} = \frac{1}{N} \sum_{i=1}^{K} \sum_{x \in C_i} ||x - z_i||^2, \quad \text{inter} = \min \left(||z_i - z_j||^2\right), \quad i \neq j
\]
6.2.3 Concept-based partitioning

The objective of this step is to group semantically related frames under one common concept according to the ontology (i.e. abstraction). The associated actions of each main entity frame (extracted from the top cluster of the weight-based partitioning) are passed through the concept-based partitioning and a list of concepts with their corresponding frames is returned. If an action frame of a main entity frame was not grouped with any of the other action frames, the associated entity frames of that action frame are grouped using concept-based partitioning. So, the new summarized meaning representation contains (1) the main entity frames, (2) the grouped concepts associated with them as new action frames, (3) the ungrouped action frames around the main entity frames, and (4) the grouped concepts of entity frames around them as new entity frames. The following steps illustrates how to conceptually partition concepts around each main entity frame.

1. Group frames of the exact concept (i.e. ontological distance = 0).
2. Merge two frames whose concepts has the shortest path in the ontology.
3. Repeat step 2, until the count of the groups $\leq G_{th}$ (We used $G_{th} = 6$).

The bottom-up manner of our conceptual grouping algorithm behaves as a variant of agglomerative hierarchical clustering. The algorithm mainly analyzes the selected frame(a) and its neighbors and try to do conceptual partitioning if convenient as illustrated in Fig. 11 for Einstein and Fig. 2 for Shakespeare. The advantage of this model is that each high-level frame could be expanded into details (the DMR regions). The highest level of groups serves as the abstracted Meaning representation. the DMR region for each abstracted frame is generated by including all the frames that are descendants of the given group frame following the agglomerative hierarchical clusters.

In Shakespeare's example, “Shakespeare”, as a main entity frame, is detected by the weight assignment and partitioning steps. Afterwards, Shakespeare’s actions are grouped conceptually using our conceptual-based partitioning through the ontology. For instance, action frames of “earn” (living), “wrote” (35 good plays), and “is” (great literature) are

![Einstein Multi-level MindMaps](image-url)
grouped under “Work” concept in the ontology, while, action frames of “lived in” (Stratford), “born” (in 1564), and “had” (3 children) are grouped under “Life/Personal Life” concept. From this example, it is intuitive that conceptual partitioning is done in a bottom-up manner, which is adopted in our algorithm. Hence, It takes only 1–2 recursive calls in these examples. In general, the algorithm recursive calls depend on the ontology and the number of concepts in the given instance.

6.3 Interactive MLMR generation

MLMR Generation could be also interactive as follows. First, the DMR is summarized by MRSA. The summarized MR is then passed to MindMap Generation, detailed in the next section, to pictorially visualize the most abstract level of the MindMap. The user then can interacts with the generated MindMaps by selecting one of the group frames, which triggers running MSRA for the subset of DMR referred by the group frame. The Mindmap generation then visualizes the output MR, which represents the details of the selected group frame. The same process could be repeated interactively until the most detailed level is reached. Previous steps could be stored to allow going back to parent levels and down to the detailed levels. In this interactive mode, the generation is also effective since only the top level needs to be computed, and group frames are detailed based on the interactions by the user.

7 MindMap generation

In the MindMap generation step, an arbitrary meaning representation is converted into a MindMap that contains images for visual frames and dynamically allocate them on the screen. Visual frames are determined by checking whether the frame’s concept is visual in the ontology. Then, a query text is generated for each visual frame to retrieve a relevant image from Google Image Search [20].

