

Detecting off-topic pages within TimeMaps in Web archives

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Abstract Web archives have become a significant repository of our recent history and cultural heritage. Archival integrity and accuracy is a precondition for future cultural research. Currently, there are no quantitative or content-based tools that allow archivists to judge the quality of the Web archive captures. In this paper, we address the problems of detecting when a particular page in a Web archive collection has gone off-topic relative to its first archived copy. We do not delete off-topic pages (they remain part of the collection), but they are flagged as off-topic so they can be excluded for consideration for downstream services, such as collection summarization and thumbnail generation. We propose different methods (cosine similarity, Jaccard similarity, intersection of the 20 most frequent terms, Web-based kernel function, and the change in size using the number of words and content length) to detect when a page has gone off-topic. Those predicted off-topic pages will be presented to the collection’s curator for possible elimination from the collection or cessation of crawling. We created a gold standard data set from three Archive-It collections to evaluate the proposed methods at different thresholds. We found that combining cosine similarity at threshold 0.10 and change in size using word count at threshold -0.85 performs the best with accuracy = 0.987, F_1 score = 0.906, and AUC = 0.968. We evaluated the performance of the proposed method

on several Archive-It collections. The average precision of detecting off-topic pages in the collections is 0.89.

Keywords Web archiving · Document filtering · Information retrieval · Document similarity · Archived collections · Web content mining · Internet Archive

1 Introduction

Much of our cultural discourse occurs primarily on the Web and its preservation is a fundamental pre-condition for research in history, sociology, political science, media, literature, and other related disciplines [41]. We consider archival existence and integrity to be a requirement for any scholarly pursuit that involves Web pages. Since mining the past Web is different from traditional data mining [23], it is necessary to have novel approaches for utilizing the content of page histories for knowledge-discovery purposes and to assist the curators of archived collections to create quality collections that will be ready for researchers and practitioners.

The Internet Archive [40] (IA) is the largest and oldest of the various Web archives, holding over 400 billion Web pages (as of November 2015) with archives as far back as 1996 [25]. Archive-It¹ is a collection development service that has been operated by the Internet Archive since 2006. As of November 2015, Archive-It has been used by over 340 institutions in 48 states, and featured over 9 billion archived Web pages in nearly 3200 separate collections. Archive-It’s collections have three main categories. First, there are collections that are devoted to archiving governmental pages (e.g., all Web pages published by the State of South Dakota²). Second, there

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¹ <https://archive-it.org/>.

² <https://archive-it.org/collections/192>.

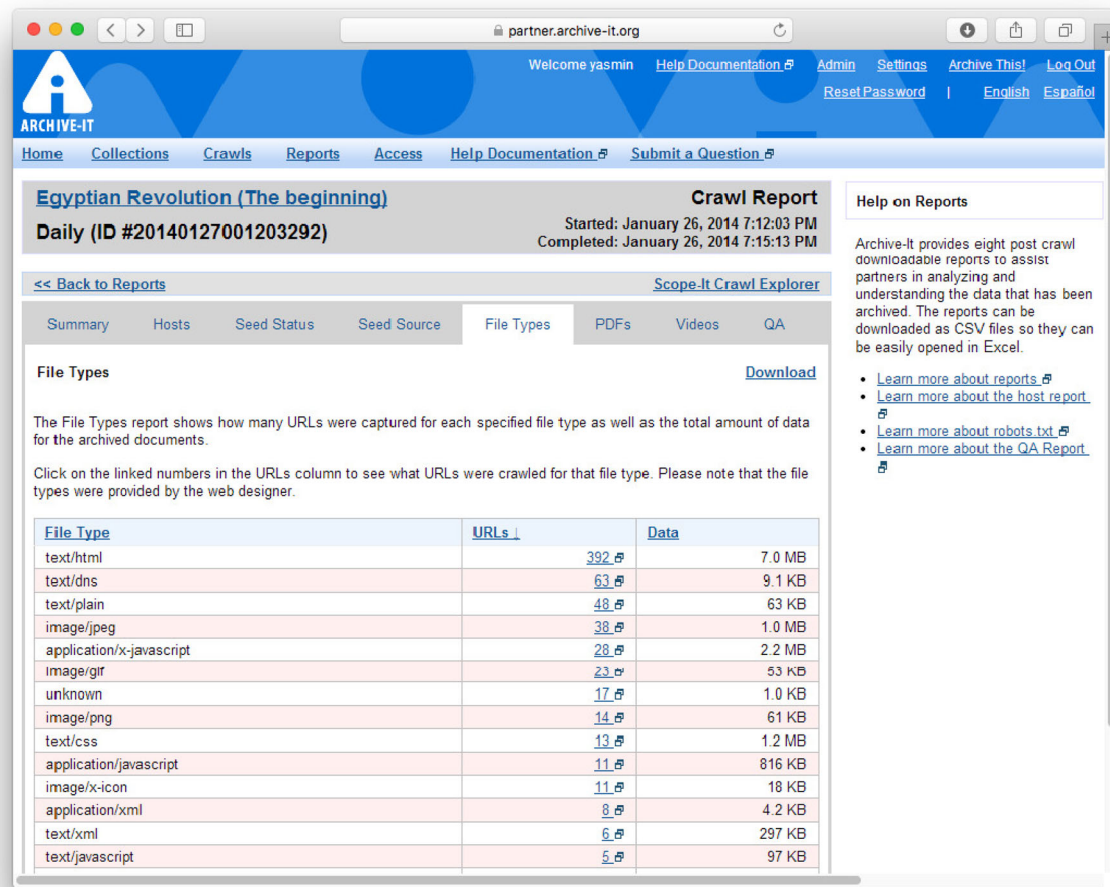


Fig. 1 Archive-It provides the collection curators with information about their crawls

are collections that are event based (e.g., Occupy Movement collection³ and SOPA Blackout collection⁴). Third, there are theme-based collections (e.g., the Columbia Human Rights collection⁵).

Archive-It provides its partners with tools that allow them to build themed collections of archived Web pages hosted on Archive-It's machines. This is done by the user manually specifying a set of *seeds*, uniform resource identifiers (URIs) that should be crawled periodically (the frequency is tunable by the user), and to what depth (e.g., follow the pages linked to from the seeds two levels out). Archive-It also creates collections of global events under the name of Internet Archive Global Events. The seed URIs by asking the people to nominate URIs that are related to these events. The seed URIs are manually collected by asking people to nominate URIs that

are related to these events, or are selected by the collection's curator(s).

The Heritrix [39] crawler at Archive-It crawls or recrawls these seeds based on the predefined frequency and depth to build a collection of archived Web pages that the curator believes best exemplifies the topic of the collection. Archive-It has deployed tools that allow collection's curators to perform quality control on their crawls, as shown in Fig. 1. However, the tools are currently focused on issues such as the mechanics of HTTP (e.g., how many HTML files vs. PDFs, how many HTTP 404 responses) and domain information (e.g., how many .uk sites vs. .com sites). Currently, there are no content-based tools that allow curators to detect when seed URIs go off-topic. We define off-topic archived pages as those that have changed through time to move away from the scope of the initial seed URI, which should be relevant to the topic of the collection.

In previous work [3] and extended in this paper, we introduce different approaches for detecting off-topic pages of the seed URI in the archives. The approaches depend

³ <https://archive-it.org/collections/2950>.

⁴ <https://archive-it.org/collections/3010>.

⁵ <https://archive-it.org/collections/1068>.

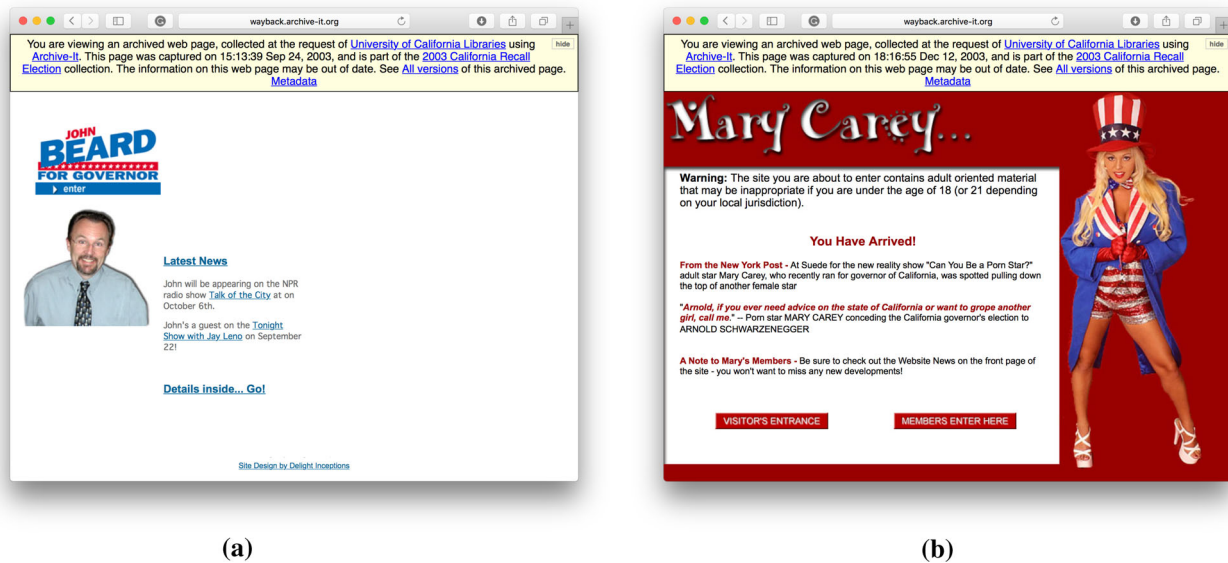


Fig. 2 Example of johnbeard4gov.com in the 2003 California Recall Election collection that went off-topic. **a** September 24, 2003: johnbeard4gov.com was for a California gubernatorial candidate. **b** December 12, 2003: johnbeard4gov.com became spam

on comparing the versions of the pages through time. We assume that the first copies of seed URIs were originally on-topic for the topic of the collection, since they were selected manually and judged by the collection curator. Three methods depend on the textual content (cosine similarity, intersection of the most frequent terms, and Jaccard coefficient), one method uses the semantics of the text [Web-based kernel function using the search engine (SE)], and two methods use the size of pages (the change in the number of words and the content length). In this paper, we extend our analysis by providing more details of how these methods work. We also investigate how a page’s aboutness changes through time, based on a data set from Archive-It. We found five different behaviors for how the aboutness of a page changes between on-topic and off-topic. We also quantified these behaviors based on a data set from archived collections.

