Microblog Topic Identification using Linked Open Data

Ahmet Yıldırım* Suzan Uskudarli

Complex Systems Research Lab, Department of Computer Engineering, Bogazici University, Istanbul, Turkey

* ahmet.yil@boun.edu.tr

Abstract

The extensive use of social media for sharing and obtaining information has resulted in the development of topic detection models to facilitate the comprehension of the overwhelming amount of short and distributed posts. Probabilistic topic models, such as Latent Dirichlet Allocation, and matrix factorization based approaches such as Latent Semantic Analysis and Non-negative Matrix Factorization represent topics as sets of terms that are useful for many automated processes. However, the determination of what a topic is about is left as a further task. Alternatively, techniques that produce summaries are human comprehensible, but less suitable for automated processing. This work proposes an approach that utilizes Linked Open Data (LOD) resources to extract semantically represented topics from collections of microposts. The proposed approach utilizes entity linking to identify the elements of topics from microposts. The elements are related through co-occurrence graphs, which are processed to yield topics. The topics are represented using an ontology that is introduced for this purpose. A prototype of the approach is used to identify topics from 11 datasets consisting of more than one million posts collected from Twitter during various events, such as the 2016 US election debates and the death of Carrie Fisher. The characteristics of the approach with more than 5 thousand generated topics are described in detail. The potentials of semantic topics in revealing information, that is not otherwise easily observable, is demonstrated with semantic queries of various complexities. A human evaluation of topics from 36 randomly selected intervals resulted in a precision of 81.0% and F1 score of 93.3%. Furthermore, they are compared with topics generated from the same datasets from an approach that produces human readable topics from microblog post collections.

Introduction

Microblogging systems are widely used for posting short messages (microposts) to online audiences. They are designed to encourage short messages that are easily composed with minimal investment of time and effort. People typically post about topics of current relevance, such as election campaigns, product releases, entertainment, sports, conferences, and natural disasters. The convenience of microblogging systems result in a continuous stream of a very large volume of posts; over 500 million posts per day [1].

The abundance of posts on topics of current relevance make microblogging systems valuable sources for extracting topics. However, making sense of large volumes of posts is far from trivial. Microposts are often posted by users while they are engaged in some activity that distributes their attention. This, coupled with limits imposed on the length of posts result in contributions that tend to be informal, untidy, noisy, and cryptic. These factors, insufficient context within individual posts and the distribution of information over numerous posts make topic extraction challenging.

The problem of extracting what people are posting about within a set of microposts has been addressed by several topic detection approaches. Most of them represent topics as a list of words. We will be referring these approaches as word list based (WLB) approaches. Among these, the widely utilized probabilistic method called Latent Dirichlet Allocation (LDA), is used to profile users and extract keywords [2, 6]. Methods based on matrix factorization such as latent semantic analysis (LSA) [7], and non-negative matrix factorization (NMF) [8] are often used in recommendation and information retrieval. Variations of these approaches have been used to capture topics in microblogs based on temporal changes. Basically, they track the changes in the frequency of terms and hashtags to identify topics [9, 13] (hashtags start with # sign and utilized by users to relate their posts with the posts containing the same hashtag). Density based approaches [14, 15] identify topics of documents based on the frequency of words, phrases, and tags.

While all of the approaches mentioned detect the presence of topics, understanding what they are about requires further processing. To address this issue, some natural language processing (NLP) approaches produce human readable topics by associating
content with Wikipedia page titles \[16\] or summarizing content through a reinforcement method based on the consecutiveness and the co-occurrence of words in the posts \[17\].

Some approaches propose making sense of individual microblog posts by linking the meaningful parts with external resources \[18\]-\[20\]. However, making sense of single posts will likely not convey the topics of collective interest, since they miss out on the contextual information present in the crowd-generated content. The topics of most interest are typically those that have gained traction within the crowd.

Unconventional and creative associations between terms are often found in microposts, which are not likely to be found in traditional knowledge resources. For example, *Pumpkin Pie Spice* and *Donald Trump* in a satirical reference to his skin color. These kinds of posts are generally interesting, especially when they are related to issues that gain traction.

