Improving Readability for Tweet Contextualization using Bipartite Graphs

Amira Dhokar, Lobna Hlaoua and Lotfi Ben Romdhane
SDM Research Group, MARS Research Lab ISITCom, University of Sousse, Tunisia

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Abstract: Tweet contextualization (TC) is a new issue that aims to answer questions of the form What is this tweet about? The idea of this task was imagined as an extension of a previous area called multi-document summarization (MDS), which consists in generating a summary from many sources. In both TC and MDS, the summary should ideally contain most relevant information of the topic that is being discussed in the source texts (for MDS) and related to the query (for TC). Furthermore of being informative, a summary should be coherent, i.e. well written to be readable and grammatically compact. Hence, coherence is an essential characteristic in order to produce comprehensible texts. In this paper, we propose a new approach to improve readability and coherence for tweet contextualization based on bipartite graphs. The main idea of our proposed method is to reorder sentences in a given paragraph by combining most expressive words detection and HITS (Hyperlink-Induced Topic Search) algorithm to make up a coherent context.

1 INTRODUCTION

With the diffusion of social networks such as Facebook or YouTube, social media have become one of the most popular Internet services in the world. Such sites offer today's youth a portal for entertainment and communication and have grown exponentially in recent years. Twitter stands actually as the most popular micro-blogging service (Duggan et al., 2015). It allows its users to communicate with short messages known as tweets, limited by a maximum number of characters that does not exceed 280, often in real time and from a mobile phone. But this type of messages generates a large amounts of data and are sometimes non understandable for a reader because of their limited size. Since they must be written respecting this limitation, a particular vocabulary is used and providing additional informations seems to be necessary to understand tweet's context without time consuming.

In tweet contextualization, a context is a summary related to the tweet and that does not exceed 500 words. This summary should be informative and coherent (readable). Given a tweet, and a set of relevant documents, the task of producing an informative and coherent summary of those documents in response to this tweet has attracted a great deal of attention recently. However, the problem of organizing information for contextualization so that the generated summary is coherent has received relatively little attention.

In this paper, we propose an approach for tweet contextualization based on semantic and coherence between sentences: our objective is to select most relevant and coherent information in relation with the tweet, extract the most important ones to provide informativeness excerpt and reorder phrases to guarantee coherence and readability. In this respect, the following questions arise: how to select the most important phrases coming from many documents and that deal with topics expressed in the tweet? How to enhance the order of selected sentences to be able to obtain a readable and coherent context?

This paper has been organized as follows. Section 2 cites some related works. Section 3 presents our motivation and the architecture of our model. Section 4 discusses relevant sentences extraction from a document. Section 5 develops the idea of sentence aggregation based on cliques detection. Section 6 details the proposed approach for sentence reordering to improve readability for a given context. Section 7 describes our experimental results. The conclusion and future work are presented in Section 8.