For evaluation purposes, we built our gold standard data set from three Archive-It collections, then we employ the following performance measurements: accuracy, F_1 score values, and area under the ROC curve (AUC). Experimental results show that cosine similarity at the 0.15 threshold is the most effective single method for detecting the off-topic pages with 0.983 accuracy, followed by the word count at threshold -0.85 with 0.982 accuracy. We combined the tested methods and found that the best-performing combined method across the three collections is cosine at threshold 0.10 with word count at threshold -0.85 . Cosine and word count combined improved the performance over cosine alone with a 3 % increase in the F_1 score, 0.7 % increase in AUC, and 0.4 % increase in accuracy. We chose cosine at threshold 0.10 combined with word count

at threshold -0.85 , and evaluated the performance on a different set of Archive-It collections. Based on manual assessment of the detected off-topic pages, the average precision of the proposed technique for the tested collections is 0.9.

2 Motivating examples

We can define off-topic pages as the Web pages that have changed through time to move away from the initial scope of the page. There are multiple reasons for pages to go off-topic, such as hacking, loss of account, domain expiration, owner deletion, or server/service discontinued [37]. Expired domains should return a 404 HTTP status that will be caught by Archive-It quality control methods. However, some expired domains may be purchased by spammers who desire all the incoming traffic that the site accrued while it was “legitimate” (see Fig. 2). In this case, the Web page returns a 200 HTTP response, but with unwanted content [8].

There are also many cases in which the archived page redirects to another page which is not relevant, but still not spam. In Fig. 3, the Facebook page contained relevant content in the beginning (Fig. 3a), then later redirects to the homepage of Facebook as shown in Fig. 3b. The example in Fig. 3 shows how a page in a collection goes off-topic, even though the particular Web site has not been lost.

Figure 4 shows a scenario of a page that goes off-topic for many different reasons. In May 2012, hamdeensabahy.com Web page, which belonged to a famous politician and a candidate in Egypt’s 2012 presidential election, was originally relevant to the “Egypt Revolution and Politics” collection

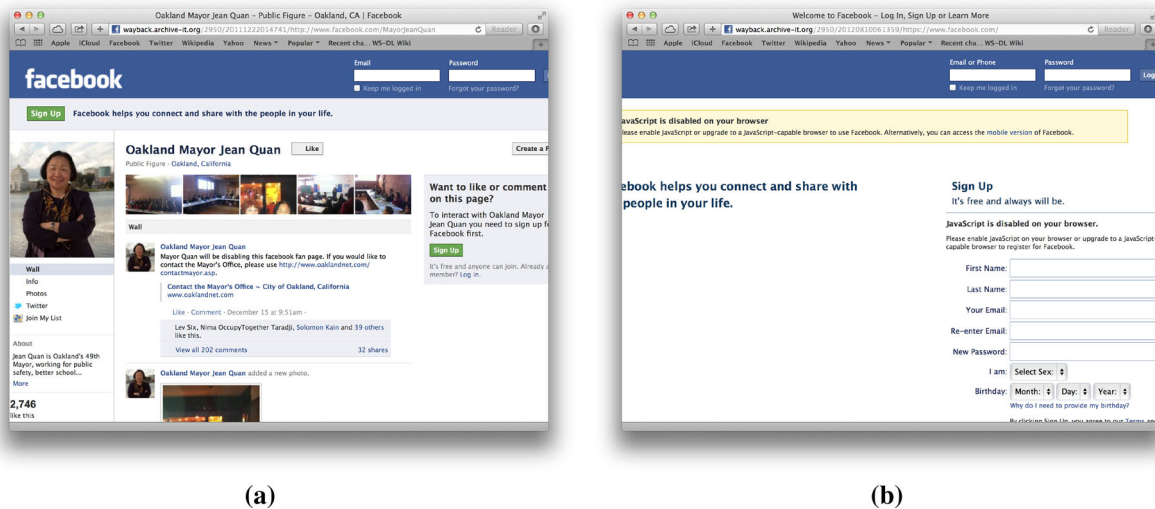


Fig. 3 Example of a Facebook page from the Occupy Movement collection that went off-topic. **a** December 22, 2011: Facebook page was relevant to the Occupy collection. **b** August 10, 2012: URI redirects to <http://www.facebook.com>

(Fig. 4a). Then, the page went back and forth between on-topic and off-topic many times for different reasons. Note that there are on-topic pages between the off-topic ones in Fig. 4. In the example, the page went off-topic because of a database error on May 24, 2012 (Fig. 4b), and then it returned on-topic again. After that, the page went off-topic because of financial issues (Fig. 4c). The page continued off-topic for a long period (from March 27, 2013 until July 2, 2013) because the site was under construction (Fig. 4d). The page went on-topic again for a period of time, then the site was hacked (Fig. 4e), and the domain was lost by late 2014 (Fig. 4f).

The Web page hamdeensabahy.com has 266 archived versions, or mementos. Of these, over 60 % are off-topic. While it might be useful for historians to track the change of the page in Web archives (possibly, the hacked version is a good candidate for historians), the 60 % off-topic mementos such as the ones in Fig. 4b–f do not contribute to the Egypt Revolution collection in the same way as the on-topic archived Web site in Fig. 4a.

Although the former can be kept in the IA's general Web archive, they are candidates to be purged from the Egyptian Revolution collection. Even if the archivist keeps them in the collection, once identified, these off-topic pages can be excluded from story summarization services [1, 2] or thumbnail generation [6].

3 Background

Despite the fact that Web archives present a great potential for knowledge discovery, there has been relatively little research that is explicitly aimed at mining content stored in

Web archives [23]. In this section, we highlight the research that has been conducted on mining the past Web. First, we define the terminology that will be adopted throughout the rest of the paper.

3.1 Memento terminology

Memento [55] is an HTTP protocol extension that enables time travel on the Web by linking the current resources with their prior state. Memento defines the following terms:

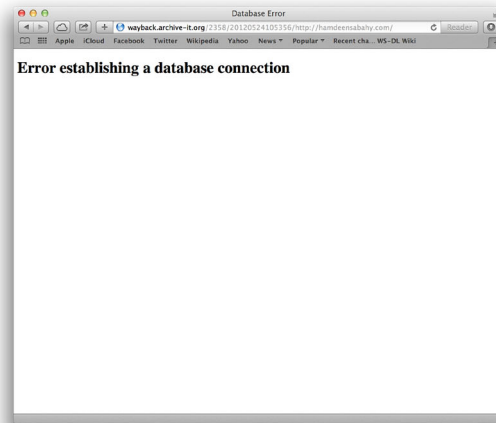
- URI-R identifies the original resource. It is the resource as it used to appear on the live Web. A URI-R may have 0 or more mementos (URI-Ms).
- URI-M identifies an archived snapshot of the URI-R at a specific datetime, which is called Memento-Datetime, e.g., $URI-M_i = URI-R@t_i$. We refer to an archived snapshot as a “memento”.
- URI-T identifies a TimeMap, a resource that provides a list of mementos (URI-Ms) for a URI-R with their Memento-Datetimes

3.2 Related work

Because the Web is a dynamic information space, the resources may change, disappear, and move from one location to another frequently [26, 31]. Many studies have shown that the expected lifetime of a Web page is short (between 44 and 190 days) [11, 24, 34, 37] and that Web resources disappear quickly [28, 30, 48]. This could be for various reasons such as service discontinuance, deliberate deletion by authors or system administrators, death, removing information that was publicly known at a certain time, and preventing third



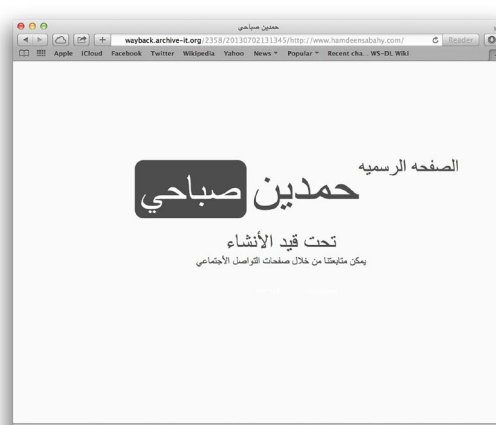
(a)



