Users' Traces for Enhancing Arabic Facebook Search

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ABSTRACT

This paper proposes an approach on Facebook search in Arabic, which exploits several users' traces (e.g. comment, share, reactions) left on Facebook posts to estimate their social importance. Our goal is to show how these social traces (signals) can play a vital role in improving Arabic Facebook search. Firstly, we identify polarities (positive or negative) carried by the textual signals (e.g. comments) and non-textual ones (e.g. the reactions love and sad) for a given Facebook post. Therefore, the polarity of each comment expressed on a given Facebook post, is estimated on the basis of a neural sentiment model in Arabic language. Secondly, we group signals according to their complementarity using features selection algorithms. Thirdly, we apply learning to rank (LTR) algorithms to re-rank Facebook search results based on the selected groups of signals. Finally, experiments are carried out on 13,500 Facebook posts, collected from 45 topics in Arabic language. Experiments results reveal that Random Forests combined with *ReliefFAttributeEval* (RLF) was the most effective LTR approach for this task.

CCS CONCEPTS

• **Information systems → Information retrieval**;

KEYWORDS

Facebook Search, Sentiment Analysis, User Generated Content

1 INTRODUCTION

Social media has largely contributed to the launch of the so-called *Arab Spring*. Since then, the penetration of social media has grown steadily. The number of Facebook users in the Arab world is estimated at 164 million[1]. This movement reflects the democratization of the ways of production and interaction in the Web (user-generated content) thanks to new technologies. Among these ways increasingly accessible to a wide audience include social networks, blogs, microblogs, etc. User-Generated Content (UGC) refers to a set

[1]https://arabiawithclass.com/164-million-active-facebook-users-in-the-arab-world-study-shows/

of data (e.g. comments, posts, reactions) whose content is primarily either produced or directly influenced by end users. It can also be seen as a result of a computer-mediated communication [21].

The main task in information retrieval (IR) is to find a set of relevant documents to a specific information need (query). For this, effective approaches have existed for many years that exploit two classes of features to rank documents responding to a given query. The first class, the most used one, is query-dependent, which includes features corresponding to particular statistics of query terms such as term frequency, and term distribution within a document or in the collection of documents. The second class corresponds to query-independent features, which measure the a priori importance of the document. For example, number of backlinks [25], URL [32], PageRank [14], document authors [26] and social signals [6, 7].

This paper investigates the impact of users' traces (like, share, positive comment, negative comment, love, haha, angry, wow and sad) on the effectiveness of the relevance ranking of Arabic Facebook search. In order to design our approach, fundamental tasks are carried out. First, we identify the polarity for each comment left on a given post using a neural sentiment analysis in Arabic language. Then, we use feature selection algorithms to identify the most fruitful features (users' traces) for IR task. Finally, we evaluate the impact of these features on the relevance of Facebook search results. More specifically, we try to select the most effective features and combine them with Learning-To-Rank (LTR) approaches to improve IR on Facebook. The main contributions discussed in this paper are twofold:

(C1). Evaluate the impact of social features (users' traces and comment sentiment) on Facebook search. We try to answer the following research questions: a) What are the best social features suitable for this task? ; b) What is the impact of these features on the performance of Facebook's search ranking?

(C2). Build a test dataset (documents, topics, qrels) from Facebook. This dataset is useful to evaluate social IR systems in Arabic language. A user study is conducted to collect relevance judgments.

2 BACKGROUND AND RELATED WORKS

This section presents an overview of the Social Information Retrieval (SIR) and their major components related to our work. Beginning with a presentation of different types of UGCs, description and interrelationships of the Arabic sentiment analysis and our SIR approach. Then a focused overview of SIR approaches exploiting users' traces and social networks is presented.

User Generated Content is often linked to a specific social network with different operating rules (see table 1). The popularity of UGCs, especially in the context of social media, has given rise to many new problems in IR [13]. More specifically, how to exploit these social contents in favor of IR is an open question.