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2 RELATED WORK

In tweet contextualization, an excerpt provided from many documents must be informative and readable. Hence it should be grammatically correct. Coherence is an essential characteristic in order to produce comprehensible texts. This aspect has received relatively little attention in tweet contextualization. Hence, the paper focused on document summarization to deal with this problem. In this context, several approaches have been proposed. Barsilay and Lapata (Barzilay and Elhadad, 2002) proposed to study the proprieties of ordering information in the news genre. They develop a method that combines constraints from chronological order of events and topical relatedness to improve order of sentences in multi-document news summarization. In (Barzilay and Lee, 2004) another method is presented: it is an unsupervised model that focus on text organization in a particular domain. An adaptation of algorithms for Hidden Markov Models is used to capture topic shift in a text, where topics are represented by hidden states and sentences are observations. In (Barzilay and Lapata, 2008) authors proposed a method based on entities to assess and improve textual coherence. Their model is inspired by Centering Theory (Grosz et al., 1995) which supposes that adjacent sentences are coherent if they share the same entities: authors created an entity grid model to capture discourse transitions at the sentence-to-sentence level. Following the same spirit, Soricut and Marcu (Soricut and Marcu, 2006) and Elsner et al.(Elsner et al., 2007) proposed a combination between the entity-based and HMM-based models to improve information ordering task. In 2011, Lin et al. (Lin et al., 2011) proposed an approach of text ordering using discourse relation transitions. their method is to transform the discourse relation into a discourse role matrix that represents term occurrences with its discourse roles in the text units (sentences). To distinguish coherence from incoherence, n-gram subsequences of transitions per term in the discourse role matrix are used. In (Guinaudeau and Strube, 2013), authors modeled the text into a graph of sentences by using a bipartite graph. They suppose that one set of nodes represents entities and the other set represents sentences of a document. Their work is based on the fact of using a one mode projection on sentence nodes (Newman, 2011), and then the average out degree of sentence nodes is computed to determine how coherent a document is. This method takes into account the number of shared entities between sentences and their grammatical functions. In (Parveen and Strube, 2015), authors proposed a graph-based method for extractive single document summarization to improve and evaluate local coherence for scientific articles. They combine ILP (integer linear programming) and a graph-based ranking algorithm to reorder and optimize sentence ranking on the basis of importance. In (Parveen et al.,), authors deal with single-document summarization based on weighted graphical representation of the document where one set of nodes corresponds to topics. The Latent Dirichlet Allocation (LDA) is used for topic modeling and to measure the semantic relatedness between words and the topical coherence of a given document. In (Li and Hovy, 2014), authors proposed an approach that learns a syntactico-semantic representation for sentences automatically,using either recurrent or recursive neural networks. The proposed architecture obviated the need for feature engineering, and learns sentence representations, which are to some extent able to capture the rules governing coherent sentence structure. In (Ermakova, 2016) the author proposed three completely automatic approaches for sentence order assessment where the similarity between adjacent sentences is used as a measure of text coherence. Her method is based on graph model, where the vertices correspond to sentences and the edges represent the similarity measure between them. She exploited the similarities of terms, nouns and named entities. Recently, authors in (Ermakova et al., 2017) presented a self-sufficient metric for sentence ordering assessment based on text topic-comment structure of a text that requires only shallow parsing. they proposed a metric that considers the pairwise term similarities of the topics and the comments of the adjacent sentences in a text since word repetition is one of the formal signs of text coherence (Barzilay and Elhadad, 2002).

Methods using bipartite graph in document summarization had encouraging results in ordering task. Inspired by the above approaches, in this paper, a method for improving readability for tweet contextualization combining cliques detection, bipartite graphs and a ranking algorithm is proposed.

3 MOTIVATION AND ARCHITECTURE OF THE MODEL

In tweet contextualization, a context is a summary related to the tweet and that does not exceed 500 words. Indeed, the main objective of a TC system is to enhance the readability of a given tweet (that acts as a query), to identify a list of potential topic-related resources (documents) that we attempt to summarize.

The process of tweet contextualization can be divided into three sub-tasks: tweet Analysis, passage and/or XML elements retrieval and construction of the answer (context). Respecting this process, the proposed method for tweet contextualization is presented in Figure. 1. It involves the following three steps: **tweet analysis** that aims to clean tweets and eliminate unnecessary symbols such as #, @...and URLs, **passages/XML documents retrieval** where cleaned query is transmitted to the search engine to determine the most relevant articles to the tweet and **tweet contextualization** that aims to extract then reorder most relevant sentences related to the tweet. Top-ranked phrases are selected to form context (within the limit of 500 word).

The main objective of this work is to guarantee informativeness and coherence between different parts of the context to be able to construct an appropriate summary. In view of importance of both relevance and coherence in a contextualization system, we have considered that this work must combine these two aspects to achieve good performances in informativeness and readability. Hence, it is interesting to consider that a sentence included in the final context should be relevant regarding the query, informative and coherent with other sentences. The proposed method is divided into two main modules: the first one aims to enhance the informativeness by selecting the most relevant sentences from many documents considering some measures, and the second module aims to improve the readability of the contextualization system by reordering selected sentences to ensure higher degree of coherence to the constructed context. This approach will be detailed in next sections.

4 RELEVANT SENTENCE EXTRACTION FROM A DOCUMENT

The goal of this part of the proposed system is to extract the most relevant phrases from the most relevant documents. For that, this step into two sub-tasks: document filtering regarding the tweet and sentence scoring.