To identify topics within crowd-generated microposts, this work proposes an approach (S-BOUN-TI) for extracting machine processable topics from collections of microblog posts (Fig 1). Therefore, in the context of this work a topic is considered to be a collection of elements that are related by having occurred in multiple posts – a form of aggregating social signals \[21\]. The elements refer to the essential aspects of who, where, when, and what the topic is about. These elements are represented with semantic resources from Linked Open Data (LOD) – an ever growing web of resources that covers a vast domains of human interests such as music, sports, news, and life sciences \[22\]-\[23\]. The topics are represented with an ontology, *Topico*, which is introduced for this purpose.

The topics enable posing queries in conjunction with the LOD resources to reveal information that is not directly present in the original posts. For example, to inquire about the references to religion and ethnicity in a set of tweets posted during the 2012 and 2016 US election debates? resulting in African Americans, Jews, Mexican Americans, Arabs, and Israelis.

This work presents the proposed approach, and a prototype of the proposed approach which is implemented using Twitter as a microblogging system. Over one million tweets across 11 datasets were used to identify topics. The utility of these topics is demonstrated with SPARQL queries of various complexities.

The key inquiry in this work is to examine the feasibility of linking short, untidy, and fast flowing microposts to entities in LOD and to identify interesting processable topics. To the authors’ knowledge, this is the first approach proposed for identifying semantic topics from collections of microblog posts.

The main contributions of this work, in summary are:

- an approach for identifying semantic topics from crowd-generated microposts,
- the *Topico* ontology to represent semantic topics,
- a prototype implementation,
- an analysis of the semantic topics identified from various datasets,
- a demonstration of the opportunities that semantic topics linked to LOD offer, and
- an analysis of entity linking of microposts.
To enable reproducibility and support the research community for future work, we contribute:

- sets of tweet ids from 11 datasets (tweet identifiers associated with the datasets may be found at [24]),
- the topics identified from the datasets (semantic topics can be explored at: [25] and is available at [24]), and
- manual relevancy-annotations of semantic topics and their corresponding tweet ids (36 sets of approximately 5,760 tweets each where manual annotations can be found at: [24]).

The remainder of this paper is organized as follows: The next section describes background needed to follow this work. Then, the next two sections present the proposed ontology, the approach to identifying topics and a prototype implementation, followed by two sections, presenting the results using the data gathered during the 2016 US presidential debates and a discussion of this approach and the results. Then, the next section presents an overview of the related works. The final section presents the conclusions drawn from this study.

**Background**

This section describes the basic concepts and tools related to entity linking various ontologies that are utilized in this work.

**Entity linking**

Entity linking aims to identify and link fragments of text documents with external resources that represent real-world entities [26]. Such text fragments are often referred to as *surface forms* or *spots*. The external resources may be dictionaries and encyclopedias such as Wikipedia, but could also be any domain specific knowledge base. NLP techniques are employed for this purpose. Conventional NLP techniques fall short when handling informal language present in microposts, due to abbreviations, jargon, and the limited context. However, recent work has been taking on this challenge [18,27–31]. Among them, TagMe [18] is an online entity linker that offers a convenient and well documented fast responding RESTful API [32] for this purpose. Therefore, TagMe was chosen as an entity linker in this work.

Fig 2 shows an entity linking for a tweet, where entities correspond to Wikipedia articles. A goodness value ($\rho$) is shown above each spot and a probability ($p$) that indicates the suitability of linked entities are shown next to each entity. For example, the text *Stop and Frisk* is linked to https://en.wikipedia.org/wiki/Terry_stop with $\rho = 0.305$ and $p = 0.366$ indicating the suitability of the spot and link respectively. Higher values for $\rho$ and $p$ indicate higher confidence. In this work, thresholds are used for these values when accepting linked entities.

**Ontologies relevant for topic representation**

There are several useful ontologies and taxonomies for representing what microposters post about. Among which are people and places. In this work we propose a basic topic ontology that utilizes predefined well established ontologies. The reuse of ontologies is significant from an interoperability perspective for applications that utilize the data represented in terms of them. Here we introduce the ontologies that we utilize.