(b)



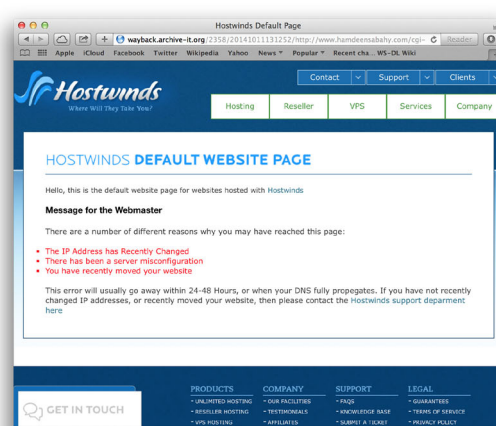
(c)



(d)



(e)



(f)

Fig. 4 A site for one of the candidates for Egypt’s 2012 presidential election. Many of the captures of hamdeensabhay.com are not about the Egyptian Revolution. Later versions show an expired domain. **a** May 13, 2012: The page started as on-topic. **b** May 24, 2012: Off-topic due to

a database error. **c** March 21, 2013: Not working because of financial problems. **d** July 2, 2013: under construction. **e** June 5, 2014: The site has been hacked. **f** October 10, 2014: The domain has expired

parties to access this information. Archiving the political process has become popular, both in terms of Web pages [19,45,50] and YouTube and blogs [13,36]. Web archives are becoming important for studies in social science and humanities research [1]. It is a challenge for Web archiving institutes to balance between the completeness and quality of archived materials while avoid wasting time and space for storing and indexing [46].

The limitation of the resources of Web archives, such as storage and site politeness rules, attracted much attention from many researchers toward optimize the processes of Web archiving lifecycle such as the selection, storage and preservation [4,5,9,15,16,43,46].

Ben Saad et al. [46] proposed a framework that optimized page indexing and storage by discovering patterns from the temporal evolution of page changes using the data from the archive of French public TV channels. They claimed that these patterns can be a useful tool to predict changes and thus efficiently archive Web pages.

Moreover, focused crawling has become an active area of research to make such collection-building crawls more effective [9,14,17]. As Bergmark et al. mentioned [9], the goal of the focused crawl is to make a “best-first” crawl of the Web.

The previous techniques focused on optimizing Web archives materials during the life cycle of Web archiving. Although these techniques are a good trend to avoid wasting time and space for storing and indexing Web pages, there is also a need to check the quality of archived materials that already exist in Web archives.

Excluding the off-topic pages from TimeMaps will significantly affect large-scale studies on archived materials. For example, the thumbnail summarization work [6] that was done by AlSum and Nelson would show off-topic pages in the generated summaries if these pages have not been detected before generating the summaries.

Mining the past Web is different from Web content mining because of the temporal dimension of the archived content [23,33,53]. Despite nearly two decades of Web history, there has not been much research conducted for mining Web archive data. The benefit of utilizing the Web archives for knowledge discovery has been discussed many times [7,21,23]. Below, we outline some of the approaches that have been used for mining the past Web using data in Web archives.

Jatowt and Tanaka [23] discussed the benefits of utilizing the content of the past Web for knowledge discovery. They discussed two mining tasks on Web archive data: temporal summarization and object history detection. They also presented different measures for analyzing the historical content of pages over a long time frame for choosing the important versions to be mined. They used a vector representation for the textual content of page versions

using a weighting method, e.g., term frequency. They presented a change-detection algorithm for detecting the change in the past versions of a page through time. In a later study, Jatowt et al. [22] proposed an interactive visualization system called Page History Explorer (PHE), an application for providing overviews of the historical content of pages and also exploring their histories. They used change detection algorithms based on the content of archived pages for summarizing the historical content of the page to present only the active content to users. They also extended the usage of term clouds for representing the content of the archived pages with simple highlighting techniques.

To help people in understanding Web content change, Teevan et al. [54] introduced DiffIE, a browser plug-in that caches the page a user visits, and then detects and highlights any changes to that page since the user’s last visit. They compared the Document Object Model representation of the page’s text to highlight the differences.

Tools like PHE and DiffIE are a good way to understand the changes of Web pages through time. In our work, we are not looking for a deep reading between versions, but rather flagging off-topic pages for non-consideration for other processes (e.g., story summarization [1] and thumbnail generation [6]).

AlSum and Nelson [6] proposed various summarization techniques to optimize the thumbnail creation for TimeMaps based on information retrieval techniques. They found that SimHash similarity fingerprints have the best prediction for the visualization change. They proposed three algorithms, threshold grouping, K clustering, and time normalization. They minimized the number of generated thumbnails by 9–27 % on average.

Spaniol and Weikum used Web archive data to track the evolution of entities (e.g., people, places, things) through time and visualize them [52]. This work is a part of the LAWA project (Longitudinal Analytics of Web Archive data), a focused research project for managing Web archive data and performing large-scale data analytics on Web archive collections. Jatowt et al. [21] also utilized the public archival repositories for automatically detecting the age of Web content through the past snapshots of pages.

Recently, Odijk et al. [42] introduced tools for selecting, linking, and visualizing the second World War (WWII) collection from collections of the NIOD,⁶ the National Library of the Netherlands, and Wikipedia. They also link digital collections via implicit events, i.e., if two articles are close in time and similar in content, they are considered to be related. Furthermore, they provided an exploratory interface to explore the connected collections. They used Manhattan distance for textual similarity over document terms in

⁶ <http://www.niod.nl/en>.

Table 1 Description of the Archive-It collections

Collection name	Occupy movement 2011/2012	Egypt revolution and politics	Human rights
Collection ID	2950	2358	1068
Curator	Internet Archive Global Events	American University in Cairo	Columbia University Libraries
Timespan	2011/12/03–2012/10/09	2011/02/01–2013/04/18	2008/05/15–2013/03/21
Total URI-Rs	728	182	560
Total URI-Ms	21,268	18,434	6341

a TF-IDF weighted vector space and measured temporal similarity using a Gaussian decay function. They found that textual similarity performed better than temporal similarity, and combining textual and temporal similarity improved the nDCG score.

Web archiving research has focused on the selection, storage, and preservation of Web content and solving the challenges that face them [38]. Despite the existence of crawl quality tools that focus on directly measurable things like MIME types, response codes, etc., there are no tools to assess if a page has stayed on-topic through time. The focus of this paper is on assisting curators in identifying the pages that are off-topic in a TimeMap.

4 Data set

In this section, we describe our gold standard data set. We evaluate our techniques using the ODU mirror of Archive-It’s collections. ODU has received a copy of the Archive-It collections through April 2013 in Web ARchive file format (WARC) [20]. The three collections in our data set differ in terms of the number of URI-Rs, number of URI-Ms, and timespan, which is the range of time over which the Web pages have been archived. Next, we will describe the three collections that we constructed our samples from; then we will present the results of manually labeling the samples.

The “Occupy Movement 2011/2012” collection was built over a period of 10 months between December 2011 and October 2012 by Archive-It. This collection covers the Occupy Movement protests and the international branches of the Occupy Wall Street movement around the world. This collection contained 728 seed URIs and a total of 21,268 mementos.

The “Egypt Revolution and Politics” collection was started in February 2011 and is still ongoing. This collection covers the January 25th Egyptian Revolution and Egyptian politics. It contains different kinds of Web sites (e.g., social media, blogs, news) that have been collected by the American University in Cairo. As of April 2013, this collection contained 182 seed URIs and a total of 18,434 mementos.

The “Human Rights” collection was started in May 2008 by Columbia University Libraries and is still ongoing.

Table 2 The results of manually labeling the collections

Collection	Occupy movement 2011/2012	Egypt revolution and politics	Human rights
Sampled URI-Rs	255 (35 %)	136 (75 %)	198 (35 %)
Sampled URI-Ms	6570	6886	2304
Off-topic URI-Ms	458 (7 %)	384 (9 %)	94 (4 %)
URI-Rs with off-topic URI-Ms	67 (26 %)	34 (25 %)	33 (17 %)

The Human Rights collection covers documentation and research about human rights that have been created by non-governmental organizations, national human rights institutions, and individuals. As of April 2013, this collection contained 560 seed URIs and a total of 6341 mementos.

Table 1 provides the details of the three collections. The time span in the table represents the range of the crawls for the ODU mirror which ends in April 2013. The collections contain pages in different languages, including English, Arabic, French, Russian, and Spanish.

We randomly sampled 589 URI-Rs from the three collections (excluding URI-Rs with only one memento). Together, the sampled URI-Rs had over 18,000 URI-Ms, so for each of the sampled URI-Rs we randomly sampled from their URI-Ms. This resulted in our manually labeling 15,760 mementos as on-topic or off-topic. We labeled the URI-M as off-topic if the content in the URI-M was no longer relevant to the content in the URI-R@ t_0 , which is assumed to be relevant to the topic of the collection.