Table 1: List of different types of UGCs (social signals)

Type	Example	Social Networks
Vote	Like, +1	Facebook, LinkedIn, Google+, StumbleUpon
Message	Tweet, Post	Facebook, Google+, LinkedIn, Twitter
Share	Share, Re-tweet	Google+, Twitter, Buffer, Facebook, LinkedIn
Tag	Bookmark, Pin	Delicious, Pinterest, Diigo, Digg
Comment	Comment, Reply	Facebook, Google+, LinkedIn, Twitter
Emotion	Love, Haha, Wow	Facebook
Event Reaction	Thankful (Mother's day)	Facebook
Relation	Followers, Friends	Facebook, Twitter

Arabic Sentiment Analysis is useful for quantifying the polarity of Arabic textual UGCs such as comments and tweets. However, to the best of our knowledge, just a few works have been done on sentiment analysis in Arabic language. This can be explained by the lack of standard datasets. Farra *et al.* [20] proposed a linguistic method based on a set of patterns to extract the polarities from a financial document. Al-Kabi *et al.* [2] have set up a tool that determines the subjectivity, the polarity of an opinion and its intensity. They used two general lexicons and sixteen specific lexicons. Abdulla *et al.* [1] proposed a statistical approach to detect subjectivity and polarity in social networks using morphological attributes. Bayoudhi *et al.* [12] compared three classifiers: SVM, Naive Bayes and a simple neural network. Ibrahim *et al.* [23] used a lexicon of 5244 adjectives, a lexicon of 3296 idioms to improve sentences classification with using SVM. Refaee and Rieser [31] applied a hybrid approach for predicting the intensity of polarity in tweets. They used logistic regression specifically to predict initial scores that are adjusted by applying rules extracted from a polarity lexicon. Other recent works apply deep learning techniques for opinion analysis [11, 18]. Barhoumi *et al.* [11] used continuous representations of documents combined with a MultiLayer Perceptron (MLP) while Dahou *et al.* [18] used CNN (Convolutional Neural Network). Barhoumi *et al.* [10] illustrated a relevant comparison between several systems of Arabic sentiments detection, experienced in the Large-scale Arabic Book Review dataset (LABR)[2]. They showed that the best results were obtained by Dahou *et al.* [18] using CNN (77.39% of accuracy). The second best system is that of ElSahar and El-Beltagy [19], they have built a large Arabic lexicon multi-domains for sentiment analysis. The reviews was collected from various websites (e.g. hotels[3], movies[4]). We recall that our goal in this paper is exploiting social features to improve Arabic Facebook search. For this, we used the approach proposed in [18] (see section 3.1) to measure comment polarity and consider it as an additional relevance factor.

Social Information Retrieval has extended traditional IR with different social features in order to satisfy social motivations behind the user's information needs. In 2012, Jaime Teevan[5], a researcher at Microsoft, defines social IR as follows: "*Social search is an emerging research area that explores how social interactions and social data can enhance existing information-seeking experiences, as well as enable new information retrieval scenarios. This session will showcase different models of social search, including 1) the use of social data to augment search, 2) social data as new information to be searched, and 3) social interaction and collaboration as part of the search process.*"

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[2]https://github.com/mohamedadaly/LABR
[3]https://www.tripadvisor.com/
[4]https://www.elcinema.com/
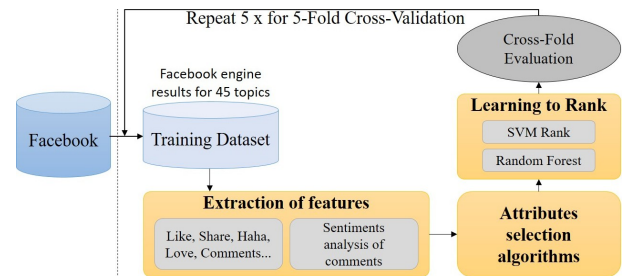[5]https://www.microsoft.com/en-us/research/video/social-search-panel/

Our work concerns both the first and second axes mentioned by Jaime Teevan, we propose an approach to improve Facebook search using its UGCs. While considerable work has been done in the context of social IR in English language, there is still a lack of studies that would analyze the impact of users' traces on Facebook search in Arabic language. The most related works to ours include [4, 5, 7, 15, 16, 30]. These works focus on the exploitation of social features to improve IR in English on the Web and on social networks. The approach we propose in this paper is in the same vein as these works, i.e exploiting social features around Facebook posts (documents) to improve the ranking of search results. However, our work differs from the state of the art in the following points. First, our approach is to search for information in Arabic language on Facebook. A sentiment analysis of the comments left by the users on a given publication is necessary. Next, we use Learning To Rank algorithms combined with feature selection techniques. More specifically, we estimate the social importance of a Facebook post by exploiting these social traces (like, share, polarity of comment: positive or negative, love, haha, angry, wow and sad) to improve the effectiveness of Arabic language search in Facebook.

