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Domain-Level Cross-Social Media Context Aggregation

Chamwenga M. CHILUFYA †1 Mizuho IWAIHARA†1

Abstract: Aggregating content across social media or Social Networking Services (SNS) has the benefit of discovering interesting information that may not be available on a single social media. However, in the face of information overload it becomes imperative to employ fine grained cross-social media aggregation. Social media interaction is characterized by threaded conversations initiated by a post on domain specific topics for example, politics, health or personal life; this creates a post-feedback context. Research on cross-social media aggregation has focused mainly on high-level identification of trending topics, however, providing users with a parallel view of contexts from multiple social media, irrespective of popularity, can realize discovery of related contents with less effort. In this paper, we propose a framework that, given a context on one social media retrieves highly relevant context on another social media by using informative keywords extracted from a given context and special "#" prefixed words called hashtags, while maintaining the premise of being relevant in time.

Keywords: Social Media , SNS, hashtag, context, aggregation

1. Introduction

The massive popularity of social media platforms can be attributed to the benefits they offer such as fast propagation of information, exposure to a wide array of opinions and interaction with persons of similar interests. The need to have greater reach has seen organizations and persons having multiple accounts, a survey conducted in [1] shows that 42% of online adults now use multiple social media sites. Being two of the most popular social media platforms, this research takes Twitter and Facebook as its case study.

Content in SNS is shared in form of multimedia messages called *postings*, subsequent messages or gestures of approval on a posting constitute its *feedback*. Table 1 shows *posting-feedback* term equivalence as used on Twitter and Facebook.

Twitter	Facebook	Definition
Tweet	Post	A posting made on social media
Hashtag	Hashtag	"#" preceded word/s serving as topic markers
Reply	Comment	Opinionated message on posting
Retweet	Share	Repost of another user's posting
Favourite	Like	Gesture of approval of posting

Table 1 *posting-feedback* term equivalence on Facebook and Twitter

Social media platforms are not created equal; one may gravitate towards collaborative projects, another microblogging and yet another social networking, however, postings tend to overlap. Figure 2 is an example of such overlap. Both postings refer to the arrival of team Japan at the sochi2014 winter games. However, differences are seen in posting detail and feedback provided.

Figure 1 posting overlap on Twitter and Facebook

The differences can be attributed to inherent characteristics of each platform. In keeping with the findings in [2], Twitter being inherently a news media, the feedback provided (retweet, favourite) aid the propagation of content. Facebook on the other hand, exhibits high levels of user engagement as a study in [1] showed; hence, comments are posted in addition to other content propagation gestures. Given the differences, if one sought to analyze the sentiments expressed on the arrival of team Japan, simply relying on the Twitter posting may not suffice but aggregating the two contexts may.

Content shared in social media is vast and aggravate the problem of information overload. In dealing with this problem, postings are annotated with special "#" prefixed words called *hashtags* which categorize contents and make common topics searchable. Hashtags have been widely studied [3], [4], [5] in the context of Twitter. As with other social media Facebook recently made the use of the hashtag official [6]. The long standing problem with hashtags has been the lack of uniformity

†1 Graduate School of Information, Production and Systems, Waseda University, Fukuoka 808-0135, Japan
Email: c.chamwenga@fuji.waseda.jp iwaihara@waseda.jp

in naming convention. This lack of uniformity tends to defeat the purpose of hashtag usage; as an example, in annotating postings on the same football match, different hashtags *"#SaintsGame*", *"#Saints*" and *"#SaintsMatch*" may be used, as a result, even though these postings carry the same theme, they will not be aggregated as such. To understand the usage patterns of hashtags, we conducted a preliminary experiment on the domain of American Football League (NFL) by collecting Facebook and Twitter hashtags over a three month period. The aspects of hashtags investigated were:

Maturity (Longevity): defined as the difference in days between a hashtag's last usage date and its first usage date.

Usage frequency (popularity): overall usage count of a hashtag.