Table 2 contains the results of manually labeling the sampled data of each collection. We sampled from 35 % of the seed URIs of each collection, except for the Egypt Revolution collection; it has fewer URIs than the other two collections, so we sampled from 75 % of its URIs. The labeled gold standard data set is available for download at <https://github.com/yasmina85/OffTopic-Detection>.

We found that 24 % of the TimeMaps we sampled contain off-topic pages. Detecting these pages automatically for the collection curator will not only avoid diluting the value of their collections, but also save the time required for a manual

Table 3 The statistics of TimeMap behaviors in archived collections

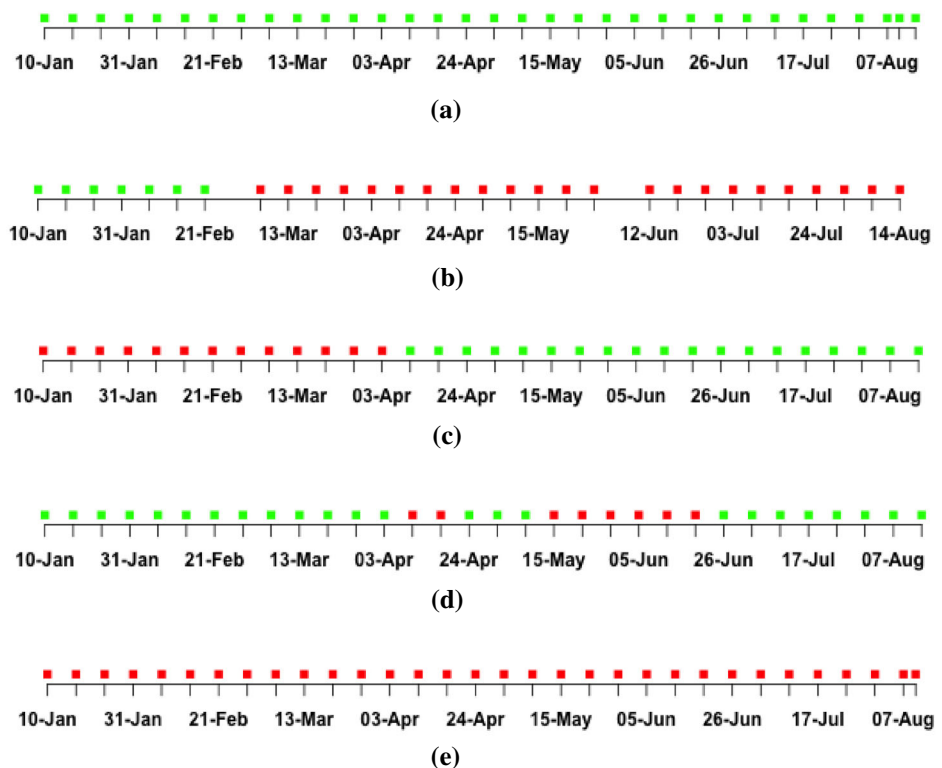
TimeMap behavior	Occupy movement 2011/2012 (%)	Egypt revolution and politics (%)	Human rights (%)
Always on	73.7	75.0	83.3
Step function on	11.4	11.0	7.6
Step function off	1.2	0.7	0.0
Oscillating	13.3	12.5	9.1
Always off	0.4	0.7	0.0

check of the relevance of the URIs and the storage required for these pages.

5 TimeMap behavior

Many studies have been performed on the key aspects of document “aboutness”, such as the page’s title [27], tags [26], and lexical signatures [29]. Section 6.2 enumerates different methods we explored to distill a page’s aboutness and quantify how this aboutness changes through time. Here, we define five general classes of TimeMaps based on how a page’s aboutness changes through time. Table 3 shows the percentage of each type of TimeMap present in our three manually labeled collections.

Fig. 5 Example showing different behaviors for TimeMaps (*green* = on-topic, *red* = off-topic). **a** Always On http://wayback.archive-it.org/2950/*/http://occupypsl.org. **b** Step Function On http://wayback.archive-it.org/2950/*/http://occupygs0.tumblr.com. **c** Step Function Off http://wayback.archive-it.org/2950/*/http://occupyashland.com. **d** Oscillating http://wayback.archive-it.org/2950/*/http://www.indyows.org. **e** Always Off http://wayback.archive-it.org/2950/*/http://occupy605.com (color figure online)



An Archive-It collection (C) is a set of seed URIs collected by the users from the Web (W), where $C \subset W$. Each seed URI has many mementos ($URI-Ms$), and a set of mementos for a seed URI composes a TimeMap ($URI-T$). A collection C can be formally defined as the following:

$$C = \{URI-R_1, URI-R_2, \dots, URI-R_n\} \text{ and} \\ \forall URI-R_i \in C, \exists URI-T \text{ where} \\ URI-T = \{URI-M_0, URI-M_1, \dots, URI-M_n\} \\ \text{and } URI-M_i \text{ is } URI-R@t_i \quad (1)$$

We define $URI-R@t$ to be: on-topic, if $aboutness(URI-R@t) \approx aboutness(URI-R@t_0)$, and off-topic, if $aboutness(URI-R@t) \not\approx aboutness(URI-R@t_0)$, where $URI-R@t_0$ is relevant to C .

For the gold standard data set (Sect. 4), we manually assess if a memento is relevant to C . We empirically observed five classes of TimeMaps based on the page’s aboutness.

Always On: This is the ideal case, in which the page does not go off-topic (Fig. 5a):

$$\forall t \text{ } aboutness(URI-R@t) \approx aboutness(URI-R@t_0), \\ \text{and } URI-R@t_0 \text{ is relevant to } C.$$

This is the majority case in the gold standard data set, with at least 74 % of the TimeMaps always on-topic (Table 3).

Step Function On: $URI-R@t_0$ is on-topic, but then at some t goes off-topic and continues $\forall t$ (Fig. 5b):

$\forall t \geq i$, where $i \geq 1$, and i is an integer, $aboutness(URI-R@t) \not\approx aboutness(URI-R@t_0)$, where $URI-R@t_0$ is relevant to C .

We found that 8–11 % of the TimeMaps are Step Function On.

Step Function Off: $URI-R@t_0$ is off-topic, but then at some t goes on-topic and continues $\forall t$ (Fig. 5c):

$\forall t \geq i$, where $i \geq 1$, and i is an integer, $aboutness(URI-R@t) \approx aboutness(URI-R@t_0)$, where $URI-R@t_0$ is not relevant to C .

The case where the TimeMap starts with an off-topic memento and then goes on-topic is very rare. We found that only 0–1 % TimeMaps are Step Function Off. This case violates our assumption that the $URI-R@t_0$ is relevant to C . In our gold standard data set, we manually shifted the first memento to be the first memento relevant to the collection.

Oscillating: The aboutness of pages changes between on-topic and off-topic more than once (Fig. 5d):

$\exists t$ where $aboutness(URI-R@t) \not\approx aboutness(URI-R@t+i)$ and $aboutness(URI-R@t) \approx aboutness(URI-R@t-j)$ where $i, j \geq 0$ and i, j are integers.

We found that 9–13 % of the TimeMaps were Oscillating between on-topic and off-topic.

Always Off: This is the most challenging case, where all the mementos are off-topic (Fig. 5e):

$\forall t, URI-R@t$ is not relevant to C .

We manually identified these cases (totaling 3 seed URIs) and excluded these from the gold standard data set. This situation can arise if seed URIs were included by accident, or if their content changed (e.g., site shutdown) in the interval between when the seed URI was identified and when the crawling began.

6 Research approach

In this section, we explain the methodology for preparing the data set and then the methodology for applying different measures to detect the off-topic pages.

6.1 Data set preprocessing

We applied the following steps to prepare the gold standard data set:

1. Obtain the seed list of URIs from the front-end interface of Archive-It.
2. Obtain the TimeMaps of the seed URIs from the CDX file.⁷

⁷ http://archive.org/web/researcher/cdx_file_format.php.

3. Extract the HTML of the mementos from the WARC files (locally hosted at ODU).
4. Extract the text of the page using the Boilerpipe library [32].
5. Extract terms from the page, using scikit-learn [44] to tokenize, remove stop words, and apply stemming.

6.2 Methods for detecting off-topic pages

In this section, we use different similarity measures between pages to detect when the $aboutness(URI-R)$ over time changes and to define a threshold that separates the on-topic and the off-topic pages.

Cosine similarity

Cosine similarity [35] is one of the most commonly used similarity measures to solve different problems in IR and text mining, such as text classification and categorization, question answering, and document filtering. Cosine similarity measures the cosine of the angle between two vectors (d_1 and d_2) by taking the dot product between them [49,51]:

$$\cos(d_1, d_2) = \frac{d_1 \cdot d_2}{\|d_1\| \|d_2\|}. \tag{2}$$

After text preprocessing, we calculated the TF-IDF for mementos, and then we applied cosine similarity to compare the $aboutness(URI-R@t_0)$ with $aboutness(URI-R@t)$ by calculating the similarity between the mementos.

Jaccard similarity coefficient

The Jaccard similarity coefficient measure is the size of the intersection of two sets divided by the size of their union [35]. The Jaccard between set A and set B is formulated as follows:

$$J(A, B) = \frac{A \cap B}{A \cup B}. \tag{3}$$

After preprocessing the text (result from step 5), we apply the Jaccard coefficient on the resulting terms to specify the similarity between the $URI-R@t$ and $URI-R@t_0$.