3 ARABIC FACEBOOK SEARCH APPROACH

Our approach is based both on the classical traces (e.g. the frequencies of the signals "like" and "share", etc.) and on the emotional traces (e.g. the frequencies of the reactions "love" and "sad", etc.) as well as on the sentiment analysis of the comments expressed on each Facebook post (document). We note that Facebooks reactions allow users to express more nuanced emotions compared to classical signals. The goal of our approach is to improve the relevance of the results returned by the Facebook search engine in Arabic language by exploiting all these Facebook traces (or signals). They are considered as a priori knowledge to be taken into account in the Arabic Facebook search process.

3.1 Social Traces-Based Search Process

Three main steps are required: 1) extracting features and estimating sentiments for Arabic comments; 2) selecting the best features for IR task; and 3) combining LTR algorithms with selection techniques. The figure 1 illustrates our adopted Learning To Rank (LTR) process.

Figure 1: LTR process for Arabic Facebook search

Arabic Sentiment Analyzer. The sentiment of comment is estimated using the model proposed by Dahou *et al.* [18] whose implementation is publicly available[6]. Dahou *et al.* [18] proposed a CNN approach to identify the polarity of Arabic comments. When

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[6]https://pan.baidu.com/s/1eS2mxCe#list/path=%2F

considering the semantics of words, it has been shown that neural word embedding captures semantic similarities between the words [27]. Such distributed representations of words in a dense vector space are learned efficiently on large collections. Therefore, Dahou *et al.* [18] investigated different neural word embedding architectures using a corpus of 3.4 billion words chosen from a collected web-crawled corpus of 10 billion words. Then, the CNN was trained on top of the pre-trained word embeddings to classify the sentiments without considering aspect-level (topic on which the sentiment is concerned). They trained the model word2vec on web pages [27] using Skip-gram (SKIP-G) and Continuous Bag Of Words (CBOW) methods of constructing the training data for the neural network. Their experiments resultas showed that CBOW is more efficient and their architecture outperforms existing methods on several publicly available datasets presented in [3, 19, 29].

Selection of the Best Relevance Features. In this step, we relied on feature selection techniques to determine the best features groups that can be considered into the LTR of the IR process.

Combining LTR Algorithms with Selection Techniques. In this step, we studied the effectiveness of some feature selection techniques by confronting them with LTR algorithms. Since the performance of social features differs from one LTR algorithm to another, we identified the best feature selection techniques to find the best performing features according to the LTR algorithms.

3.2 Facebook Data and Relevance Judgments

To the best of our knowledge, there is no standard Arabic Facebook dataset containing posts, users' traces, topics and qrels to evaluate the effectiveness of Arabic IR on Facebook. Therefore, we collected 13,500 Arabic posts with their users' traces extracted from Facebook via its API and also using *parsing*, between 16 and 28 January 2018. These data were collected via the Facebook search engine for 45 topics that we have defined (Table 2 shows an example of Arabic topics). Table 3 presents statistics on the nature of the 45 topics. We note that we have exploited only public Facebook posts that are also open to indexing by search engines like Google or Bing. Unlike the Scandal Facebook-Cambridge Analytica[7] where private and personal data were exploited for fraudulent purposes as for politicians. In our work any personal or private information has been exploited for our experimental evaluation. Table 4 gives some statistics about our dataset. It presents the 10 features we considered for estimating the relevance of Facebook posts for a given Arabic topic. The nature of the features from f_1 to f_{10} is a simple count, for example the feature f_1 and f_4 represent the number of "Like" and emotional reaction "Sad", generated on the document. Concerning the last two features f_9 and f_{10}, they represent the number of opinions expressed on the document according to their polarity (positive or negative), respectively. These two features are calculated based on the Arabic sentiment model presented in 3.1.