In document filtering regarding the tweet, our objective is to choose most informative sentences that deal with topics expressed by the tweet. Hence we opted for filtering the relevant document by keeping only sentences that are correlated to the query. This can be easily done by calculating the cosine similarity between the tweet and the candidate sentences given by the following formula:

$$Similarity(Q,S) = \frac{\sum_{i=1}^{n} Freq(q_i,Q)}{\sqrt{\sum_{i=1}^{n} (Freq(q_i,Q))^2}} \times \frac{\sum_{i=1}^{n} Freq(s_i,S)}{\sqrt{\sum_{i=1}^{n} (Freq(s_i,S))^2}} \quad (1)$$

Where Q=q_1,q_2,...,q_i is a query, S=s_1,s_2,...,s_i is a sentence, Freq(q_i,Q) is the occurrence of the i-th token in a query and Freq(s_i,S) is the occurrence of the i-th token in a sentence. If the token is not presented in the query or in the sentence, q_i (resp.s_i) is equal to 0 respectively.

In every filtered document, sentences do not have the same importance in term of relevancy according to the tweet. For that, we propose to make the difference between most relevant phrases and less ones (Dhokar et al., 2017): for each candidate sentence, a score is computed. This score takes into account the relevance of the sentence compared to the title of the document and the importance of the sentence in its original document compared to other sentences in the same article. Best scored sentences are selected and the score of each phrase is given by:

$$Sp_i = Similarity(T,S_i) + Imp(S_i) \quad (2)$$

Where Sp_i is the associated score of a sentence S_i, Similarity(T,S_i) is the similarity estimated between a sentence S_i and the title of the document T and Imp(S_i) is the score that estimates the importance of a sentence (S_i) in a document. The similarity between a sentence S_i and the title of the document T is calculated using the following equation:

$$Similarity(T,S) = \frac{\sum_{i=1}^{n} Freq(t_i,T)}{\sqrt{\sum_{i=1}^{n} (Freq(t_i,T))^2}} \times \frac{\sum_{i=1}^{n} Freq(s_i,S)}{\sqrt{\sum_{i=1}^{n} (Freq(s_i,S))^2}} \quad (3)$$

Where T=t_1,t_2,...,t_i is the title of the corresponding document, S=s_1,s_2,...,s_i is a sentence, Freq(t_i,T) is the occurrence of the i-th token in a title and Freq(s_i,S) is the occurrence of the i-th token in a sentence. If the token is not present in the title or in the sentence, q_i (resp.s_i) is equal to 0 respectively.

The importance of a sentence (S_i) in a document is calculated until divergence and given by (Brin and Page, 2012):

$$Imp(S_i) = (1-d) + d \times \sum_{S_j \in Neighbors(S_i)} \frac{Sim(S_i,S_j)}{\sum_{S_k \in Neighbors(S_i)} Sim(S_k,S_i)} \times Imp(S_i) \quad (4)$$

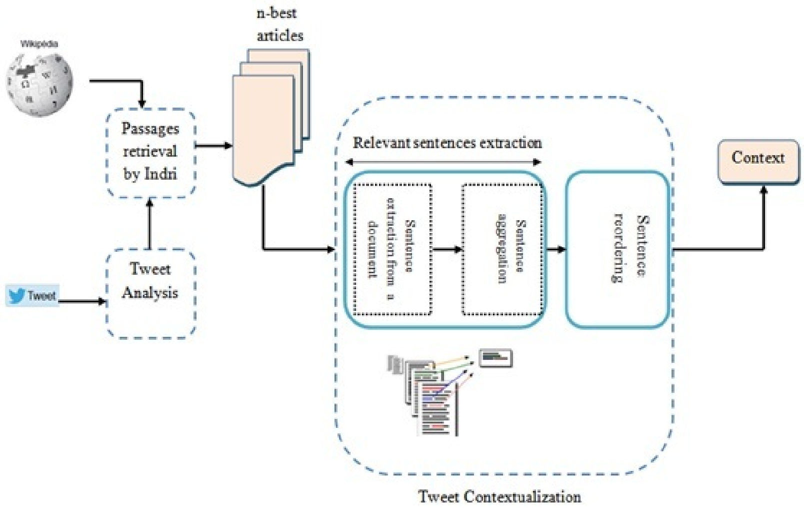


Figure 1: The proposed contextualization model.

Where d is a dumping factor (usually set to 0.85), Neighbors S_i is the set of sentences connected with S_i and Sim(S_i,S_j) is the similarity score between sentences S_i and S_j and given by (Mihalcea, 2004):

$$Sim(S_i,S_j) = \frac{\sum_{m\in S_i,S_j} freq(m,S_i)+freq(m,S_j)}{\log|S_i|+\log|S_j|} \quad (5)$$

Where , freq(m,S_i) is the occurrence of a word m in a sentence S_i, respectively S_j and log $|S_i|$ is the length of a sentence S_i, respectively S_j.