FOAF [33] (Friend of a Friend) is commonly used to describe agents with emphasis on people and their relationships. The DCMI [34] (Dublin Core Metadata Initiative) terms (namespace: dcterms) vocabulary is used to describe meta information about
resources like title, creator, description, and date. The W3C basic Geo vocabulary [35,36] (namespace: geo) is used to express longitude and latitude information of spatial things. Geonames [37] (namespace: geonames) is a more detailed ontology to define geolocations. The W3C time ontology [38] (namespace: time) is used to express temporal information such as duration and instants. Lastly, the Gregorian ontology [39] (namespace: greg) defines months of year.

**Linked Open Data**

Linked Data [40] is a term used to refer to best practices of connecting data in a structured format on the Web. It provides principles for publishing data that has relations with other data already published. Linked Open Data (LOD) is a term used to refer the data published under an open license. LOD uses Linked Data principles. The LOD currently contains 1,234 datasets with 16,136 links among them (as of June 2018) [41]. It provides a rich set of resources which can be used to describe elements of topics, such as relations.

DBpedia [42] is one of the significant cross-domain data resources in LOD that provides encyclopedic information derived from Wikipedia. DBpedia is utilizes Yago [43] (a taxonomy based on Wikipedia articles and Wordnet classes), Schema.org [44,45] (a shared collaborative vocabulary), Geonames, and FOAF. Another rapidly evolving resource is Wikidata [46,47], which is a collaborative knowledge platform with over 50 million items. Both Wikidata and DBpedia have SPARQL endpoints [48,49] supporting online semantic queries. In this work DBpedia is used extensively along with Wikidata, both serving information that is up to date and spans across a wide range of topics of interest.

The namespace prefixes dbr, dbo, dbc are used for DBpedia resources, foaf for FOAF, and schema for Schema vocabulary respectively. These namespaces are used whenever referring to these resources throughout this paper.

**Topic identification and representation**

Identifying semantically represented microblog topics involved two main activities: the identification of topics and their representation. Since topic representation is closely related to how topics are modeled, first the ontology developed for representing them is introduced. Following that the identification of topics from micropost collections with this representation is presented.

**Topico ontology for representing topics**

In the context of this work, a topic is considered to be a set of elements that are related by virtue of numerous people having posted them in the same context (post). More formally, a topic is a set of related persons, organization, locations, temporal references, related issues, and meta information. This information is modeled by creating a straightforward ontology (Topico) that introduces the concepts and the relations among them. It defines topic elements relevant to collective microposts, such as persons, locations, related issues, and meta information about the creation of the topic itself.

Topico is designed using Protége [50] according to the standard 7-step Ontology 101 development process [51]. The first among considerations is to determine the domain and scope of the ontology. Representing topics that emerge from collections of microblog posts is at the core of this ontology. Thus, it must reflect the concepts (classes) and properties (relations) common to microblogs. It serves as a basic ontology to represent general topics that could be extended for domain-specific cases if desired. The simplicity is deliberate in order to serve as a basic representation for an initial study. Thus, premature detailed design was avoided. In terms of consider reusing existing ontologies, existing ontologies are used in Topico whenever possible. These are mainly W3C OWL-Time ontology [38], FOAF, Schema.org, and Geonames.

The enumeration of important terms in the ontology resulting from inspecting a large volume of tweets led to people, organizations, locations, and temporal expressions. Specific to this context are the use of relative temporal expressions like today, tonight, and now. When referring to specific weeks, months, and specific dates literal absolute expressions are used. Other elements are just about anything, for which an isAbout property is defined.

Based on this information a definition of classes and class hierarchy was developed, which is shown in Fig [3]. Several existing location definitions such as schema:Place, dbo:Place, geonames:Feature, and geo:Point are defined as subclasses of topico:Location. Similarly, spatial expressions are grouped under topico:TemporalExpression. The foaf:Agent class is specified as the agent of topics.

After the classes, the definition properties of classes and slots was pursued, which are shown in Fig [4]. The object properties topico:hasAgent, topico:hasLocation, and topico:hasTemporalExpression relate topics with instances of the foaf:Agent, topico:Location, and topico:TemporalExpression classes. The object property topico:isAbout is defined to express a relation with anything which is not of these types. A topic may be related to one or more agents, locations, temporal expressions, or other issues. The domain and range of the slots are described when
Fig 3. The object properties of Topico. The classes in double circles are classes from external ontologies, such as FOAF. The numbers under class names indicate the number of its instances, for example the time:DayOfWeek class has 7 instances.
properties are defined as part of the defining the facets of the slots. Since Topico is kept very general at this stage, no cardinality restrictions are imposed.