Table 2: Examples of Arabic topics

Arabic topic	Translation of the information need
الطفل السوري عمران	What happened to the Syrian child Omran, who was bombarded with his brother at his home in Aleppo, and the global reaction to this tragedy.
اضراب جامعة بيرزيت	The reactions on the strike at Birzeit University (Palestine) and its impact on the educational process.
قتل السفير الرومي	Why was the Russian ambassador killed in Turkey? And what are Arab and other public opinions about his death?
رقصة الزومبا	What are the benefits of Zumba and does it relate to weight loss?

[7]https://fr.wikipedia.org/wiki/Scandale_Facebook-Cambridge_Analytica

Table 3: Nature of the 45 topics

Politic	Sport	Art	Leisure	Other
42%	24%	18%	11%	5%

To obtain the relevance judgments for a given topic: 6 users were asked to assess the first 300 documents returned for a given topic using a 3-point relevance scale (irrelevant, somewhat relevant and relevant). Each topic is judged by 3 users. To avoid any bias, none of the social features were displayed with the documents, but all textual content, images or video (according to the Facebook post) are displayed to facilitate the task of judgment. We computed the agreement degree between assessors for each topic using Kappa Cohen measure k [17]. The k ranges from 0.45 to 0.90. The average measure of agreement between the assessors is 75% (strong agreement).

Table 4: Facebook Data Statistics (list of exploited features)

Posts (documents) & Topics		13,500 documents	45 Arabic topics			
f_i	Feature	Description	SUM	MIN	MAX	AVG
f_1	Like	#*Like* on the document	2031958	0	32025	151
f_2	Share	#*Share* on the document	2329934	0	16781	173
f_3	Comment	#*Comment* on the document	2717589	0	24306	201
f_4	Sad	#*Sad* on the document	63970	0	80	5
f_5	Angry	#*Angry* on the document	95752	0	119	7
f_6	Love	#*Love* on the document	397679	0	496	29
f_7	Haha	#*Haha* on the document	246715	0	308	18
f_8	Wow	#*Wow* on the document	171234	0	213	13
f_9	Positive Comment	#*PositiveComment* on the document	1527546	0	13750	113
f_{10}	Negative Comment	#*NegativeComment* on the document	1134831	0	10063	84

3.3 Identification of the Most Effective Features

In order to understand the real impact of the different social features, we evaluated the impact of each of them by using feature selection techniques. The goal is to determine the best features to exploit in the LTR algorithms. Feature selection techniques aim to identify and remove the maximum amount of unnecessary, redundant and irrelevant information upstream of a learning-based process [22]. They also make it possible to automatically select the subsets of features for obtaining the best results. We used Weka[8] for these experiments, and we proceeded as follows: we identified relevant and irrelevant documents (posts) according to the "qrels", for the top 300 documents for each topic (45 Arabic topics) returned by the default Facebook search engine. The resulting set contains 13,500 documents including: 2971 relevant documents and 10529 irrelevant documents. We observed that this collection has an unbalanced relevance classes distribution. This occurs when there are many more elements in one class than in the other class of a training collection. In this case, a LTR algorithm usually tends to predict samples from the majority class and completely ignore the minority class. For this reason, we applied an approach to sub-sampling (reducing the number of samples that have the majority class) to generate a balanced collection composed of: 2971 relevant documents and 2971 irrelevant documents. Irrelevant documents for this study were selected randomly. Finally, we applied the selection algorithms on the two sets obtained, for 5-folds cross-validation.

Feature selection algorithms consist in assigning a score to each feature according to its significance for the relevance class (relevant and irrelevant). These algorithms return importance ranking of the features according to the number of times that a given feature has been selected by the algorithm in the cross-validation. We note that we used for each algorithm the default setting provided by Weka.

[8]http://www.cs.waikato.ac.nz/ml

Table 5: The selected features by the selection algorithms

Algorithm	f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}
CfsSubsetEval	+	+	-	-	-	+	-	+	+	+
WrapperSubsetEval	+	+	-	-	-	+	-	-	+	+
ConsistencySubsetEval	+	+	+	+	+	+	+	+	+	+
FilteredSubsetEval	+	+	-	+	+	+	-	-	+	+
ChiSquaredAttributeEval	+	+	+	+	+	+	+	+	+	+
FilteredAttributeEval	+	+	+	+	+	+	+	-	+	+
GainRatioAttributeEval	+	+	-	-	-	+	-	+	+	+
InfoGainAttributeEval	+	+	+	+	+	+	+	+	+	+
OneRAttributeEval	+	+	+	+	+	+	+	-	+	+
ReliefAttributeEval	+	+	-	+	+	+	+	+	+	+
SVMAttributeEval	+	+	-	+	+	+	+	-	+	+
SymetricalUncertEval	+	+	-	+	+	+	-	-	+	+
Total	12	12	5	9	9	12	7	6	12	12