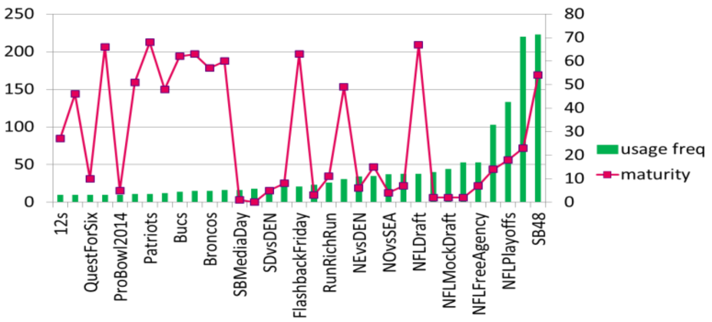

Figure 2a hashtag usage on Twitter

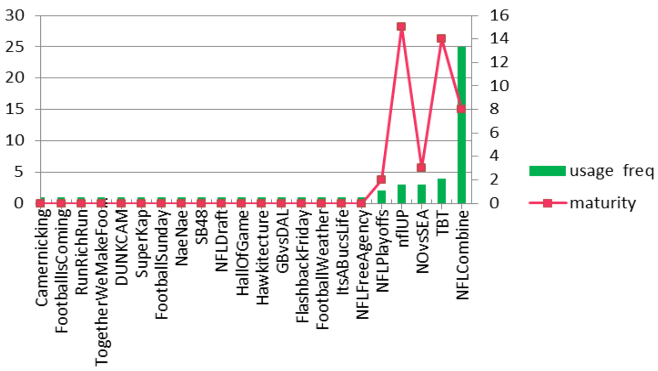

Figure 2b Hashtag usage on Facebook

Figures 2a and 2b show the results obtained. Generally, hashtag usage is not widespread on Facebook with an average usage frequency of only 2.45, while the same tarries at 41.5 on Twitter. Further analysis of Twitter hashtags review that long surviving hashtags are mostly single worded and can be considered as domain defining terms (team names) such as "*Broncos*" and "*Patriots*". Short lived hashtags on the other hand are very popular and consist of two or more unspaced words e.g "*NFLPlayoffs*", "*NEvsDEN*", these serve as trending topic markers. This could be attributed to the dual role played by hashtags as surveyed in [7]; domain definition and categorization of trending topics, the latter taking precedence. These findings influence how we extract hashtags in Section 4.

The primary definition of a context in an SNS is the posting-comment or posting-reply relationship; the posting sets the theme of discussion and subsequent comments extend the theme or express opinion on the theme. However, other types of relationships can be used, one such relationship being the hashtag relationship which aggregates postings bearing the same theme. Figures 3a and 3b illustrate context definition based on hashtag and posting-comment relationships. In Figure 3a, a context is defined considering the direct comment level feedback to a posting whereas in Figure 3b the basis is the usage of the hashtag "*#champions*". Both contexts are from the *sports domain* and bear the theme "*World Cup champions"*.

Posting: Who is going to win the world cup?
Comment 1: India lol!!
Comment 2: El Salvador all the way
:
CommentN: Brazil will be world cup champions!!

Figure 3a Posting-comment relationship context definition

Hashtag: #champions
Posting1: France #WorldCup #champions.
Posting2: Argentina are WorldCup #Champions.
:
PostingN: Uruguay 2014 world cup #champions!!!!

Figure 3b Hashtag relationship context definition

Furthermore, a level of granularity can be applied to context definition; a context can be a single posting and its comments or a collection of postings and their comments. In choosing the type of relationship to base context definition on and the level of granularity to apply, the inherent characteristics of an SNS are evaluated as will be shown in Section 3.

Given the inherent characteristics of social media, the goal of this research is to aggregate domain contexts across social media by using informative keywords extracted from a given Facebook context (to achieve more coverage) and hashtags in retrieved relevant contexts (to further streamline search) from Twitter.

Our work has the following aspects:

- Definition of Facebook context by annotating a posting with its comments.
- Extraction of domain hashtags and informative keywords by term frequency, Part Of Speech Tagging (POST) and domain specificity
- Defining Twitter context on the reply and hashtag relationship
- Evaluating relevance of Twitter context to Facebook context with a context weighting function that reflects content similarity and time relevance.