Finally, as part of the instance creation step, various temporal expressions for the names of days (i.e. Sunday), and seasons (i.e. Winter), and relative temporal expressions (i.e. Tomorrow) are defined as instances of Topico. The topic instances themselves are created as part of the topic identification system as discussed in Semantic topic instantiation section and used to populate a topic data store with a SPARQL endpoint for further access. Naturally, they are not part of the ontology.

The remainder of this paper uses the prefix topico to refer to the Topico namespace [52].

**Topic elements**

This section elaborates the classes and relations that specify the topic elements. The foaf:Agent and its subclasses foaf:Person and foaf:Organization represents the agent of a topic. The property topico:hasAgent relates instances of topico:Topic and foaf:Agent. More specific types of agents are related through the properties topico:hasPerson, topico:hasGroup, and topico:hasOrganization as subproperties of topico:hasAgent with the ranges of foaf:Person, foaf:Group, and foaf:Organization respectively. Locations are represented with topico:Location that has the well known classes representing locations such as schema:Place and dbo:Place as subclasses.

Microblog posts are highly temporal, usually referring to the present moment. Even when they refer to the past or future, it is typically close to the time of posting. As such, in posts, time may be expressed relative to the time of posting (i.e. now, tonight, tomorrow), as a duration (i.e. two hours, ten days), as a reference to a proper temporal noun (i.e. Wednesday, August), or a specific date (i.e. 20.Nov.2018).

The W3C OWL-Time ontology [38] defines many useful temporal expressions, which are used in Topico. The concepts not covered by W3C OWL-Time ontology are introduced. The base class for Temporal expressions is topico:TemporalExpression. Relative temporal expressions such as now, tomorrow, and today are defined as instances of topico:TemporalExpression (i.e. topico:Today and topico:Tomorrow). Currently, approximately thirty such instances have been defined. The topico:TemporalExpression class has two main subclasses topico:TemporalTerm and time:TemporalEntity. The class topico:TemporalTerm addresses proper nouns like the day of the week and month. It has the subclasses: time:DayOfWeek, time:MonthOfYear, topico:Season, and topico:Year. Each month is represented with an instance such as greg:January. Terms like Spring festival, Summer Workshop, Fall semester are common in microblog posts and relevant to topics. Therefore, to express seasons topico:Season class has been defined and the instances topico:Summer, topico:Winter, topico:Fall, and topico:Spring have been created. The time:TemporalEntity class is used to express exact dates and times. Its subclass time:Instant specifies dates using one of the seven data properties according to need (i.e. time:inXSDDate with range xsd:dateTime).

**Meta information**

Meta information is regarding the creation of the topic itself. The time:Interval class, a subclass of time:TemporalEntity, specifies durations. The topics identified in this work are time bound. They represent the topics that emerge on microblogging enviroments and relevant to the time of contributions. The topico:observationInterval specifies the beginning and ending timestamps associated with a duration. When related to a topic it signifies the earliest and latest post within a post collection. Thus, topics are interpreted according to when they emerged. Since topics evolve over time this is significant. The presence of time expressions contributed by the poster, the time intervals of topics, as well as the creation time of the topic provides any processing tasks over topics a rich context of temporal information. For example, a large number of contributions including the term NOW at some duration D likely indicates anticipation (excited mood) of many individuals during time D.

The topic creation timestamp is specified with the topico:topicCreationAt data property, with the domain topico:Topic and the range xsd:dateTime. The topic creator is an instance of foaf:Agent, who is related to a topic with the foaf:maker property. The creator may represent a software or a person. In this work, only automated topic generation is considered.

Fig[7] in Semantic topic characteristics section shows a topic extracted from one of the 2016 presidential debates.

**Topic identification**

There are several steps involved in identifying topics from collections of microposts as outlined in Algorithm[1]. The first task is to identify relevant parts from the posts, which serve as the building blocks of topics. This is achieved by identifying the relevant parts of each post (spot) and linking them to external resources via entity linking (See Entity linking section). These entities serve as candidate topic elements.