Intersection of the most frequent terms

Term frequency (TF) refers to how often a term appears in a document. The aboutness of a document can be represented using the top- k most frequent terms.

After text extraction, we calculated the TF of the text $URI-R@t$ and then compared the top 20 most frequent terms of the $URI-R@t$ with the top 20 most frequent terms of the $URI-R@t_0$. The size of the intersection between the

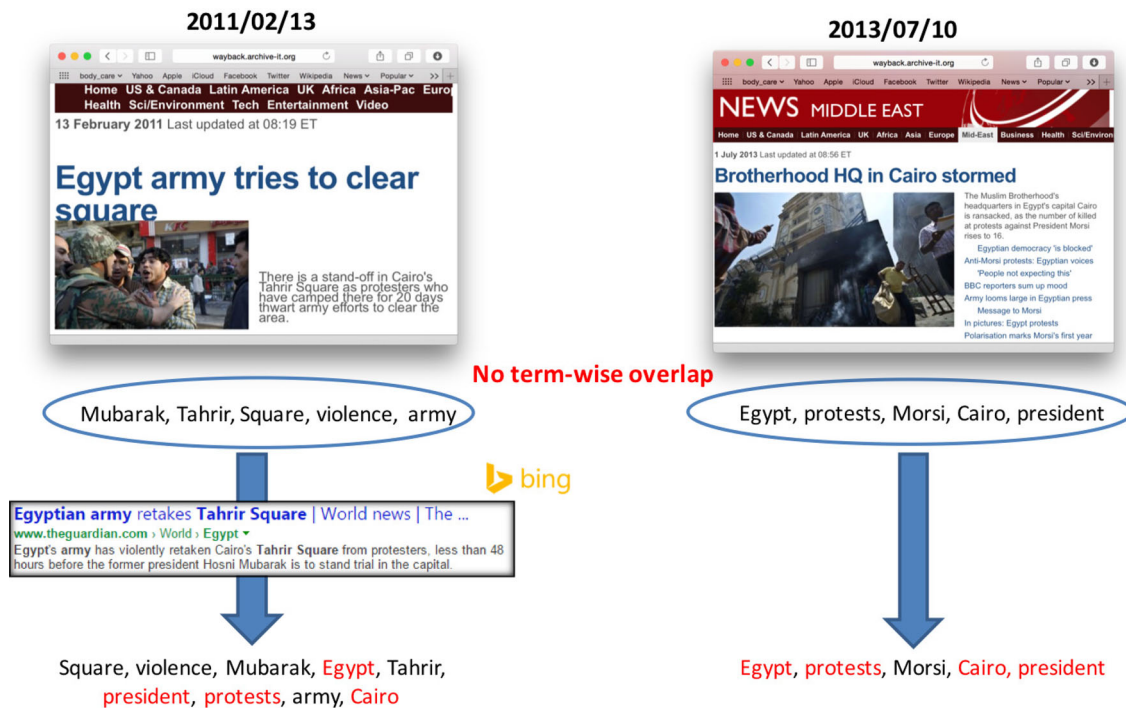


Fig. 6 An example for increasing the semantic context by the Web-based kernel function using a search engine (SE)

top 20 terms of $URI-R@t$ and $URI-R@t_0$ represents the similarity between the mementos. We name this method TF-Intersection.

Web-based kernel function

The previous methods are term-wise similarity measures, i.e., they use lexicographic term matching. But these methods may not be suitable for archived collections with a large time span or pages that contain a small amount of text. For example, the Egyptian Revolution collection is from February 2011 until April 2013. Suppose a page in February 2011 has terms like “Mubarak, Tahrir, Square, violence, army” and a page in April 2013 has terms like “Egypt, protests, Morsi, Cairo, president”, the two pages are semantically relevant to each other, but term-wise the previous methods might not detect them as relevant. With a large evolution of pages through a long period of time, we need a method that focuses on the semantic context of the documents.

The work by Sahami and Heilman [47] inspired us to augment the text of $URI-R@t_0$ with additional terms from the Web using a search engine to increase its semantic context. This approach is based on query expansion techniques [12], which have been well studied in the Information Retrieval field. We used the contextually descriptive snippet text that was returned with search engine results, which we call “SEkernel”. Snippet text has been shown to be a good source for query expansion terms [56]. Snippet text has shown effec-

tiveness in representing the documents. We used the returned results from the Bing Search API.

We augment the terms of $URI-R@t_0$ with semantic context from the search engine as follows:

1. Format a query q from the top five words x of the first memento ($URI-R@t_0$).
2. Issue $q(x)$ to the search engine SE .
3. Extract the terms p from the top ten snippets returned for $q(x)$.
4. Add the terms of the snippets p to the terms of the original text of the first memento d to have a new list of terms, $ST = p \cup d$.
5. $\forall t$, calculate the Jaccard coefficient between ST (the expanded aboutness of the $URI-R@t_0$) and the terms of $URI-R@t$, where $t \geq 1$.

Figure 6 shows an example of how we apply the Web-based kernel function on a memento from the Egyptian Revolution collection. As the figure illustrates, we use terms “Mubarak, Tahrir, Square, violence, army” of the first memento as search keywords to generate the semantic context. The resulting snippet will have new terms like “Egypt, President, Cairo, protests”, which term wise overlaps with the page that contains “Egypt, protests, Morsi, Cairo, president”. The resulting similarity between the two mementos in Fig. 6 after extending the terms of the first memento is 0.4.

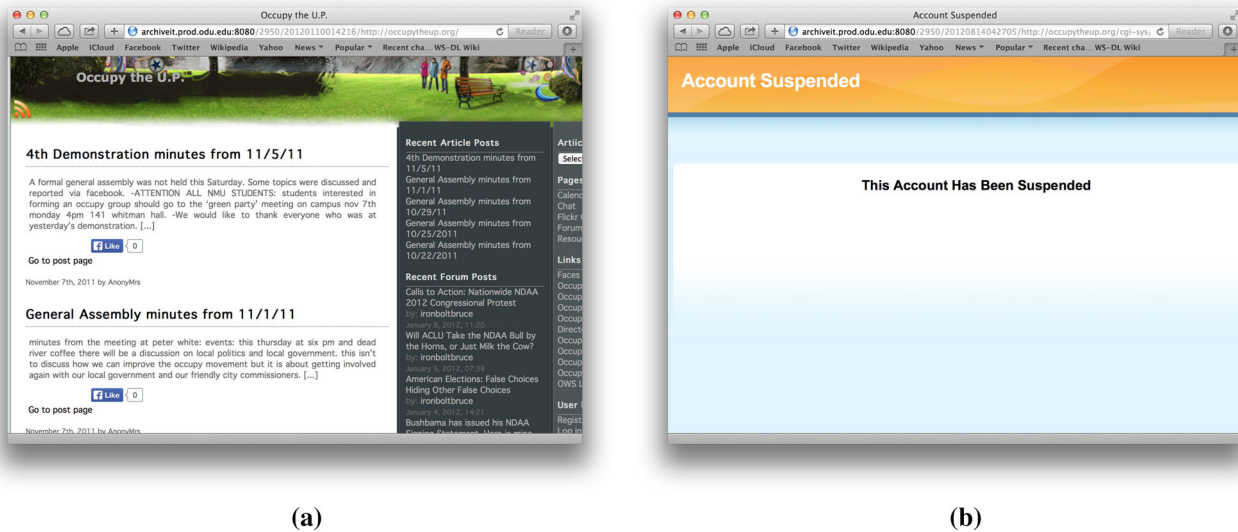


Fig. 7 Later versions of occupytheup.org are off-topic **a** Occupy the U.P. on January 10, 2012. **b** Expired on August 14, 2012, but no textual content

Change in size

We noticed that the sizes of off-topic mementos are often much smaller in size than the on-topic mementos. We used the relative change in size to detect when the page goes off-topic. The relative change of the page size can be represented by the content length or the total number of words (e.g., egypt, egypt, tahrir, the, square) in the page. For example, assume $URI-R@t_0$ contains 100 words and $URI-R@t$ contains five words. This represents a 95 % decrease in the number of words between $URI-R@t_0$ and $URI-R@t$. The change in size, denoted by $d(A, B)$, can be defined formally as follows:

$$d(A, B) = 1 - \frac{s(A)}{s(B)}, \tag{4}$$

where s is the size of document.

We tried two methods for measuring the change in size: the content length (Bytes) and the number of words (Word-Count). Although using the content length, which can be extracted directly from the headers of the WARC files, saves the steps of extracting the text and tokenization, it fails to detect when the page goes off-topic in the case when the page has little to no textual content but the page template is still large. For example, the Facebook page in Fig. 3 went off-topic in Fig. 3b and has 62 KB, but the on-topic page in Fig. 3a is nearly similarly sized with 84 KB. Using bytes is recommended when the size of the collection is large and the curator wants to detect potential off-topic pages in a short time.

There are many cases where the page goes off-topic and the size of the page decreases or in some cases reaches 0

bytes, e.g., the account is suspended, has transient errors, or has no content in the page. One of the advantages of using the structural-based methods over the textual-based methods is that structural-based methods are language independent. Many of the collections are multi-lingual, and each language needs special processing. The structural methods are suitable for those collections. Figure 7 has an example where the account is suspended and the size of the page is almost 0 bytes.