2. Related work

Mika Timonen et al. [8] proposed an unsupervised Informativeness-based Keyword Extraction (IKE) method for short documents. The work enumerated the term frequency (TF) =1 challenge and proposed a three level evaluation of the word;

document, cluster and corpus level. In our work, the TF=1 challenge motivated how we define context; however, a context is regarded as a single document.

Zhe Xue et al [9] proposed cross-media topic detection associated with hot search engine queries. This work is closely related to ours, however in their setting the queries are derived from hot search queries. In our work, we derive query terms from a given context.

With regard to Twitter, Romain Deveaud and Florian Boudin [10] proposed a method to contextualize tweets by finding relevant Wikipedia articles. In their work, they use hashtags and URL`s embedded in tweets. In our work, time being a factor in context definition, Wikipedia articles though updated frequently do not meet this factor.

3. Proposed Method

This section describes our method in finding relevant contexts on Twitter, given a context on Facebook. As illustrated in Figure 4, our framework has the following components: (1) Domain vocabulary (2) Facebook context definition, (3) context word weighting, (4) keyword selection, (5) Twitter search, (6) search result ranking, (7) domain hashtag extraction (8) Twitter context definition and (9) final results.

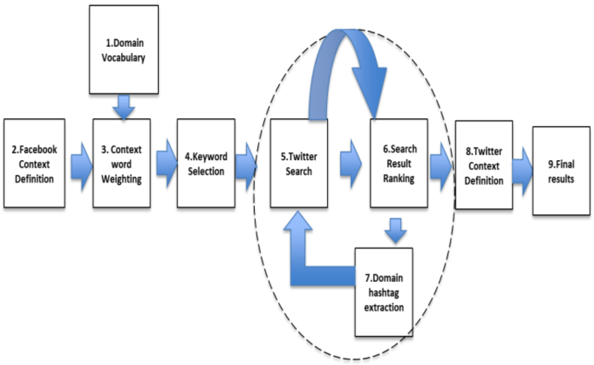

Figure 4 Framework overview

3.1 Domain Vocabulary

Different domains, such as sports, politics, and entertainment have different words that represent each domain. In extracting keywords, our goal is to retrieve terms representative of a domain, we refer to this attribute as *domain specifity* (*ds*). In the domain of the American National Football League (NFL) for example, named entities, e.g. “49ers”,”NFL” have high domain specificity. To construct a domain vocabulary, a collection of domain postings independent of comments is used, preprocessing is performed to remove stop words, each term is in stored along with its frequency of usage in the domain.

3.2 Facebook Context Definition

Given the high user engagement rate on Facebook and minimal hashtag usage we define a Facebook context (c_{fb}) based on the posting-comment relationship. This annotation of a posting with its comments is legitimate as comments can be said to add theme information to the posting; as an example, assessing responses on a picture-only posting may give insight on its theme. However, it is to be pointed out that some comments carry little, if any theme information, “Aaahhh, no”, picture comments, “lol” being examples. We therefore filter these out along with stop words. Given the temporal aspect of social media content, we assume that the comments have minimal time difference with the posting, we assign the date d_{fb} of the posting p_{fb} to be the date of the context c_{fb}. In validating this assumption, a posting’s comment level lifespan was evaluated on the NFL domain on Facebook, where 420 postings were used. Defining lifespan as the difference in days between the dates on which the first and last comments were made. Figure 5 shows the results.

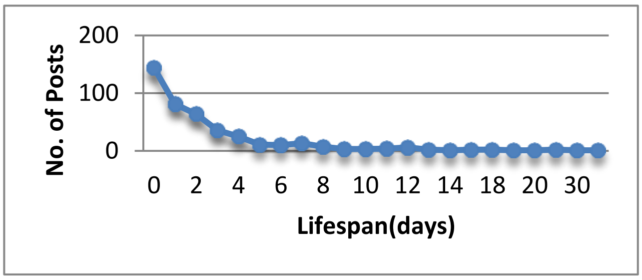

Figure 5 Comment-level posting lifespan on Facebook

From the results, we define a Facebook context as below.