7.1 Query generation and image web retrieval

We propose two approaches to generate the query. In the first approach, the given frame name is associated with its filled attributes. For instance, if there exist an entity frame (Ball: Color = Red, Size = small), the generated query will be “small red ball”. On the other hand, the second approach involves frame combination. For example, if we have a sentence like “Shakespeare performed before the queen in December”. If “the queen” is web-searched as suggested by the first approach, an irrelevant image will likely be retrieved. However, if the query combines “Shakespeare” and “queen”. The query is more likely to return a picture of “Queen Elizabeth”, which is meant by this sentence. That is why we tried to combine frames in the query. We implemented the second approach as follows. Given frame $i$, we add, to the query generated by the first approach, the name of frame(s) within two edges from frame $i$ (i.e., relevant frame). However, we add the names of the frames, only if it is significantly more important. In other words, relative weight of frame $i$ should be high, with respect to frame $j$. Mathematically speaking, $\frac{W_{Fi}}{W_{Fj}} > th$ where $W_{Fi}$ is the weight of frame $i$, $W_{Fj}$ is weight of frame $j$, $th$ is the relative importance threshold ($th = 6$ in our experiments).

Finally, the displayed images in the generated MindMap are retrieved using Google Image Search (GoIS). We used the GoIS API to retrieve the relevant images using the generated query and the first image in the results is chosen.
7.2 Automatic layout allocation

A graph drawing algorithm must take into account aesthetics: criteria for making salient characteristics of the graph easily readable. Example aesthetic criteria include minimizing number of edge crossings, maintaining straight edges as possible, maximizing display symmetry, etc. In our work, we achieved an acceptable layout by adopting the spring model by Thomas Kamps et al in [25]. Spring model meets two aesthetic principles. First, all edges are preferred to have the same length. Second, the layout should be as symmetric as possible. The main idea is to model the cost function by attaching a spring between the edges of the desired length as in (4).

\[ E = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} K_{ij}((x_i - x_j)^2 + (y_i - y_j)^2 + l_{ij}^2 - 2l_{ij}\sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}) \]  

where \((x_i, y_i)\) is the location of the node \(i\), \(l_{ij}\) is the desired length between node \(i\) and node \(j\) (It is not necessary to have an edge between node \(i\) and node \(j\)). There are four parameters that we designed while adopting the spring model: (1) \(l\), which is the desired length of directly connected nodes; we set \(l\) to 50. (2) \(D\), which is the diameter of the drawing (i.e. the maximum distance between a pair of nodes in our system); we set \(D\) to 600. (3) \(l_{ij} = l\), if there is an edge between node \(i\) and node \(j\). Otherwise, \(l_{ij} = \frac{D \cdot d_{ij}}{\min_{m \neq l,m} \{d_{lm}\}}\), where \(d_{lm}\) is the length of the shortest path between node \(l\) and node \(m\). (4) In our system, all-pairs shortest paths are computed, between every pair of nodes, using Floyd Warshall algorithm [19]. \(K_{ij}\) is the weight assigned for the cost function between node \(i\) and node \(j\), which indicates the strength of the spring associate between node \(i\) and \(j\). \(K_{ij} = \frac{1}{d_{ij}^{2}}\), where \(d_{ij}^{2} = d_{ij}\) if there is no edge between node \(i\) and node \(j\), \(d_{ij}^{2} = l\) otherwise. This indicates less restrictive springs, when nodes are not directly connected.

While nodes are assumed to be points in [25], each node \(i\) in our setting is a rectangular area \(R_i\) of width \(W_i\) and height \(H_i\), centered around the node position \((x_i, y_i)\). For instance, \(R_i\) will be the size of the image to be rendered, if node \(i\) is associated with an image. To tackle this problem, we add, to each \(l_{ij}\), \(M_{i} + M_{j}\), where \(M_k\) is the diameter of Rectangle \(R_k\) of node \(k\). The rationale behind adding \(M_{i} + M_{j}\) is that when the distance between the centers of two rectangles is \(M_{i} + M_{j}\), the rectangles does not intersect regardless their positions. Finally, the gradient of the cost function is computed and used to find a local minimum. We used random re-initialization strategy to reach a good solution minimizing (4). We run the spring model 10 times with different initial seeds selected randomly on the drawing canvas where MindMap needs to be drawn and the layout with the minimum cost is selected.