7 Evaluation

In this section, we define how we evaluate the methods presented in Sect. 6.2 on our gold standard data set. Based on these results, we define a threshold th for each method for when a memento becomes off-topic.

7.1 Evaluation metrics

We used multiple metrics to evaluate the performance of the similarity measures:

- False positives (FP), the number of on-topic pages that are predicted as off-topic
- False negatives (FN), the numbers of off-topic pages that are predicted as on-topic
- Accuracy (ACC), the fractions of the classifications that are correct.

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + FN + TN)} \tag{5}$$

Table 4 The results of evaluating the similarity approaches averaged on three collections

Similarity measure	Threshold	FP	FN	FP + FN	ACC	F_1	AUC
Cosine	0.15	31	22	53	0.983	0.881	0.961
WordCount	-0.85	6	44	50	0.982	0.806	0.870
SEKernel	0.05	64	83	147	0.965	0.683	0.865
Bytes	-0.65	28	133	161	0.962	0.584	0.746
Jaccard	0.05	74	86	159	0.962	0.538	0.809
TF-Intersection	0.00	49	104	153	0.967	0.537	0.740

Bold values indicate the best performing method based on the highest F_1

TP is the number of true positives (off-topic pages that are predicted as off-topic) and TN is the number of true negatives (on-topic pages that are predicted as on-topic).

- F_1 score (also known as F -measure or the harmonic mean), the weighted average of precision and recall.

$$F_1 = \frac{2TP}{(2TP + FP + FN)} \quad (6)$$

- The ROC AUC score, a single number that computes the area under the receiver operating characteristic (ROC) [18] curve, which is also denoted by AUC.

7.2 Results

We tested each method with 21 thresholds (378 tests for three collections) on our gold standard data set to estimate which threshold for each method is able to separate the off-topic from the on-topic pages. To determine the best threshold, we used the evaluation metrics described in the previous section, and averaged the results based on the F_1 of the three collections at different thresholds. To say that $URI-R@t$ is off-topic at $th = 0.15$ means that the similarity between $URI-R@t$ and $URI-R@t_0$ is <0.15 . On-topic means the similarity between $URI-R@t$ and $URI-R@t_0$ is ≥ 0.15 .

For each similarity measure, there is an upper bound and lower bound for the value of similarity. For Cosine, TF-Intersection, Jaccard, and SEKernel, the highest value is at 1 and the lowest value is at 0. A similarity of 1 represents a perfect similarity, and 0 similarity represents that there is no similarity between the pages. The word count and content length measures can be from -1 to $+1$. The negative values in the change of size measures represent the decrease in size, so -1 means the page has a 100 % decrease from $URI-R@t_0$. When the change in size is 0 that means there is no change in the size of the page. We assume that a large decrease in size between $URI-R@t$ and $URI-R@t_0$ indicates that the page might be off-topic. Therefore, if the change in size between $URI-R@t$ and $URI-R@t_0$ is a 95 % decrease in the size, that means $URI-R@t$ is off-topic at $th = -0.95$.

Table 4 contains the summary of running the similarity approaches on the three collections. The table shows the best result based on the F_1 score at the underlying thresh-

old measures averaged on all three collections. From the table, the best-performing measure is Cosine with average $ACC = 0.983$, $F_1 = 0.881$, and $AUC = 0.961$, followed by WordCount. Using SEKernel performs better than TF-Intersection and Jaccard. Based on the F_1 score, we notice that TF-Intersection and Jaccard similarity are the least effective methods.

Figure 8 shows how cosine separates the off-topic from the on-topic pages for each collection. It shows that the off-topic pages are concentrated near 0.0–0.2 similarity and there is no FNs past $th = 0.40$. Figure 9 shows how WordCount identifies on-topic and off-topic mementos at different thresholds. We see from the figure that there are no on-topic pages near 100 % decrease (i.e., -100 % change), while the majority of the off-topic mementos are concentrated near the 80–100 % decrease (i.e., $-(80-100)$ % change).

There was consistency among the best-performing values for TF-Intersection, Jaccard, and SEKernel methods over the three collections. For example, for all collections, the best performance of the SEKernel method is at $th = 0.05$. However, there was inconsistency among the values of th with the best performance for each collection for Cosine, WordCount, and Bytes measures. For the methods with inconsistent threshold values, we averaged the best thresholds of each collection. For example, the best th values of Cosine for the Occupy Movement collection, Egypt Revolution collection, and Human Rights collection are 0.20, 0.15, and 0.10, respectively.

We took the average of the three collections at $th = 0.20$, $th = 0.15$, and $th = 0.10$; then based on the best F_1 score, we specified the threshold that has the best average performance, which is $th = 0.15$.

Specifying a threshold for detecting the off-topic pages from archived pages is not easy with the differences in the nature of the collections. For example, long-running collections such as the Human Rights collection (2009-present) have more opportunities for some pages to change dramatically, while staying relevant to the collection. There is more research to be done in exploring the thresholds and methods. We plan to investigate different methods on larger sets of labeled collections, so that we can specify the features that affect choosing the value of the threshold.

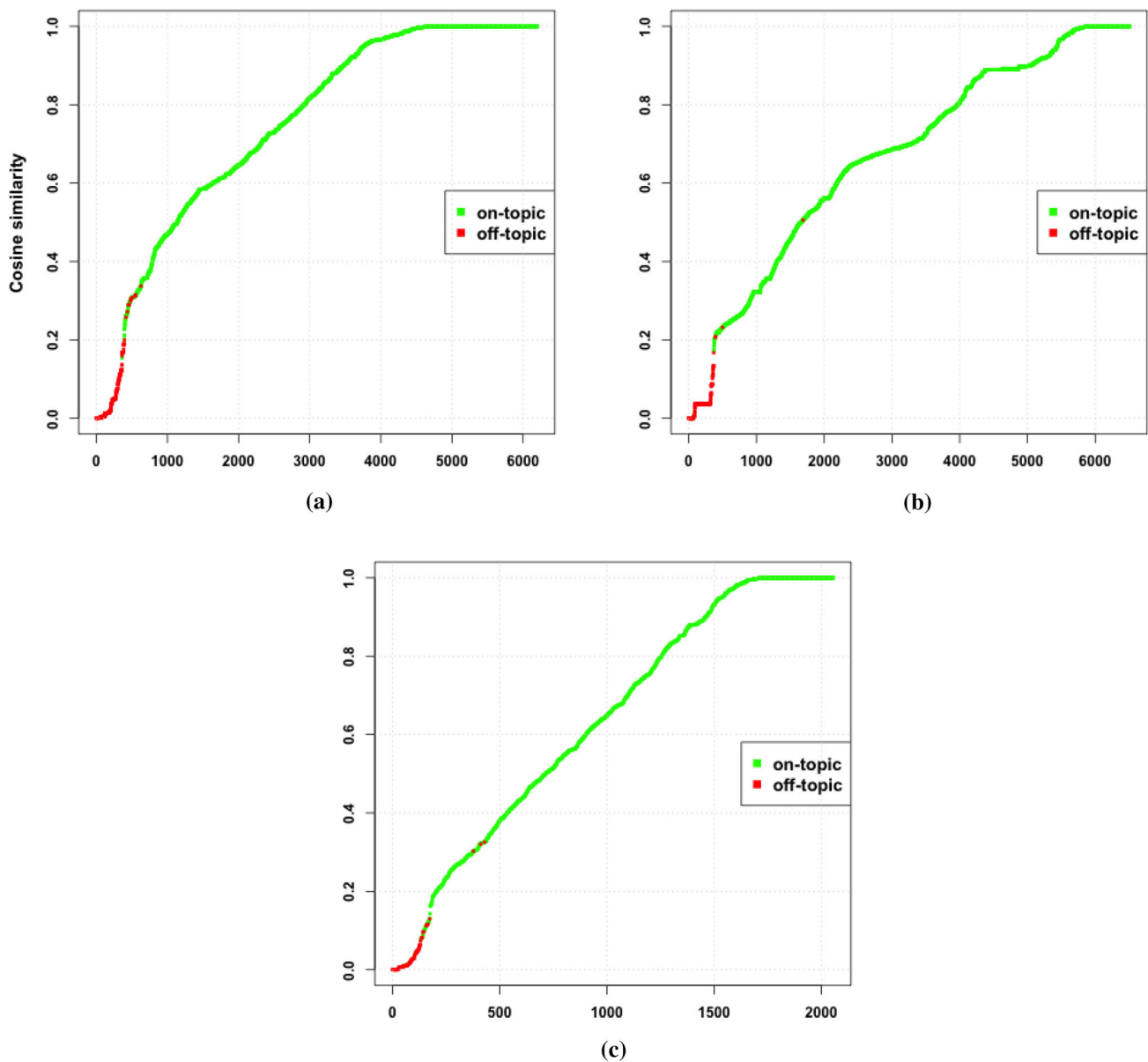


Fig. 8 How cosine similarity separates the off-topic from the on-topic pages **a** Occupy Movement Collection. **b** Egypt Revolution Collection. **c** Human Rights Collection

7.3 Combining the similarity measures

We tested 6615 pairwise combinations (15 method combinations \times 21 \times 21 threshold values). A page was considered off-topic if either of the two methods declared it off-topic. Performance results of combining the similarity approaches are presented in Table 5. We present the three best average combinations of the similarity measures based on the F_1 score and the AUC. The performance increases with combining Cosine and WordCount (Cosine, WordCount) at $th = (0.10, -0.85)$. There is a 36 % decrease in errors (FP + FN) as compared to

the best-performing single measure, Cosine. Furthermore, (Cosine, WordCount) has a 3 % increase in the F_1 score over Cosine. (Cosine, SEKernel) at $th = (0.10, 0.00)$ has 2 % increase in F_1 over Cosine. (WordCount, SEKernel) at $th = (-0.80, 0.00)$ has lower performance than Cosine.