Definition 1 *Facebook Context* c_{fb}: A Facebook c_{fb} is a posting p_{fb} published on date d_{fb} and its succeeding comments.

3.3 Context Word Weighting

Words in a context have varying informativeness; to assess the informativeness of each word in a given context, we introduce a context word weighting function $f(c_{fb}, t)$ defined as below:

Definition 2 *Context word weighting function* $f(c_{fb}, t)$: Given a Facebook context c_{fb} and a word t in c_{fb}, $f(c_{fb}, t)$ assigns a weight $0 <= f(c_{fb}, t) <= 1$.

Definition 3 *Context Corpus CA* is a word vector over all Facebook contexts C_{fb}.

In calculating $f(c_{fb}, t)$,we consider the following factors:

- The relative term-frequency (TF-score(c_{fb},t)) of a term of term t in c_{fb}:

$$\text{TF-score}(c_{fb}, t) = \frac{count(\mathrm{t})}{\sum_{w \in c_{fb}} count(\mathrm{w})} \quad (1)$$

- Domain specificity ($ds(t)$): A score given to a term t to indicate its domain representativeness. To determine $ds(t)$, the domain vocabulary is used to calculate the relative frequency of t over domain terms.
- Part of Speech Weight $w_{POS}(t)$: Given a POS (Part Of Speech) for a term t, $w_{POS}(t)$ assigns a predefined weight to t based on its POS. As our quest is to find informative words expressed as themes, a study in [11] shows that themes are mostly nouns, adjectives and prepositions and

rarely any other Parts Of Speech, we therefore give highest predefined weight to noun phrases.

- *Context Corpus* probability $cp(t)$: the c*ontext* corpus level probability of the word t given as:

$$\text{cp}(t) = \frac{count(\text{t})+1}{\sum_{w\in CA} count(\text{w})+1} \quad (2)$$

With these factors, $f(c_{fb}, t)$ is computed as below:

$$f(c_{fb}, t) = \lambda_1 \text{TF-score}(c_{fb}) + \lambda_2 \text{ds}(t) + \lambda_3\, w_{\text{POS}}(t) + \lambda_4 \text{cp}(t) \quad (3)$$

Here, λ_1, λ_2, λ_3, λ_4 are non-negative parameters adding up to 1. Let T, denote the top ranked words evaluated by $f(c_{fb}, t)$,a set, *context words* $CW_{fb}(c)$, representing informative words in context c_{fb} is created with T.

3.4 Keyword Selection

A single word may not have domain specificity in its own right, for example a term like "*game*" can refer to an NFL game or a basketball game. Therefore, in selecting keywords to use as search queries on Twitter, we create bigram keywords from $CW_{fb}(c)$ that maximize domain specificity. In the NFL domain, if these words were present in $CW_{fb}(c)$ {"game","NFL"…"Playoffs"}, the bigrams "NFL Playoffs" and "NFL game" maximize domain specifity as opposed to "game Playoffs". We call the overall approach to keyword selection as Domain Specific Keyword Extraction (DSKE).

3.5 Search Results Ranking

Let K denote the number of top ranked bigram keywords, search is performed using the Twitter Search API with K keywords. In evaluating the relevance of the retrieved tweets to the Facebook context c_{fb}, a preliminary step called *local context creation* is taken. Tweets are sparse, containing at most 140 characters; it is therefore not effective to match a single tweet with the entire c_{fb}. With an algorithm fully described in [12], reconstruction of the posting-reply relationship is performed on the retrieved tweets, if one exists; this defines a Twitter local context lc_{tw}. If a retrieved tweet is a reply (child) we find its parent (the original tweet it replied to) and its siblings (other replies). On the other hand, if it is a parent, we find its replies (children). Having reconstructed a local context, a preprocessing step is taken to remove mentions, URL's, and stop words. Content similarity is a strong indication that lc_{tw} is relevant to c_{fb}; however, this relevance is only at topic level. Time being a critical component of social media; we define a content similarity function that discounts the similarity based on how far apart in time lc_{tw} is from c_{fb}. As was the assumption in assigning a date to a Facebook context, we assign the date d_{tw} of the parent posting as the date of the Twitter local context lc_{tw}