5 SENTENCE AGGREGATION BASED ON CLIQUES DETECTION (SACD)

As mentioned in the previous section, we work with n top documents from the search phase. From each document, best scored sentences are selected and aggregated together. However, a good context should have a good quality respecting two fundamental aspects of a contextualization system: relevance and coherence. We therefore propose to refine the choice of relevant and coherent sentences to include in the context. In this respect, it is proposed to model sentences in a graph then use cliques detection to select most coherent groups of phrases. Our hypothesis is that a set of sentences belonging to the same clique can form a coherent and semantically linked passages. Usually, each node in a clique is, in some way, highly related to every other node. This characteristic makes clique identification a very important approach to uncover meaningful groups of sentences from a graph. In this work, we opted for finding maximal cliques of a graph to identify coherent sentences in order to produce a readable context (Dhokar et al., 2017).

5.1 Cliques Computation

In the literature, many pieces of work have been proposed to model a set of sentences by a graph in order to obtain links between phrases and passages (Salton et al., 1997),(Yeh et al., 2008). In this work, we try to adapt the same concept in order to model a group of phrases (here aggregated sentences resulted from the first step of the proposed system) as a graph, in order to obtain a network of sentences that are related to each others, resulting in a sentence similarity graph. This graph is composed of nodes and edges linking nodes and each node represents a sentence. A connection between two nodes exists if and only if they are similar with respect to a similarity threshold α. The degree of connection between two sentences S_i and S_j is measured by the formula used in equation 5. Our approach to identify cliques is based on the notion of a maximal clique. A maximal clique of a graph G is a clique that cannot be extended by including one more adjacent vertex (Regneri, 2007). Cliques are allowed to overlap, which means that sentences can be members of more than one clique. The purpose of this step of this work is to detect all maximal cliques present in the graph using Tomita algorithm (Tomita et al., 2011).

5.2 Cliques Selection

In tweet contextualization, a context is a summary related to the tweet, containing coherent and related groups of sentences and that does not exceed 500 words. Respecting this constraint, the aim of this step is to propose a method for cliques selection to determine cliques to be considered in the final context. Hence the proposed method is depicted in figure 2. A set of cliques (resulted from the previous

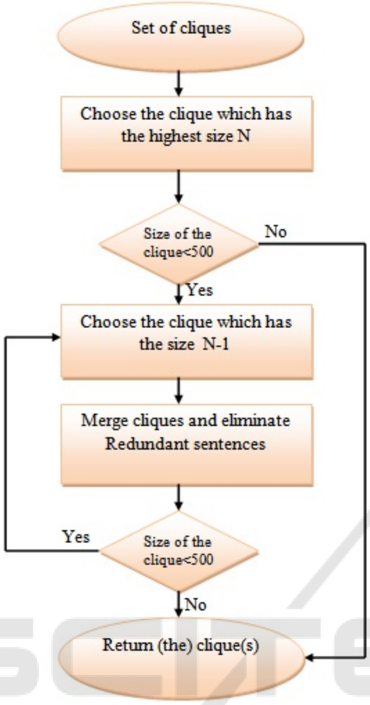


Figure 2: Our proposed method for cliques selection.

step) is considered as an input of the algorithm. then, the clique which has the highest size N is chosen to be included in the final context. If the limited size of the excerpt (500 words) is achieved, we consider only the selected clique. If not (we didn't achieve 500 words), the clique which has the size N-1 is added. The operation of cliques selection is repeated until having 500 words in the final context. After merging all selected cliques, redundant sentences are eliminated.

6 SENTENCE REORDERING

6.1 Motivation

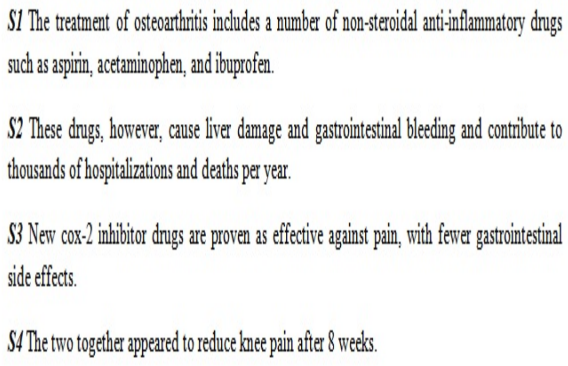
This section highlights the proposed approach for sentence reordering in order to generate a readable context for a given tweet. According to the previous step, the obtained context is composed of a set of cliques. The proposed method is divided into two steps: the first step aims to reorder sentences into the same clique and the second step aims to reorder cliques between them.