Table 5 presents the selected features by the 12 feature selection algorithms. A feature selected by the algorithm is a feature designated by a "+" and an unselected feature is designated by a "-". We remark that the features f_{10}: *Negative Comment*, f_9: *Positive Comment*, f_1: *Like*, f_2: *Share* and f_6: *Love* are the most selected and height ranked compared to other features. The features f_4: *Sad*, f_5: *Angry* are moderately favored by the feature selection algorithms, except algorithms *CfsSubsetEval*, *WrapperSubsetEval* and *GainRatioAttributeEval* that did not selected them. The features f_7: *Haha*, f_8: *Wow* are only selected by 7 and 6 algorithms, respectively. Finally, the weakest and most disadvantaged feature is the f_3: *Comment*, it is only selected by 5 out of 12 algorithms.

3.4 Social Features-Based Learning to Rank

Other experiments were carried out exploiting these social features in supervised approaches based on LTR models. We used the instances (Facebook posts) of the 45 topics as training sets. Then we used two LTR algorithms. This choice is explained by the fact that they often showed their effectiveness in IR: RankSVM [24] and Random Forests [28]. Regarding RankSVM, we use the implementation[9] with its default settings proposed by Joachims [24]. While for Random Forests, we used Weka's implementation[10]. We have set the option "*max depth*" to 0 (unlimited) and the number of trees to 100. The input of each algorithm is a vector of features (see table 4), that is all the features or only the features selected by a given selection algorithm. LTR algorithms predict the relevancy ranking of search results. Finally, we applied a cross-validation for 5-folds.

In order to take into account the selected social features in LTR models, we have carried out several experiments to identify the best features selection techniques allowing to find the most effective features according to the LTR techniques. Based on this study, we found the following best pairs of LTR algorithms and the feature selection techniques: a) Features selected by *CfsSubsetEval* (CFS) and *WrapperSubsetEval* (WRP) are learned using RankSVM and Random Forests; b) Features selected by *ReliefFAttributeEval* (RLF) are learned using Random Forests; and c) Features selected by *SVMAttributeEval* (SVM) are learned using RankSVM. We recall that features selection algorithms have highlighted 3 sets of features:

Table 6: Selected features sets (groups)

Selection algorithms	Selected features
CfsSubsetEval (CFS)	$f_1, f_2, f_6, f_8, f_9, f_{10}$
WrapperSubsetEval (WRP)	$f_1, f_2, f_6, f_9, f_{10}$
SVMAttributeEval (SVM)	$f_1, f_2, f_4, f_5, f_6, f_7, f_9, f_{10}$
ReliefFAttributeEval (RLF)	$f_1, f_2, f_4, f_5, f_6, f_7, f_8, f_9, f_{10}$

In order to check the significance of the results compared to Facebook (baseline), we conducted the Student's t-test. We attached

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[9] http://www.cs.cornell.edu/people/tj/svm_light/svm_rank.html
[10] http://weka.sourceforge.net/doc.dev/weka/classifiers/trees/RandomForest.html

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* (strong significance) and ** (very strong significance) to the results in table 7 when *p-value < 0.05* and *p-value < 0.01*, respectively.