8 Experimental results

This section presents the evaluation methodology and experiments of our MindMap automation framework. The evaluation was based on 4900 Mechanical Turk (MTurk) [9] rating responses, with different system parameters. As indicated in [7], MTurk users have less than 2% of the workers have no high school degree and average education years of 14.9. In order to improve the quality of the responses, the workers were exposed to illustrative examples.

---

4Other third party commercial tools/methods could be used also here (e.g. Microsoft AGL http://research.microsoft.com/en-us/projects/msagl/)
before getting introduced to the instances used for the evaluation. Furthermore, we also required that the MTurk-workers have at least a 95% approval rate and 1,000 approved assignments\(^5\) to work on our experiments. The following subsections details the evaluation dataset, three experiments to evaluate different aspects of our framework.

8.1 Historical figures dataset and evaluation metrics

Since there is no existing datasets to evaluate MindMap visualization, we created our own dataset to validate our framework. We chose articles of historical figures (e.g., Shakespeare, George Washington, etc) to build our dataset. Thirty five historical figures were chosen from the BBC historical figures’ section [6] of size between 150 words to 250 words. We used our framework to generate 455 different MindMaps from these chosen articles. Thirteen MindMaps were generated for each article, one for each parameter setting (detailed in this section), which resulted in 455 MindMaps. The 455 cases were evaluated based on Human Subject Rankings by 4900 MTurk workers’ responses on the following five question survey.

1. To what extent does the generated output represent the text (Regardless the pictures)? Grade 1–5.
2. To what extent are the generated pictures relevant? Grade 1–5.
3. How many missing actions are there in the shown diagram (if no missing actions, please put 0)?
4. How many missing entities are there in the shown diagram (if no missing entities, please put 0)?
5. How many repeated entities/actions are there in the shown diagram (if no repeated entities/actions, please put 0)?

Our evaluation is partitioned into three experiments to evaluate the effect of changing the system parameters. The framework was evaluated upon three main variations. (a) GoIS Parameters (Size, Image Type) [20] for single-level MindMap in Experiment 1 (b) Concept combination in Experiment 2 (c) Multi-level MindMaps in Experiment 3. The responses of the experiments were evaluated based on three metrics: (1) Mean, (2) Standard deviation to indicate the stability of the response, and (3) For grading questions (i.e., Q1,2), Satisfaction Ratio (SR) that is defined as \(SR = \frac{\# \text{ of responses } \geq 4}{\# \text{ of responses }}\). Figures 12, 13, 14, and 15 show the generated single-level and multi-level MindMaps for Akhentan, Van Gokh, George Washington, and Newton, a subset of the evaluated outputs. More automatically generated MindMaps are attached in the supplementary materials. While, the framework can allow the user to change the retrieved images, we only evaluate results with images automatically retrieved by our method.

8.2 Experiment 1 (315 cases, 3150 responses)

In Experiment 1, we evaluate the MTurk workers’ satisfaction with single-level MindMaps, and test whether their responses are biased by varying the displayed image parameters. We tested nine variations: three different image types (All [any image], ClipArt, LineArt) and three sizes (All, Auto, Small). The auto size is a size mode, we implemented to determine the image size according to the weight of the frame to be visualized, computed in Section 6.2.1. Our implementation uses medium size image (biggest suitable size for MindMaps) if the

\(^5\)This is based on their previous history that is maintained in MTurk system
number of relations to it is greater than six, otherwise, the system uses small image size. The MindMap generation phase in this experiment did not involve concept combination (which is evaluated in Experiment 2). Overall, we have 315 (9 × 35) cases with ten MTurk responses each (i.e. 3150 responses).

Table 1 (top part) presents the user response statistics grouped by all the nine variations. The results indicate general satisfaction by the MTurk workers. Q1 and Q2 are the most
relevant questions to the appearance of the generated MindMap and the generated images. The results of these questions are grouped for each of the nine variations in this experiment. Figure 16 shows the three evaluation metrics for the nine cases on Q1 and Q2, which indicates that changing the image type or size almost did not affect the responses of the MTurk workers. In other words, these responses were not biased to specific image type or size.