In this work, we focus on the first step and our goal is to propose a method to reorder sentences into the same clique. The intuition we have behind this idea is that sentences belonging to the same clique are correlated and treat the same themes. In this respect, their reorganization remains indispensable in order to have a coherent and grammatically compact passage (paragraph). This section describes the adopted technique to improve readability for tweet contextualization. In this context, we model the text using a graphical representation and then apply HITS algorithm to reorder sentences belonging to the same clique. A graph can easily capture the essence of the whole text without leading to high computational complexity and a ranking algorithm (here is HITS algorithm) takes into account global information to calculate the rank of a corresponding node (sentence). These two characteristics can help us to improve readability and coherence to a given context. In this work we opted to combine a bipartite graph and HITS algorithm. We start by introducing the graphical representation of a clique, followed by a description of the algorithm used to quantify the importance of phrases in a clique and reorder considered sentences.

6.2 Proposed Method for Sentences Reordering

6.2.1 Graphical Representation of a Clique

Considering a graphical representation of a text is not recent. It is adopted by various approaches (Mihalcea and Tarau, 2004; Radev et al., 2004). In 2014, Parveen and Strube proposed to use a bipartite graph representation of text based on the entity grid representation proposed by Barzilay and Lapata (Barzilay and Lapata, 2008). Employing this type of representation can help us to determinate the importance of sentences and to detect correlations between phrases. A bipartite graph is an unweighted graph G=(V_s,V_e,L), containing two sets of nodes, where V_s is the set of sentences, V_e is the set of most expressive words (here we will consider two types of expressive words: named entities and most frequent words) and L is the set of edges. An edge exits between a sentence and an expressive word only if the word is mentioned in a sentence; and there are no edges between nodes of the same set. Figures 3, 4 and 5 show an example of a text, its associated entity grid and its bipartite graph.


S1 The treatment of osteoarthritis includes a number of non-steroidal anti-inflammatory drugs such as aspirin, acetaminophen, and ibuprofen.

S2 These drugs, however, cause liver damage and gastrointestinal bleeding and contribute to thousands of hospitalizations and deaths per year.

S3 New cox-2 inhibitor drugs are proven as effective against pain, with fewer gastrointestinal side effects.

S4 The two together appeared to reduce knee pain after 8 weeks.

Figure 3: An example of a text.

	TREATMENT (e1)	OSTEOARTHRITIS (e2)	NUMBER (e3)	DRUGS (e4)	ASPIRIN (e5)	ACETAMINOPHEN(e6)	IBUPROFEN (e7)	DAMAGE (e8)	BLEEDING (e9)	THOUSANDS (e10)	DEATHS (e11)	YEAR (e12)	PAIN (e13)	EFFECTS (e14)	TWO (e15)	WEEKS (e16)
S_1	x	x	x	x	x	x	x	-	-	-	-	-	-	-	-	-
S_2	-	-	-	x	-	-	-	x	x	x	x	x	-	-	-	-
S_3	-	-	-	x	-	-	-	-	-	-	-	-	x	x	-	-
S_4	-	-	-	-	-	-	-	-	-	-	-	-	x	-	x	x

Figure 4: Entity grid of the model summary from Figure 3.

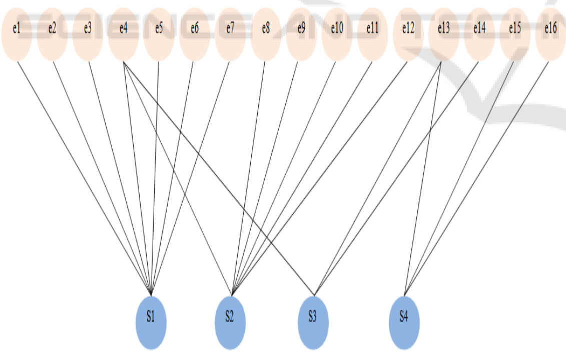


Figure 5: Bipartite graph derived from the entity grid from Figure 4.