Once the candidate elements are determined, a weighted co-occurrence graph is constructed to represent their relations that have emerged through having been referenced within the same posts. Note that the actual co-occurrence is the text (spot) within the post, whereas what is represented in the graph is the entity corresponding to that text. In other words, the graph intends to capture what is intended as opposed to how it is expressed. Furthermore, since entities are further connected to other web resources it provides a much richer context of interpretation. The vertices (entities) and the edges (co-occurrence) in this graph are weighted. The graph is pruned to remove weak relations which are eliminated according to certain thresholds (Eq[1] and 2).

The pruned co-occurrence graph is processed to determine which elements belong to the same topic. For this, subgraphs of closely connected vertices are computed with the maximal cliques algorithm [53]. This assures that vertices in each subgraph is related to each other in a context (mentioned in the same post). The resulting subgraphs are then processed to eliminate weak candidates that would not reflect the collective
perspective such as the ones that have few elements and the ones that are extracted from a few posts. The similar ones are merged to avoid similar topics. The resulting subgraphs are each considered a topic, where the vertices correspond to the elements of a topic. A corresponding topic:Topic instance is created for each subgraph to represent the resulting topics. In this step, making sure of existence of a relationship between two vertices by maximal cliques is crucial especially when the relationships are to be expressed as semantic Web statements and published in the Web which means the agents utilizing the resulting topics feed these relationships to their knowledge base.

The details of topic identification are elaborated in the remainder of this section.

### Algorithm 1 Topic extraction from microposts

1: Input: \( P \) ▶ post set
2: Output: \( T \) ▶ topic set
3: \( u\text{spots}, e\text{lements}, t\text{ypes} \leftarrow [] \)
4: \( l\text{e} \leftarrow [] \) ▶ linked entities
5: \( G, G' : \text{graph} \)
6: \( T \leftarrow \{ \} \) ▶ semantic topics
7: # identify candidate elements
8: for each \( p \) in \( P \) do
9: \( \text{elements}[p] \leftarrow \text{entities}(p) \cup \) mentions\( (p) \cup \) temporalExpressions\( (p) \)
10: \( \text{us\text{pot}s}[p] \leftarrow \text{unl\text{inkedSpots}}(p) \)
11: end for
12: # improve candidate elements with collective info
13: for each \( p \) in \( P \) do
14: \( \text{le}[p] = \text{re\text{Link}}(\text{elements}[p], \text{elements}) \)
15: \( \text{le}[p] = \text{link\text{Spots}}(\text{us\text{pot}s}[p], \text{elements}, \text{us\text{pot}s}) \)
16: end for
17: # Identify and create topics
18: \( G = \text{relate}(\text{le}) \)
19: \( G' = \text{prune}(G, \tau_e) \)
20: for each \( v \) in \( G' \) do
21: \( \text{types}[v] = \text{getType}(v, P, \tau_{i\text{oc}}) \)
22: end for
23: \( gt = \text{identify\text{Topics}}(G') \)
24: for each topic \( \text{in} \) \( gt \) do
25: \( T.\text{insert}(\text{sem\text{-}topic}(\text{topic}, \text{types})) \)
26: end for
27: return \( T \)

### Candidate element extraction

Each microblog post is processed to identify elements for the potential topics, which are referred to as candidate elements. These elements are either DBpedia resources or temporal expressions from topico:TemporalExpression. The former represents known entities related to a topic and the later provided temporal information. DBpedia is a good resource for identifying entities such as known persons, places, and events, which often occur in microposts.

Candidate elements are identified from each post via entity linking (see Entity linking section) and then mapping to corresponding DBpedia entity. For example, the spot *Hillary Clinton* within a post is linked to [http://dbpedia.org/resource/Hillary_Clinton](http://dbpedia.org/resource/Hillary_Clinton). The type of each element is determined to verify whether it is an agent, a location, or a temporal expression based on the type of the entity in the semantic Web (i.e. DBpedia) and the context of the spots of the entity. For example, the agent type is referred to with either agent’s name (i.e. Heidi Heitkamp) or with their handle on a platform (i.e. @HeidiHeitkamp). In order to increase the odds of linking user handles within posts, such as in this case to [http://dbpedia.org/resource/Heidi_Heitkamp](http://dbpedia.org/resource/Heidi_Heitkamp), handles are expanded as described in Person identification section. The results of this step are a set of candidate elements and unlinked spots.
Location identification

Location identification is a complex task. Not only are location names ambiguous, but many entities also serve as location descriptions, such as institutions (i.e. Come listen to #SBNordic19 speaker - James Ehlich - a Senior Technologist at Stanford University...). Therefore, when examining entities, it is common to find location indicators. For example, the entity http://dbpedia.org/resource/Stanford_University has many rdf:type properties including geo:SpatialThing, dbo:Agent, dbo:Organisation, and dbo:University.