8.3 Experiment 2 (105 cases, 1050 responses)

Experiment 2 focuses on evaluating the user satisfaction of the MindMaps in case of Concept Combination mode (described in Section 7.1). To evaluate whether the MTurk workers were biased to the pictures, we created Concept Combination cases with three variations of
image types resulting in 105 cases (3 × 35 historical figures). Each case was evaluated by ten different MTurk anonymous workers (1050 responses).

Table 1 (middle part) shows summarized results for the experiment. Compared to Experiment 1, there is an improvement of 2 % in the mean and 7 % in the satisfaction ratio for Q1 with the use of concept combination. However, the satisfaction ratio of Q2 (pictures satisfaction) decreased by 10 %. This indicates that the retrieved image using direct query is relatively better than retrieved image using Concept Combination query. The results were also grouped by the three variations of Experiment 2, which indicate a similar behavior to Experiment 1 (i.e. No bias); see Table 2.

It is important to mention that, the relevance of the MindMap images currently depends only on the quality of the firstly-ranked image retrieved by our generated query from GoIS. After careful look on the MTurk responses and our own evaluation of this experiment, we found that most of the retrieved images are relevant using direct queries. However, in some
cases, it does not retrieve a relevant image. For example, “new capital” node in Akhentan example, is assigned to an unsatisfactory image; see Fig. 12. Our intuition is that context information is not considered in this retrieved images in direct query mode, which we tried to model by concept combination (CC) queries. After applying CC mode to Akhentan example, we managed to retrieve an image of a pharaonic land for this “new capital” query, which is more relevant. However, the CC mode negatively affected the overall performance of remaining queries since it badly affects most of the remaining frames, as illustrated in the results of this experiment.
### Table 1  Human Subject Responses for Experiments 1, 2, 3

| Experiment   | Q1   | Q2   | Q3   | Q4   | Q5   |
|--------------|------|------|------|------|------|
| **Experiment 1** |      |      |      |      |      |
| Mean         | 4.42 | 4.34 | 0.54 | 0.59 | 0.48 |
| StdDev       | 0.84 | 0.87 | 1.58 | 1.74 | 1.68 |
| SR           | 0.86 | 0.84 |      |      |      |
| **Experiment 2** |      |      |      |      |      |
| Mean         | 4.51 | 4.27 | 0.45 | 0.5  | 0.23 |
| StdDev       | 0.65 | 0.82 | 1.25 | 1.47 | 0.58 |
| SR           | 0.92 | 0.79 |      |      |      |
| **Experiment 3** |      |      |      |      |      |
| Mean         | 4.48 | 4.33 | 0.59 | 0.61 | 0.25 |
| StdDev       | 0.87 | 0.94 | 1.51 | 1.55 | 0.93 |
| SR           | 0.89 | 0.84 |      |      |      |

**Fig. 16**  Experiment1 grouped results (Q1,2): Mean and StdDev is on the left while SR is on the right

### Table 2  Experiment 2 (Q1, 2) grouped results

|       | Q1     |       | Q2     |       |
|-------|--------|-------|--------|-------|
|       | Mean   | StdDev| SR     | Mean   | StdDev | SR   |
| All   | 4.56   | 0.63  | 0.937  | 4.31   | 0.825  | 0.8  |
| LineArt | 4.53   | 0.61  | 0.939  | 4.24   | 0.827  | 0.76 |
| ClipArt | 4.46   | 0.71  | 0.91   | 4.26   | 0.825  | 0.81 |
Table 3 Experiment 3 worst 15 % Q1 and Q2: The first row shows the 15 % over the all responses, while, the second row shows the mean of the average of the 15 % for each of historical figure

|                      | Q1  | Q2  |
|----------------------|-----|-----|
| Mean of 15 % percentile worst responses | 4   | 3   |
| Mean of the average 15 % percentile for each 35 historical figures | 3.78 | 3.57 |

8.4 Experiment 3 (35 cases, 700 responses)

The purpose of this experiment is mainly to rate the partitioning of the information in the multi-level MindMaps and not the evaluation of the retrieved images (evaluated in Experiment 1 and 2). Hence, we selected one case for each historical figure (with the best images retrieved in Experiment 1). Q2 was changed to evaluate of conceptual grouping instead of the pictures as they was already evaluated in Experiments 1 and 2. Question 2 became “To what extent are you satisfied with the structure of the multi-level MindMap?6 Grade 1-5”. To evaluate it interactively, we have generated 35 interactive flash files (one for each historical figure). Each flash file was evaluated by twenty MTurk Users (i.e., 700 responses).