6.2.2 Using HITS Algorithm for Sentence Reordering

The aim of this step is to reorder sentences in the same clique to improve readability in the context. Hence, coherence improvement is presented as a ranking problem. Inspired by (Parveen et al., 2015), it is proposed to use HITS algorithm to calculate the rank of a sentence in a clique. This algorithm considers two types of nodes: hub nodes and authority nodes. Since our graph is a bipartite graph, we can consider sentences as authority nodes and words as hub nodes (Kleinberg, 1999), to reorder sentences in the associated bipartite graph. For every sentence in the graph, the importance of the phrase should be calculated in two steps:

1. Calculate the hub score of a node (word) using the following formula:

$$HubScore = A.AuthorityScore \quad (6)$$

   Where A is an adjacency matrix which represents the connection between nodes in a graph. Each node's hub score has to be updated and the associated score is equal to the sum of authority scores of each node that it points to.

2. Calculate the authority score of a node (sentence) using the following formula:

$$AuthorityScore = A^T.HubScore \quad (7)$$

   Hence the authority weight is high if it is pointed at by a hub having high weights.

The rules given by equations 3 and 4 are applied until convergence (values of authorities and hubs are stable). Also, all nodes in the graph have to be initialized. Initial rank of a sentence is given by the following formula:

$$ItitialRank(S_i) = 1 + similarity(S_i, Tweet) \quad (8)$$

Here $similarity(S_i, Tweet)$ is the cosine similarity between a sentence S_i and a tweet. We consider that initial importance of a sentence S_i is related to the tweet. Initial rank of a word is given by:

$$InitialRank(w_i) = 1 + tf(w_i, C) + occurence(w_i, tweet) \quad (9)$$

Here $tf(w_i, C)$ is the term frequency of w_i in a clique C and $occurence(w_i, tweet)$ indicates the occurrence of w_i in a tweet. Hence if w_i is not present in the tweet then $occurence(w_i, tweet) = 0$. If it is present then $occurence(w_i, tweet) = 1$. We consider that initial importance of a word depends on the clique and the tweet.

7 EXPERIMENTAL RESULTS

This section highlights experimental results given by the proposed contextualization system. Obtained results are compared with results provided by INEX 2014. Before reporting experimental results, it is essential to indicate the Test Data and the evaluation criteria that we will consider.

7.1 Description of the Test Data

In this study, we use the collection of articles and tweets made available by INEX . The corpus has been rebuilt in 2013 from a dump of the English Wikipedia from November 2012. All notes and bibliographic references were removed to facilitate the extraction of plain text answers. It is composed of 3 902 346 articles and 240 tweets selected from the CLEF RepLab (Amigó et al., 2013) 2013 to build the 2014 INEX collection. 70 tweets were considered for evaluation.

7.2 Evaluation Measures

Contexts are evaluated according to readability and informativeness (Bellot et al., 2013). Readability aims at measuring how clear and easy it is to understand the summary and is manually evaluated. However, informativeness aims at measuring how well the summary explains the tweet or how well the summary helps a user to understand the tweet content (Bellot et al., 2013).

7.2.1 Informativeness

This criteria calculates the dissimilarity between a reference text and the proposed summary (Bellot et al., 2013), (SanJuan et al., 2012). It is a measure that varies between 0 and 1, and the lower this dissimilarity, the more the proposed summary is similar to the reference text. It is given by:

$$Dis(T,S) = \sum_{t \in T} (P-1) \times \left(1 - \frac{min(\log(P), \log(Q))}{max(\log(P), \log(Q))}\right)$$

Where: $P = \frac{f_T(t)}{f_T} + 1$ and $Q = \frac{f_S(t)}{f_S} + 1$
T, is a set of query terms present in a reference summary and for each $t \in T$, $f_T(t)$, the frequency of a term t in a reference summary, S, a set of query terms present in a submitted summary and for each $t \in S$ and $f_S(t)$, the frequency of term t in a submitted summary. T may takes three forms: *unigrams* made of single lemmas, *bigrams* made of pairs of consecutive lemmas (in the same sentence) and *bigrams with 2-gaps* also made of pairs of consecutive lemmas but allowing the insertion between them of a maximum of two lemmas.

7.2.2 Readability

In this evaluation the assessor indicates where he misses the point of the answers because of highly incoherent grammatical structures, unsolved anaphora, or redundant passages. Each summary consists in a set of passages and for each passage, assessors had to tick four kinds of check boxes. The guideline was the following(Bellot et al., 2013): *syntax (S)* box is ticked if the passage contains a syntactic problem (bad segmentation for example), *anaphora (A)* box is ticked if the passage contains an unsolved anaphora, *redundancy (R)* box is ticked if the passage contains a redundant information, and *trash (T)* box is ticked if the passage does not make any sense in its context.