Without context, it is difficult to know whether an entity with a location type indicator refers to a location. In the post Stanford University’s Central Energy Facility by ZGF Architects is a Top Ten Green Project award winner. http://bit.ly/1NpoAXe the type of the entity is not a location, whereas in the post I’m at Stanford Medical Practice in Brighton, Brighton and Hove it is a location.

To determine whether an entity is a location, first, the value of its rdf:type is checked for location related values like geo:SpatialThing, geonames:Feature, and schema:Place. For entities with location indicators, only those that correspond to spots that occur after the prepositions in, on, and at are deemed locations. Since, topics are determined on collections of posts, only location references with collective significance are considered. A threshold $\tau_{loc}$ is defined to eliminate infrequent entities of location type. Thus, only when $\text{#preposition(entity,posts)/\#posts} > \tau_{loc}$ holds, entities with location indicators are considered as topic elements of location type. The challenges related to location identification are further discussed in Section Improving topic elements under the Discussion section.

Improving candidate elements

The candidate elements obtained from individual posts are semantic Web resources. In a given collection of posts, it is possible for identical spots (i.e. Clinton) to be linked to different entities (i.e. Hillary Clinton, Bill Clinton, Clinton Foundation) due to the context in which the spot exists. Furthermore, identical spots may get linked in some posts and not in others. This may occur when: (1) the entity linker chooses not to link the spot due to context, or (2) the thresholds we use disregard the link.

An inspection of multiply linked or unlinked spots revealed that in most cases the dominant linking was the best choice. In such instances the most frequently linked entity for the spot is preferred. This choice is based on the assumption that the context of the most of the posts is likely to yield the best linking. While this is the case most often, there are exceptions when a spot should indeed be linked to multiple entities (i.e. Trump that may refer to various people, services, products, and businesses) in the same context (collection of posts). However, in general, choosing the entity that is linked the most often within a collection improves the candidate elements and more accurately representing its weight. Handling the case of multiple links remains as future work. This process of preferring the dominant link among multiple links is referred to as relinking.

Any spots that remain unlinked after this process are eliminated. The remaining entities form the set of candidate elements.

Relating elements

Once the candidate elements are identified, they are related to each other according to how people have posted. Since the payload of microposts are quite limited, the terms chosen to be expressed within them is considered relevant. Thus, candidate elements are considered related whenever their corresponding spots have co-occurred in the same posts. The more often the same co-occurrence is encountered the more trusted that relation is considered, since numerous posts encompass the same elements.

A weighted entity co-occurrence graph is constructed based on this premise. Let $G = (V, E)$ be the element co-occurrence graph. $V = \{v_1, v_2, ..., v_n\}$ be the set of vertices. Let $E = \{e_1, e_2, ..., e_m\}$ be the set of edges, where each edge $(v_i, v_j) \in V$. Let $w: E \rightarrow \mathbb{R}_{0,1}$ be a function that returns the weight of an edge, which is the strength of the relationship between two elements.

In order to represent collective topics (those relevant to many people), the elements that occur rarely are eliminated. The edges in $G$ where $w(e) < \tau_e$ are considered weak and removed. Furthermore, the vertices that become disconnected due to edge removal are also removed. The following equations are applied to $G = (V, E)$ to obtain $G' = (V', E')$ – a co-occurrence graph of candidate elements connected with non weak edges:

$$E' = \{e | e \in E \land w(e) > \tau_e\} \quad (1)$$

$$V' = \{v | \exists x \in (x, v) \in E' \lor (v, x) \in E'\} \quad (2)$$

Identifying topics

The final step in producing semantic topics is the identification of topics within $G'$ and their semantic representation. Each vertex in graph $G'$ is a candidate topic element. Based on the notion of topics are comprised of related elements (such as terms, phrases, posts), in this work subgraphs of $G'$ that are strongly related are considered to be topics.