Results are shown in Table 1 (bottom part). There is 1.4 % and 3 % improvement in the mean and SR respectively compared to the single-level MindMaps. The results show the satisfaction of the users with the hierarchical representation of the MindMap. While both single-level and multi-level approaches give satisfactory outputs, the multi-level approach is the only way to represent all information in large text, where single-level generation is not applicable.

In order to give a careful consideration to the criticism of the generated multi-level MindMaps, we computed the average of the lowest 15 % for all the ratings for Q1 and Q2. We also computed the mean of lowest 15 % for the ratings of each of the 35 Historical figures and we then reported the average overall the historical figures; see Table 3. We further investigated the highest errors reported by the MTurk workers, in response to Q3, Q4 and Q5, which indicate missing actions, entities, or redundancy of any of them. For each of 35 historical figure, we select the responses that have Non-zero values for Q3, Q4, and Q5. Then, we compute the average over all the historical figures; see Table 4.

However, this group of responses does not indicate high disagreement with the generated MindMaps as indicated in Tables 3 and 4, we carefully investigated the provided comments by the human subjects on the three experiments. We noticed that the main criticism of the least satisfied subjects was due to some missing/redundant pieces of information and irrelevant images in the MindMap. While, the experiments and our investigation indicates that these cases are few, it is an important feedback to consider for our future work, in which targets generalization on larger scales.

6Clarification information included in the correct class (e.g Work, Personal Life, and Political Life). As an incorrect instance, information like the historical figure’s birth or death is classified under Work. This clarification was exposed to the MTurk workers with examples
Table 4 The average of the non-zero responses’ mean of Q3, Q4 and Q5 for each historical figure in Experiment 3

|          | Q3  | Q4  | Q5  |
|----------|-----|-----|-----|
| Average of Non-zero responses | 3.57 | 2.83 | 2.00 |

9 Discussion and conclusion

Our framework has multiple limitations. For instance, it depends on the quality of the syntactic analyzer to pass information. If a statement could not be parsed, then it will be ignored, and its information will not be included in the generated MindMap accordingly. Another limitation is that the MLMR algorithm assumes that there is a central idea of a given document, which is valid for the historical figures dataset, but not valid in general. In the future, we aim at exploring different methods to generate hierarchy of abstract information in the text and use word vectors (e.g. [36]) to leverage semantically related information that might not be captured by the ontology. We aim to extend the system such that it is reliable in handling very large text (e.g., a book). Furthermore, we will investigate different approaches to retrieve more relevant images from the textual query. In order to generate MindMaps for a large in a reasonable time, the framework computational time needs to be significantly reduced. For instance, Multi-level MindMap Generation of a 250 word document take about 40 seconds on a 3.3GHZ-6GB machine; see Fig. 17). The recorded time is the average time to convert raw text to multi-Level MindMap including automatic layout allocation. Finally, rather than restricting our domain to historical figures in this work, we plan to investigate the generalization of MindMap visualization for any text and tackle ontology-related problems.