In summary, (Cosine, WordCount) gives the best performance at $th = (0.10, -0.85)$ across all the single and combined methods. Moreover, combining WordCount with Cosine does not cause much overhead in processing, because WordCount uses tokenized words and needs no extra text processing.

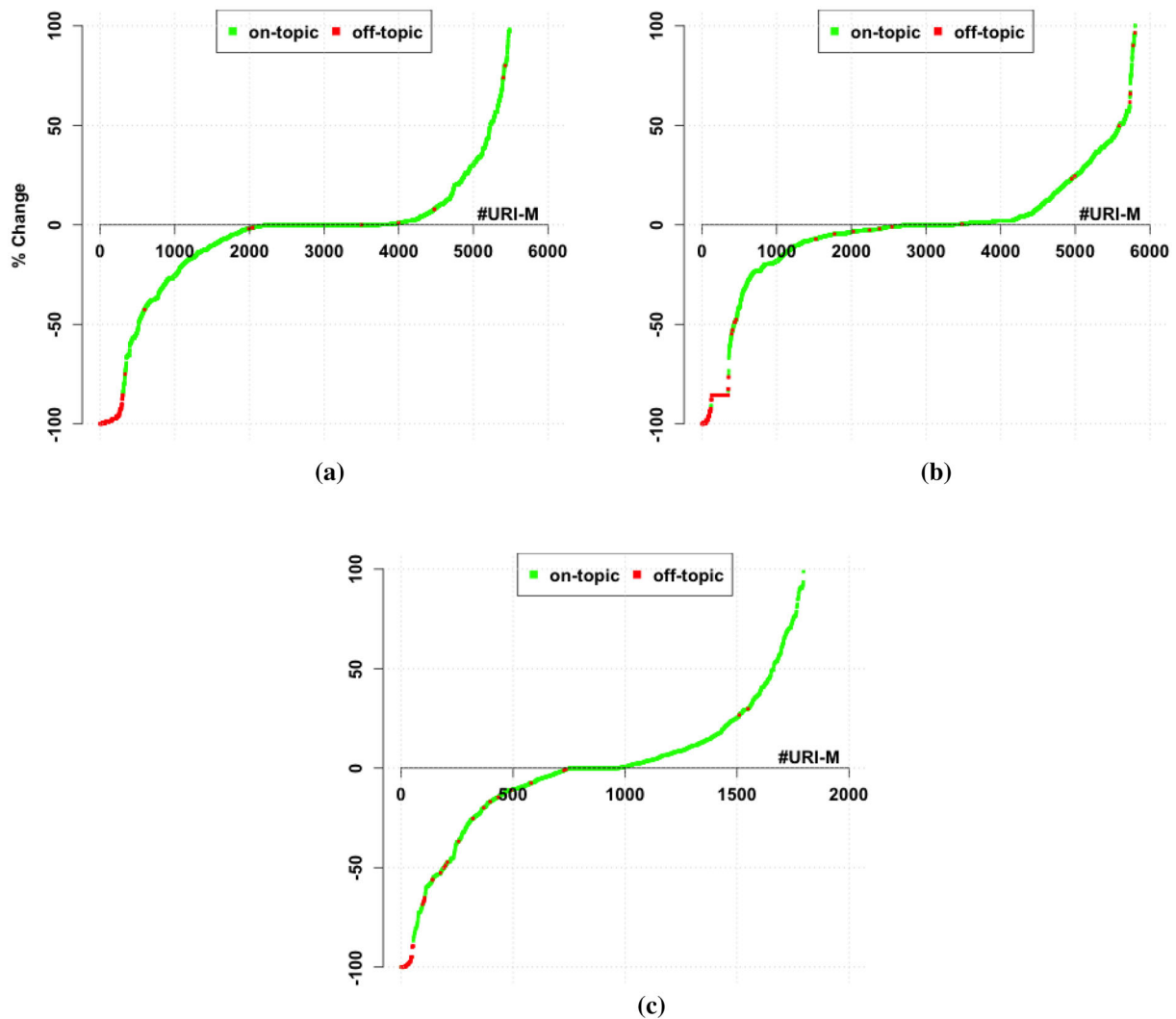


Fig. 9 How change of page size (based on word count) separates the off-topic from the on-topic pages. **a** Occupy Movement Collection. **b** Egypt Revolution Collection. **c** Human Rights Collection

Table 5 The results of the best three combined methods approaches averaged on three collections

Similarity measure	Threshold	FP	FN	FP + FN	ACC	F_1	AUC
(Cosine, WordCount)	(0.10, -0.85)	24	10	34	0.987	0.906	0.968
(Cosine, SEKernel)	(0.10, 0.00)	6	35	40	0.990	0.901	0.934
(WordCount, SEKernel)	(-0.80, 0.00)	14	27	42	0.985	0.818	0.885

Bold values indicate the best performing method based on the highest F1

8 Evaluating Archive-It collections

We used the best-performing method (Cosine, WordCount) on the labeled data set with the suggested thresholds (0.10, -0.85) and applied them on unlabeled Archive-It collections. We chose different types of collections, e.g., governmental collections (Maryland State Document Collection, Government in Alaska), event-based collections (Jasmine Revolution–Tunisia 2011, Virginia Tech Shootings, Global Health Events (the 2014 Ebola Outbreak)), and theme-based

collections (Wikileaks 2010 Document Release Collection, Human Rights Documentation Initiative, Burke Library New York City Religions). Table 6 contains the details of the 18 tested collections, such as the collection's ID and time span that comprise 4019 URI-Rs and 36,785 URI-Ms. We extracted the tested collections from the ODU mirror of Archive-It's collections, except for the Global Health Events Collection,⁸ the 2007 Southern California Wildfires Web

⁸ <https://archive-it.org/collections/4887/>.

Table 6 The results of evaluating Archive-It collections through the assessment of the detected off-topic pages using (Cosine, WordCount) methods at $th = (0.10, -0.85)$

Collection	ID	Timespan	URI-Rs	URI-Ms	Off-topic URI-Ms	Affected URI-Rs	TP	FP	P
Global food crisis	2893	2011/10/19–2012/10/24	65	3063	22	7	22	0	1.00
Government in Alaska	1084	2006/12/01–2013/04/13	68	506	16	4	16	0	1.00
Virginia tech shootings	2966	2011/12/08–2012/01/03	239	1670	24	2	24	0	1.00
Wikileaks 2010 document release collection	2017	2010/07/27–2012/08/27	35	2360	114	8	107	0	1.00
DIBAM	1019	2008/02/22–2008/03/24	25	106	4	1	4	0	1.00
Global health events	4887	2014/10/01–2015/10/21	165	3518	56	8	53	3	0.95
2003 California recall election	5947	2003/09/24–2003/12/12	178	2312	270	36	254	16	0.94
Jasmine revolution - tunisia 2011	2323	2011/01/19–2012/12/24	231	4076	107	31	107	7	0.94
Academics at baylor	3497	2013/01/28–2016/04/26	232	414	26	13	20	6	0.77
IT historical resource sites	1827	2010/02/23–2012/10/04	1459	10,283	59	34	45	14	0.76
Human rights documentation initiative	1475	2009/04/29–2011/10/31	147	1530	54	20	39	15	0.72
2007 southern california wildfires Web archive	5810	2007/10/23–2007/11/02	156	2416	335	68	215	120	0.64
Maryland state document collection	1826	2010/03/04–2012/12/03	69	184	0	0	---	---	---
April 16 Archive	694	2007/05/23–2008/04/28	35	118	0	0	---	---	---
Brazilian school shooting	2535	2011/04/09–2011/04/14	476	1092	0	0	---	---	---
Russia plane crash sept 7, 2011	2823	2011/09/08–2011/09/15	65	447	0	0	---	---	---
Burke library New York city religions 340	1945	2011/11/16–2013/02/11	107	208	0	0	---	---	---
Hurricane irene (Aug 2011)	2816	2011/09/02–2011/09/26	71	102	0	0	---	---	---