Definition 4 *Time decayed similarity* **(**TD_{sim}): Given a Twitter local context lc_{tw} published on d_{tw} and a Facebook context c_{fb} published on d_{fb}. TD*sim* scores the content cosine similarity with regard to how proximal the two contexts are in time.

$$\text{TD}_{\text{sim}}(c_{fb}, d_{fb}, lc_{tw}, d_{tw}) = \left(\frac{1}{log\,|d_{fb}-d_{tw}|+1}\right)\cos(c_{fb}, lc_{tw}) \quad (4)$$

Another aspect of responses on postings is that of deviating from the topic at hand, to ensure that the retrieved lc_{tw} is indeed relevant to the original posting p_{fb}, we introduce named-entity boosting factor function e_{bf}.

Definition 4 *Entity Boosting Factor:* Scores the entity mention overlap between the lc_{tw} and p_{fb} and calculated as:

$$e_{bf}(p_{fb}\ \ lc_{tw}) = \frac{entities(p_{fb}) \cap entities(lc_{tw})}{entities(p_{fb})} \quad (5)$$

The overall relevance is then judged by result ranking function R_f defined as:

$$R_f = \alpha\ \text{TD}_{\text{sim}}(c_{fb}, d_{fb}, lc_{tw}, d_{tw}) + (1-\alpha)\ e_{bf}(p_{fb}, lc_{tw}) \quad (6)$$

Where α discriminates between TD_{sim} and e_{bf}. The optimal value for α will be shown in Section 4.2.

Let R_1 be a context range, denoting the number of top-ranked local contexts. The top-R_1 local contexts RLC_1 are returned. These aid query refinement in the form of domain hashtag extraction.

3.6 Domain Hashtag Extraction

The purpose of the hashtag is to aggregate postings bearing the same theme or topic. Given the long standing usage of hashtags on Twitter, we can define a context on the hashtag relationship. However, as earlier alluded to, the problem with hashtags is the lack of convention in how they are created, given this limitation, hashtags having a high adoption level are more suited to be used as search queries, as an example, in the NFL domain, "*#NFLDraft*", "*#NFL*" defined by the NFL are seen to have high usage frequencies as opposed to other user-defined such as *#IamaGreatFan*. To assess the domain representativeness of a hashtag h, its *popularity* $q(h)$ is defined by the frequency of usage in lc_{tw}. Let H be a set of hashtags in lc_{tw} for hashtag h_i in H, its popularity is defined as:

$$q(h_i) = \frac{count(h_i)}{\sum_{h\in H} count(\text{h})} \quad (7)$$

Picking the top H_T hashtags, further search is carried out on Twitter. For each hashtag h_t in H_T, the retrieved tweets define a local Twitter context lc_{tw}, with constraints that the tweets are within a time proximity threshold tp_{min} from the Facebook context c_{fb} and are not already part of the top-ranked local contexts RLC_1 in the previous step. The hashtag based local contexts are then ranked by R_f to return top-R_2 local contexts RLC_2.

3.7 Twitter Context Definition

Twitter exhibits low user interactions levels, therefore the local contexts RLC_1 and RLC_2 are aggregated to define the Twitter context $c_{tw.}$

3.8 Final Results

In this step, the final top-R_{lc} local contexts from Twitter Context c_{tw} are presented as being relevant to the Facebook context c_{fb}.

4. Experiments

We next present some of the key results in evaluating the effectiveness of the proposed framework.

4.1 Experiment Setup

We used NFL's Facebook page as our domain. We considered 12 contexts, having a total of 1718 comments with the average number of comments per context being 177. In eqn 2, the POS weight for noun phrases is set to 0.7, and other parts of speech are weighed at 0.3. In the context word weighting function (eqn 3), the parameters are set as $\lambda_1 = 0.2$, $\lambda_2 = 0.4$, $\lambda_3 = 0.3$ and $\lambda_4 = 0.1$. For the ranking function R_f, α is set to 0.3. Based on the results on posting lifespan in Figure 5, the time threshold for time relevance and hashtag relationship local context definition is set to 4 days. On Twitter, a total of 8245 tweets were retrieved, with 2024 Twitter local contexts, each having on average 17 tweets.