Table 7: LTR results of P@{5, 10}, nDCG et MAP

IR Model		P@5	P@10	nDCG	MAP
Facebook search engine (baseline model)		0.1911	0.1721	0.2513	0.1002
LTR Algorithms	Selection Algorithms	P@5	P@10	nDCG	MAP
RankSVM	CfsSubsetEval (CFS)	0.2133*	0.1944*	0.2955*	0.1204*
	WrapperSubsetEval (WRP)	0.1992	0.1802	0.2674	0.1076
	SVMAttributeEval (SVM)	0.2627**	0.2441**	0.3939**	0.1654**
	All features	0.2254*	0.2066*	0.3196*	0.1314*
Random Forests	CfsSubsetEval (CFS)	0.2395*	0.2046*	0.2955*	0.1149*
	WrapperSubsetEval (WRP)	0.2072	0.1883	0.2834	0.1149
	ReliefFAttributeEval (RLF)	0.2920**	0.2735**	0.4522**	0.1921**
	All features	0.2526**	0.2340**	0.3738**	0.1563**

We now describe the results of our evaluation. We start with analyzing the effect of each features selection technique exploited with RankSVM and Random Forest algorithms. We then compare our results with those obtained by the baseline (Facebook search engine). Finally, we analyze the relative importance of each features selection technique according to their appropriated LTR algorithm.

Results obtained by RankSVM. The results obtained by RankSVM using the selection algorithm *SVMAttributeEval* (SVM), where only the two features f_3 and f_8 were not selected, are better than those obtained using (CFS, WRP or all features). We recorded improvement rates of 57% and 65% in terms of nDCG and MAP, respectively, compared to the baseline model. Using CFS which selects only 6 features f_1, f_2, f_6, f_8, f_9, f_{10}, and WRP which selects even fewer features f_1, f_2, f_6, f_9, f_{10}, the results fall with rates of -25% and -32% in terms of nDCG, respectively. Consequently, the unselected features f_4, f_5, f_7 and f_8 are fruitful for RankSVM. In addition, with the selection of all features, RankSVM achieves better results than those obtained with CFS and WRP when certain features are ignored. Indeed, some topics such as (translation Arabic to English: *the Syrian child Omran*) and (translation Arabic to English: *blockade of Gaza*) recorded the highest precision when the features f_4: *Sad* and f_5: *Angry* are taken into account (with 0.8957 and 0.9324 in terms of P@10, respectively). The features f_8: *Wow* and f_7: *Haha* are more effective with topics that represent weird, exciting, or funny information. Finally, even if the RankSVM algorithm is expensive in terms of execution time, it remains favorable to obtain significant results. We noticed that RankSVM combined with the selection algorithm (SVM) obtained the second best result after the results obtained by Random Forests combined with the *ReliefFAttributeEval* (RLF) selection algorithm.

Results obtained by Random Forests. According to the table 7, the results confirm that the Random Forests decision tree is the most appropriate model when combined with the selection algorithm *ReliefFAttributeEval* (RLF), it takes into account all the features, except for the feature f_3: *Comment*, more efficiently than the other configurations (improvement rates of 80% and 92% in terms of nDCG and MAP compared to baseline model, respectively). The improvement rates compared to the baseline model using CFS and WRP are relatively low (18% and 13% in terms of nDCG, respectively). We also note that Random Forests (combined with the RLF selection algorithm) exceeds the best RankSVM configuration (combined with the SVM selection algorithm) with a rate of 15% and 16% in terms of nDCG and MAP, respectively. In addition, the improvements are also highly significant for the configuration taking all the features with Random Forests (ranked 3rd after Random Forest with RLF and RankSVM with SVM).

4 CONCLUSION

To the best of our knowledge, we provide the first comprehensive investigation for the impact of the social features on Arabic Facebook search. This paper proposes a supervised approach of Arabic Facebook search based on social features specific to Facebook. Some features are a simple count (Like, Sad, Haha, etc.), while others represent a polarity of comments (positive or negative). We used feature selection techniques combined with learning to rank algorithms. The evaluation conducted on the Facebook dataset shows that Random Forests taking as input the features selected by RLF is the most successful configuration to estimate the relevance ranking of the results. In addition, LTR algorithms based on the most relevant features according to the selection algorithms are generally better compared to those obtained when the selection algorithms are ignored. Finally, we note that we are aware that the assessment of our approach is still limited. The main weakness of our approach is its dependence on the quality of the sentiment analysis model. An essential treatment step for an effective Arabic SIR is to use a *stemmer* for dialectal Arabic. Further large-scale experiments on other types of datasets are also envisaged. Even with these simple elements, the first results obtained encourage us to invest more in this track. As perspectives of this work in other context, we plan to adapt our approach to other types of information needs such as seeking controversial and contradictory information around specific topics, using pre-processing approaches on the detection of controversies and contradictions [8, 9].

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