In conclusion, we have designed and implemented the first automated framework generates a multi-level Mind Map visualization out of English text. The system was comprehensively tested under different parameter settings by MTurk Human Subjects and high satisfaction rates have been recorded.
References

1. Afzal S, Maciejewski R, Jang Y, Elmqvist N, Ebert D (2012) Spatial text visualization using automatic typographic maps. TVCG 18
2. Altintas E, Karsligil E, Coskun V (2005) The Effect of Windowing in Word Sense Disambiguation. doi:10.1007/11569596.65
3. Arthur D, Vassilvitskii S (2007) k-means++: the advantages of careful seeding. In: Proceedings of the ACM-SIAM symposium on Discrete algorithms. Society for Industrial and Applied Mathematics
4. Bataineh BM, Bataineh EA (2009) An efficient recursive transition network parser for arabic language. In: World Congress on Engineering (WCE)
5. Banerjee S, Pedersen T (2002) An adapted Lesk algorithm for word sense disambiguation using WordNet. CICLing
6. BBC: BBC Historical Figures (2012) [Online; accessed January-2012]. http://www.bbc.co.uk/history/historic_figures/
7. Berinsky AJ, Huber GA, Lenz GS (2012) Evaluating online labor markets for experimental research: Amazon’s mechanical turk. Polit Anal 20
8. Berinsky AJ, Huber GA, Lenz GS (2013) An evaluation of the left-brain vs. right-brain hypothesis with resting state functional connectivity magnetic resonance imaging. PLOS ONE 8
9. Buhrmester MD, Kwang T, Gosling SD (2011) Amazon’s mechanical turk: A new source of inexpensive, yet high-quality data. Perspect Psychol Sci 6
10. Collins M (2003) Head-driven statistical models for natural language parsing. Comput Linguist 29
11. Conroy JM, O’leary DP (2001) Text summarization via hidden markov models. In: ACM SIGIR
12. Coyne B, Rambow O, Hirschberg J, Sproat R (2010) Frame semantics in text-to-scene generation. In: KES. Springer
13. Das D, Martins AFT (2007) A survey on automatic text summarization. Literature Survey for the Language and Statistics II Course at CMU
14. Dhindsa HS, Makarimi-Kasim, Roger Anderson O (2011) Constructivist-visial mind map teaching approach and the quality of students’ cognitive structures. J Sci Educ and Technol 20(2)
15. Dou W, Yu L, Wang X, Ma Z, Ribarsky W (2013) HierarchicalTopics: Visually exploring large text collections using topic hierarchies. TVCG 19
16. Elhoseiny M, Elgammal A (2012) English2mindmap: An automated system for mindmap generation from english text. In: IEEE International Symposium on Multimedia (ISM)
17. Farrand P, Hussain F, Hennessy E (2002) The efficacy of the ‘mind map’ study technique. J Med Educ 36
18. Feng Y, Lapata M (2010) Visual information in semantic representation. ACL
19. Floyd RW (1962) Algorithm 97: Shortest path. Commun ACM 5
20. Google: Google Image Search [Online; accessed January-2013]. http://www.google.com/advanced_image_search/
21. van Ham F, Wattenberg M, Viegas FB (2009) Mapping text with phrase nets. TVCG 15
22. Hamdy A, ElHoseiny MH, Sahn RE, Samier S, Kamal E (2009) Mind maps automation (mma) system. In: International Conference on Semantic Web and Web Services (SWWS)
23. http://img2.mappio.com/ Shakespear Mindmap (2014). http://img2.mappio.com/miwisdom/william-shakespeare-short-biography-mind-map-Large.jpg
24. Kaikhah K (2004) Automatic text summarization with neural networks. In: International IEEE Conference on Intelligent Systems
25. Kamps T, Kleinz J, Read J (1996) Constraint-based spring-model algorithm for graph layout. In: Proceedings of the symposium on graph drawing
26. Kudelic R, Konecki M, Malekovic M (2011) Mind map generator software model with text mining algorithm. In: International Conference on Information Technology Interfaces (ICITI)
27. Lappin S, McCord M (1990) A syntactic filter on pronominal anaphora for slot grammar. In: ACL
28. learningon.theloop.school.nz Wordle example (2014). http://learningon.theloop.school.nz/moodle/pluginfile.php/78885/block_html/content/Wordle-Designs.png
29. Leass HJ (1994) An algorithm for pronominal anaphora resolution. Comput Linguist 20
30. Lenat D (1995) Cyc: A large-scale investment in knowledge infrastructure. Commun ACM 38
31. Litkowski KC (2001) Syntactic Clues and Lexical Resources in Question-Answering
32. Ma M (2006) Automatic conversion of natural language to 3d animation. Ph.D. thesis, University of Ulster
33. Maicher L, Park J (eds) (2006) Charting the topic maps research and applications landscape. Springer
34. Marcu DC (1998) The rhetorical parsing, summarization, and generation of natural language texts. PhD dissertation
de Marneffe MC, MacCartney B, Manning CD (2006) Generating typed dependency parses from phrase structure trees. In: LREC