4.2 Keyword Extraction

Baseline: adapted tf-idf weighting (TFICF)

In the baseline, agglomerative clustering is performed on the Facebook context; an adapted tf-idf we refer to as *Term Frequency Inverse Cluster Frequency* (TFICF) is then applied on the resultant clusters. To evaluate the effectiveness of a keyword extraction method, the domain specificity (*ds*) of the extracted keywords is considered. Figure 6 shows the average precision at ranks 5 and 10 of our proposed method DSKE and the baseline TFICF.

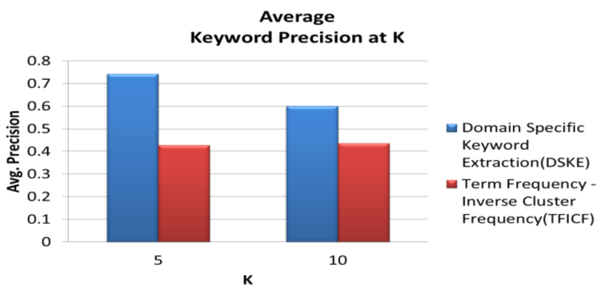

Figure 6 Average Precision at K, DSKE vs TFICF

DSKE has an average precision of 0.74 and 0.6 at ranks 5 and 10 respectively while TFICF stands at approximately 0.43 for both ranks. The results are explained by two factors; (1) nature of language and (2) nature of content. Language used in SNSs is highly informal, with misspellings and slang being the norm; this poses a challenge in extracting informative keywords from a context. Secondly, content may exhibit overlap of informative words. For example, consider a posting with a theme "*World cup Champions*" with comments: "*Brazil is playing to win, France too*" and "*Congo, but France is fierce*". If two clusters were created on this context, TFICF weighting would discount "*France*" which is informative word in this context. In the NFL, domain specific terms can be team names *(t-names)*, player names *(p-names)*, event names *(e-names)* and abbreviated football related words *(d-abbr)*. By referring to a non-domain specific word as Irrelevant (*IR*), Table 2 shows how domain specific terms are ranked by DSKE and TFICF on a Facebook context with the theme "*NFL quarterbacks (qb) team selection*". From the ranking of DSKE, any combination in creating a bigram would give informative keywords such as "maziel qb", with TFICF, a bigram like "smoke bridgewater" is only partially informative.

Rank	DSKE		TFICF	
	keyword	**ds**	**keyword**	**ds**
1	Maziel	*p-name*	round	*IR*
2	qb	*d-abbr*	Bridgewater	*p-name*
3	Bengals	*t-name*	smoke	*IR*
4	nfl	*d-abbr*	Bengals	*t-name*
5	Draft	*e-name*	hope	*IR*

Table 2 Top 5 keyword ranking by DSKE and TFICF

4.3 Local Context Ranking

Time relevance is of essence in our ranking function, however, the relative relevance of the retrieved Twitter context to the Facebook context is also important. As shown in [13], the traditional binary relevance cannot adequately express the continuous nature of relevance; documents are not equally relevant; relevance has multiple degrees. For example, given a Facebook context with a theme "*NFL Legends, Peyton and Derek Jeter*", a Twitter local context whose theme is "*Legends Peyton and Derek Jeter*" is more relevant than a local Twitter context whose theme is "*Broncos players*" with a partial mention of Peyton. Therefore, we employ a multi-grade relevance judgement on a scale of 0-3 with 0 meaning *irrelevant*, 1 and 2 meaning "*moderately relevant*" and 3 meaning *relevant*. To measure the performance of the proposed method, user relevance judgement is used based on the following conditions:

Condition 1: minimal time proximity and similar entity mentions (team names, player names, events)

Condition 2: minimal time proximity and direction of generality; if the Facebook context theme is general, such as a reference to all NFL players and Twitter local context theme is referencing a specific player, such as "*Peyton Manning*", the condition of direction of generality is upheld and we can judge the context as relevant. However, if the Facebook Context is specific to "*Peyton Manning"* and the Twitter context is general, but mentions "*Peyton Manning"*, judge as "moderately relevant" (1,2) ,otherwise judge as irrelevant .