To evaluate summary's readability, three metrics are used based on *relevancy* or *relaxed metric* where a passage is considered as valid if the T box has not been ticked, *syntax metric* where a passage is considered as valid if the T or S boxes have not been ticked and *structure* or *strict metric* where a passage is considered as valid if no box has been ticked.

7.3 Results and Disscussion

This section highlights experimental results of the proposed method. Hence we can evaluate our system according to informativeness and readability.

7.3.1 Informativeness Evaluation

To evaluate informativeness for tweet contextualization, we conducted a simulation, namely run-1, in which we evaluate our system considering the proposed method of cliques selection proposed in section 5.2. We have compared our runs with the following different runs submitted by INEX 2014 participants: in **Best-run**, participants (Zingla et al., 2014) used mining association rules between terms and in **REG-run**, participants (Torres-Moreno, 2014) used an automatic greedy summarizer named REG (REsumeur Glouton) which uses graph methods to spot the most important sentences in the document. The proposed method has ameliorate our informativeness results. We can note that our proposed approach gives encouraging informativeness results compared to other systems proposed at INEX 2014 (see table 1).

Table 1: Table of informativeness results.

Run	Unigram	Bigram	Bigrams with 2-gaps
Best-run	0.7632	0.8689	0.8702
run-1	0.8180	0.9072	0.9102
REG run	0.8731	0.9832	0.9841

7.3.2 Readability Evaluation

As mentioned in the previous section, readability is manually evaluated. Hence, contexts readability were provided by 77 assessors. To evaluate readability for

Table 2: Table of readability results.

Run	Relaxed	Strict	Syntax
Best-Read-run	94.82	72.16	72.27
run-1	88.47	50.65	67.20
run-2	91.17	60.79	75.86
run-3	90.77	55.93	74.91
run-4	84.67	54.17	70.18
run-5	82.16	52.66	71.23
run-6	92.33	62.65	77.53
Last-Read-run	90.10	24.68	53.83

the proposed system, we considered the following simulations: **run-2** where we consider contexts with sentence reordering in cliques using named entities, **run-3** where we consider contexts with sentence reordering in cliques using most frequent words (MFW) and the number of considered MFW is weighted according to sentences, **run-4** where we consider contexts with sentence reordering in cliques using most frequent words (Here we consider that the number of considered MFW is equal to 10), **run-5** in which we consider contexts with sentence reordering in cliques using most frequent words and the considered number of MFW is higher then 10, and **run-6** in which we consider overlapping words between named entities and most frequent words. We have compared our runs with the following different runs submitted by INEX 2014 participants: **Best-Read-run** which is the best readability run and **Last-Read-run** which is the last readability run. Simulation results are summarized in table 2.

By observing the results given in table 2, we can note that there is an interesting improvement for the readability results considering the used three metrics: comparing run-1 (without sentence reordering) and run-2 (with sentence reordering) we can confirm that sentence reordering based on combining HITS algorithm and named entities is efficient to ameliorate the readability of our system. We can also see that using most frequent words in sentence reordering improves readability results, in particular in run-3 compared with run-4 and run-5, what confirms the interest of sentence reordering using bipartite graphs. An other important observation is that the provided results from run-2 and run-3 are very close. this can be explained by the fact that the set of most frequent words and the set of named entities are overlapping.i.e, many words are in common between the two sets. For that we proposed an other run namely run-6 where we consider overlapping words. According to the Table 2, we can see that using overlapping words between named entities and most frequent words in sentence reordering improves readability results. Comparing our results with official results given by INEX 2014, we can see that our proposition gives encouraging results that are in line with the values obtained at INEX 2014.

8 CONCLUSION

In this paper we focus on the problem of readability of tweet contextualization. Our main contribution is the proposition of a method based on the use of bipartite graphs to reorder sentences in cliques and to improve readability for Tweet Contextualization. We opted to combine HITS algorithm and two types of words in the graph: most frequent words and named entities to make up coherent contexts. These proposals and their formal studies are complemented by an experimental study to compare them with results from INEX. We found that our model obtains encouraging results since that our returns are in line with the results of the INEX 2014 and it is essential to point out that our system proposed a compromise between informativeness and readability. We propose in our future work to make an order for cliques (paragraphs) in the context to improve the quality of the context with respect to informativeness and readability.

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