Mikolov T, Sutskever I, Chen K, Corrado GS, Dean J (2013) Distributed representations of words and phrases and their compositionality. In: Advances in neural information processing systems, pp 3111–3119

Miller GA (1995) Wordnet: A lexical database for English. Communications of the ACM 38

Navigli R (2009) Word sense disambiguation: A survey. ACM Computing Surveys 41

Niles I, Pease A (2001) Towards a standard upper ontology. In: FOIS

Novak JD (2006) The theory underlying concept maps and how to construct them. Tech rep

novamind.com: (2012) IMind tool. (accessed February, 2012). http://www.novamind.com/

Osborne M (2002) Using maximum entropy for sentence extraction. In: ACL workshop on automatic summarization

Park J, Hunting S (eds) (2003) XML topic maps: Creating and using topic maps for the web. Addison-Wesley Longman Publishing Co., Inc., Boston, MA

Qiu L, yen Kan M, seng Chua T (2004) A public reference implementation of the rap anaphora resolution algorithm. In: LREC

Ray S, Turi RH (1999) Determination of number of clusters in k-means clustering and application in colour image segmentation. In: ICAPRDT

thinkbuzan.com: (2012) IMind tool. (accessed February, 2012). http://www.thinkbuzan.com/us/?utm_noooverride=1&gclid=CPaV7saVkK4CFUff4AodtTRidg

Tony Buzan BB, Harrison J (2010) The Mind Map Book: Unlock Your Creativity Boost Your Memory Change Your Life. Pearson Education Ltd

Viegas F, Wattenberg M, Feinberg J (2009) Participatory visualization with wordle. TVCG 15

Vigas F, Wattenberg M (2014) Phrasenet example. http://hint.fm/projects/phrasenet/

W3C: (2009) W3c organization. http://www.w3.org/

Youzhi Z (2009) Research and implementation of part-of-speech tagging based on hidden markov model. In: Asia-pacific conference on computational intelligence and industrial applications

Mohamed Elhoseiny is a PhD student at the Department of Computer Science, Rutgers, the State University of New Jersey. He is also a member of the Center for Computational Biomedicine Imaging and Modeling (CBIM). He received his B.Sc. and M.Sc. degrees from the computer systems department, Faculty of Computer and Information Sciences, University of AinShams University, Egypt in 2006 and 2010, respectively. He received another MSc in Computer Science at Rutgers University. He is currently pursuing his studies in computer vision and multimedia as a PhD student in the Computer Science department at Rutgers University.
Ahmed Elgammal is an associate professor at the Department of Computer Science, Rutgers, the State University of New Jersey Since Fall 2002. Dr. Elgammal is also a member of the Center for Computational Biomedicine Imaging and Modeling (CBIM). His primary research interest is computer vision and machine learning. His research focus includes human activity recognition, human motion analysis, tracking, human identification, and statistical methods for computer vision. Dr. Elgammal received the National Science Foundation CAREER Award in 2006. Dr. Elgammal has been the Principal Investigator and Co-Principal Investigator of several research projects in the areas of Human Motion Analysis, Gait Analysis, Tracking, Facial Expression Analysis and Scene Modeling; funded by NSF and ONR. Dr. Elgammal is Member of the review committee/board in several of the top conferences and journals in the computer vision field. Dr. Elgammal received his Ph.D. in 2002 from the University of Maryland, College Park. He is a senior IEEE member.