Discounted Cumulative Gain(DCG) postulates that highly relevant documents that are ranked lower in a search result should be penalized as the graded relevance value is reduced logarithmically proportional to the rank of the result[14]. DCG at a particular rank position k is defined as:

$$DCG_k = rel_1 + \sum_{i=2}^{k} \frac{rel_i}{log_2(i)} \quad (8)$$

Further, normalized Discounted Cumulative Gain ($nDCG_k$) which normalizes the discounted cumulative gain at rank k across queries given the Discounted Cumulative Gain of an ideal ranking $IDCG_k$ is defined [15] as:

$$\mathrm{nDCG}_k = \frac{DCG_k}{IDCG_k} \quad (9)$$

To evaluate the best α for the ranking function R_f, we calculate nDCG_k with varying α for ranks 3 to 10. From the results as shown in Figure 7, the optimal nDCG_k is achieved when α is 0.3. In Figure 8, we show nDCG_k when different combinations of keywords and ranking function are used. From the results, the combination DSKE- R_f performs best overall with average nDCG_k of 0.98 and 0.92 at ranks 3 and 10 respectively. With TFICF- R_f, the results are due to TFICF based keywords having low domain specificity, therefore, retrieved local contexts have minimal theme similarity to the Facebook context. With DSKE-cosine similarity, the average time difference in days between the Facebook context and Twitter local contexts was 4.11 at rank 3 and 5.4 at rank 10 while DSKE-R_f stood at 1.64 at rank 3 and 2.88 days at rank 10; this varying difference in time relevance explains the differences in performance of DSKE-R_f and DSKE-cosine similarity as shown in Figure 8.

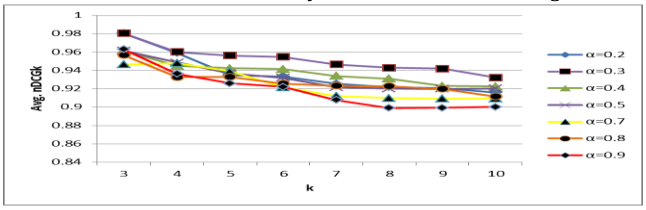

Figure 7 Average nDCG_k at k with varying α

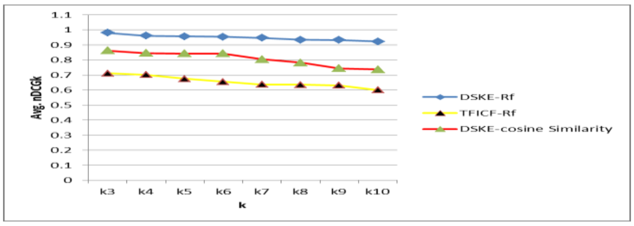

Figure 8 Average nDCG_k at k by method

Table 3 shows the leading tweets of top 3 retrieved contexts using keywords in Table 2, methods in Figure 8 and a facebook context with the theme "*NFL quarterbacks (qb) team selection*"

	DSKE-R_f	TFICF-R_f	DSKE- cosine similarity
Rank1	I think Maziel & Bottles have higher ceilings but Bridgewater….	Where there's smoke, there's fire! #NFL#Browns deny report Bridgewater	@Seanery3 we need a QB, not sure how far teddy bridgewater…
Rank 2	Top 5 QBs in this coming draft are 1. Bridgewater 2. Maziel…	MOUNT BARKER ROAD, BRIDGEWATER (Investigate Smoke	I think Maziel & Bottles have higher ceilings but Bridgewater….
Rank 3	Who do you think is the best QB…	It's like a triple reverse with a hook and lateral throw. Blowing smoke??	Who do you think is the best QB…

Table 3 Leading tweets of retrieved lc_{tw} at rank = 3 by method

5. Conclusion and Future Work

We proposed a framework that aggregates cross-social media contexts at domain level by the use of informative keywords from a given context and a ranking function that evaluates the relative relevance of retrieved contexts. In the future work, we will explore the dynamics of cross social media domain contexts that defy inherent characteristics of a given SNS in regard to the nature of interactions.

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