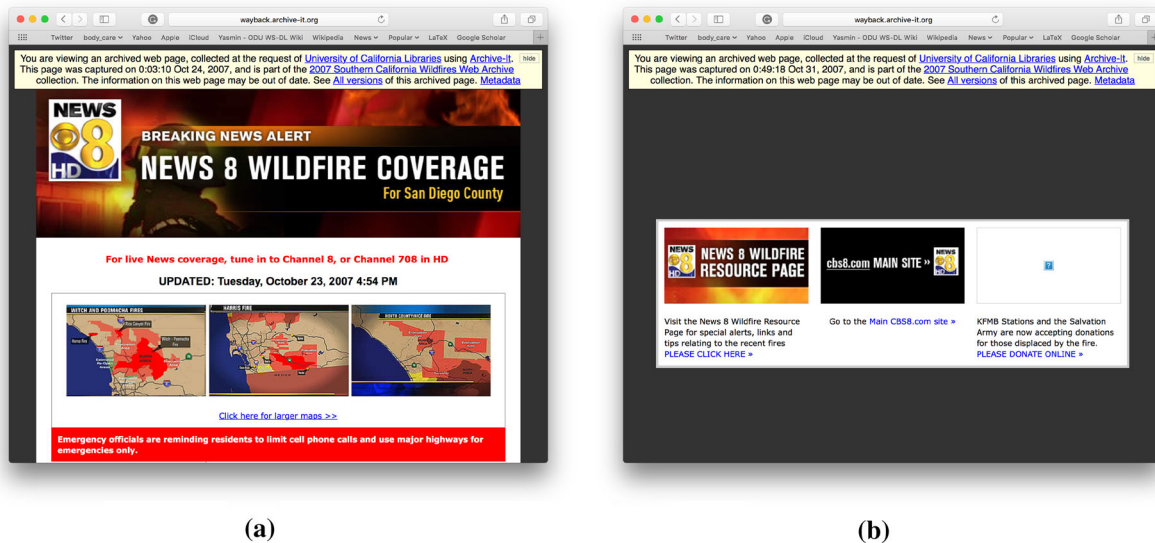


Fig. 10 Example of a significant change in cbs8.com: from October 24, 2007 to October 31, 2007 **a** cbs8.com on October 24, 2007. **b** cbs8.com on October 31, 2007

Archive,⁹ the Academics at Baylor,¹⁰ and the 2003 California Recall Election,¹¹ which we recently obtained from Archive-It.

The results of evaluating (Cosine, WordCount) at $th = (0.10, -0.85)$ are shown in Table 6. The table contains the number of affected URI-Rs in each collection. For the reported results, we manually assessed the FP and TP of each TimeMap and then calculated the precision $P = TP / (TP + FP)$ for each collection. We cannot compute recall, since we cannot know how many off-topic mementos were not detected (FN). The precision is near 1.0 for eight collections. $P = 0.72$ for the “Human Rights Documentation” collection, with 15 FPs. Those 15 URI-Ms affected three TimeMaps. An example of an affected TimeMap (https://wayback.archive-it.org/1475/*/, <http://www.fafg.org/>) contains 12 FPs. The reason is that the home page of the site changed and the new versions use Adobe Flash. The 14 FPs from the “IT Historical Resource Sites” collection affected 5 URI-Ts. The content of these five pages changed dramatically through time, resulting in FPs. The 2007 Southern California Wildfires Web Archive has 44 % (68 out of 156) of its TimeMaps affected with off-topic pages. By assessing the detected off-topic pages from this collection, we found that $P = 0.64$ with 120 FPs affected only 5 URI-Ts because of a significant change in the content of these pages through time. The two pages that dominated the FPs with 88 % are shown in Figs. 10 and 11.

⁹ <https://archive-it.org/collections/5810/>.

¹⁰ <https://archive-it.org/collections/3497/>.

¹¹ <https://archive-it.org/collections/5947/>.

There are six collections that have no reported off-topic pages. Two of these collections, the Brazilian School Shooting and the Russia Plane Crash, span less than a week, which is typically not enough time for pages to go off-topic. The other collections with no detected off-topic mementos are the Maryland State Document, the April 16 Archive, the Hurricane Irene, and the Burke Library New York City Religions. Perhaps, these collections simply had well-behaved URIs.

In summary, (Cosine, WordCount) at $th = (0.10, -0.85)$ performed well on Archive-It collections with average $P = 0.9$.

9 Conclusions and future work

In this paper, we presented approaches for assisting curators in identifying off-topic mementos of individual TimeMaps in the archive. We presented six methods for measuring the similarity between pages: cosine similarity, Jaccard similarity, intersection of the most 20 frequent terms, Web-based kernel function, change in the number of words, and change in content length. We tested the approaches on three different labeled subsets of collections from Archive-It. We found that of the single methods, the cosine similarity measure is the most effective for detecting the off-topic pages at $th = 0.15$. The change in size based on the word count comes next at $th = -0.85$. We also found that adding semantics to text using SEKernel enhanced the performance over Jaccard. We combined the suggested methods and found that, based on the F_1 score and the AUC, (Cosine, WordCount) at $th = (0.10, -0.85)$ enhances the performance to

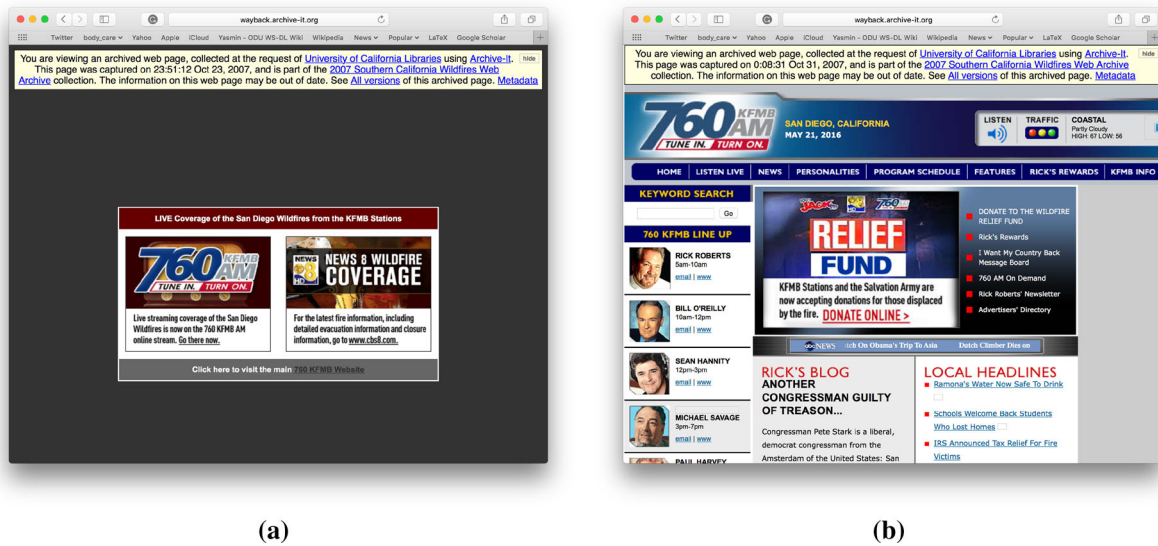


Fig. 11 Example of a significant change in 760kfm.com: from October 23, 2007 to October 31, 2007 **a** 760kfm.com on October 23, 2007. **b** 760kfm.com on October 31, 2007

have the highest F_1 score at 0.906 and the highest AUC at 0.968. We tested the selected thresholds and methods on different Archive-It collections. We tested the performance of (Cosine, WordCount) at $th = (0.10, -0.85)$ by applying them on 18 Archive-It collections, which comprise 4019 URI-Rs in which they have 36,785 URI-Ms. We manually assessed the relevancy of the detected off-topic pages. In summary, the suggested approach, (Cosine, WordCount) at $th = (0.10, -0.85)$, showed good results at detecting the off-topic pages with 0.89 precision. The presented approaches will help curators to judge their crawls and also prevent users from getting unexpected content when they access archived pages. Besides optimizing the quality of the archived collections, detecting the off-topic pages automatically will help in optimizing storage space and the time required for manual off-topic detection. Furthermore, flagging the off-topic pages will be useful for the quality of many applications such as story summarization and thumbnail generation.

We identified five different behaviors of changing the aboutness of TimeMaps: Always On, Step Function On, Step Function Off, Oscillating, and Always Off. The ideal behavior for curators is “Always On”, in which the pages do not deviate from the theme of the collection. We found that 24 % of the TimeMaps in our manually labeled sample had off-topic mementos. The majority of the affected TimeMaps are “Step Function On” and “Oscillating” with 8–13 % of the TimeMaps. We found small number of TimeMaps that were “Always Off” or “Step Function Off”. These behaviors will inform curators of the different cases of TimeMaps they may have in their collections. Furthermore,

they inform us on the challenges of detecting the off-topic pages.

This is a preliminary investigation of automatically detecting the off-topic pages from Web archives. There is more research to be done in exploring the thresholds and methods. For example, the nature of collection, such as the time span, might affect choosing the threshold. Users will be able to adjust the methods and thresholds as command-line parameters. Furthermore, there are other methods, such as probabilistic topic models [10] that can be applied to the collection that would then allow for comparison of the aboutness of the mementos to the aboutness of the collection. We generated a gold standard data set of labeled mementos that is available at <https://github.com/yasmina85/OffTopic-Detection> along with the off-topic detection source code. We are contributing this manually labeled gold standard set to the community for use in future research.

Our future work will continue to improve detection by using larger data sets and more collections with different features. The methods presented here detect off-topic pages within the context of a single TimeMap. We generated our framework with the assumption that the first memento is on-topic. The next step is to compute a model of the topic of the collection, in part to more easily detect the off-topic pages in the “Always Off” and “Step Function Off” TimeMaps.

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