In the prototype, the maximal cliques algorithm [59] is utilized for identifying subgraphs. An examination of the cliques shows that the larger sizes (number of elements) result from higher number of posts that contribute its elements. However, there are fewer number of cliques with greater size. This is not unexpected, as it is not common for high number of posts to include numerous topic elements, but it does happen when there is strong public interest. As such, these are highly interesting topics. As expected, the maximal cliques algorithm extracts cliques of size 2 and 3, since it is more likely that two or three elements are related through posts. In order to gain insight into the the resulting cliques, the occurrences of their vertices (elements) in the data sets (posts) were examined, which revealed that one or two of the elements within the clique occur far less frequently
A prototype of the proposed approach is implemented to evaluate and explore the utility of semantic topics. Fig 5 shows the overview of the system.

Prototype

A prototype of the proposed approach is implemented to evaluate and explore the utility of semantic topics. Fig 5 shows the overview of the system. The Phireose Library [54] for Twitter is used to fetch posts from the Twitter streaming API, which are processed to generate topics expressed with Topico. TagMe [18] is used for entity linking. Fuseki [55] is used to provide an endpoint for the identified topics.

Algorithm 1 outlines the implementation. Here, the getType function returns the types of entities. In the implementation this corresponds to calling the DBpedia SPARQL endpoint with chunks of size fifty, which is set according to the maximum URL length of the hyper text transfer protocol (HTTP) GET method. Since the same entities are expected to appear in collections of posts, the responses from calls to Wikidata, DBpedia and TagMe APIs are cached to avoid unnecessary network latency that would result from redundant requests. If network calls are cached, computing the frequency of the element at vertex \( v \) in the post set \( P \).

Another observation is that some elements that would have been in the same clique ended up being in different cliques due to edge pruning. For example, from the 2016 United States election debates dataset, the cliques {Hillary Clinton, Donald Trump, 2016, Answer, Muslim} and {Hillary Clinton, Donald Trump, 2016, Question, Muslim} are identical except for the elements Answer and Question. It turns out, there was a relation between these two elements, however, the corresponding edge was pruned due to low weight. To address such cases, the resulting topics are revisited for potential merges, by introducing the thresholds \( \tau_e \) for topic similarity and \( \tau_{v_{po}} \) for an absolute minimum edge relevancy weight. Clique similarity is computed using jaccard similarity, and deemed similar when its coefficient is greater than \( \tau_e \).

Let \( T_0 \) be the set of cliques obtained after applying the maximal cliques algorithm \( (T_0 \subseteq P(V)) \). Finally, \( T \) is the set of cliques after merging subgraphs, which will be used to represent the final topics:

\[
T = \begin{cases} 
( T_0 \setminus \{ t_i, t_j \}) \cup \{ t_k \} & \text{if jaccard}(t_i, t_j) > \tau_e \land \forall t_i, t_j \in T_0 \forall v_x \in t_i \forall v_y \in t_j \ w(v_x, v_y) > \tau_{v_{po}} \\
T & \text{otherwise} 
\end{cases}
\]

where \( t_k = t_i \cup t_j \).

Finally, each \( t \in T \) is mapped to an instance of topico:Topic as described in Section Semantic topic instantiation. Fig 5 shows an example graph and its corresponding topics.
Candidate element identification

The candidate element identification task involves identifying linked entities and temporal expressions. The temporal expressions are linked to definitions in Topico. They are linked using three methods. The first method identifies user mentions, and the second method identifies temporal expressions which are detailed in the following subsections. The third method utilizes the entity linker software TagMe which returns Wikipedia resources. DBpedia and Wikipedia share the same resource identifiers that come after their base URLs. We used this relation between them to refer to the corresponding semantic Web resource once an entity is linked by TagMe.

Entity names may refer to a year such as in United States presidential election debates, 2012. Year referrals are important for entity identification where the source medium is highly temporal such as in microblog posts. In this example, microblog users may actually be talking about the 2012 debates, or the entity linker may decide to return this entity due to its popularity, or it may be the only candidate for the spot. We assume that if the users are talking about past events, they refer to that year. This is because the content in microblog posts generally refers to a recent context, anything that is not about this context is expressed using absolute expressions such as "in 2012 ...". Thus, in these cases, we assume that, if the post text references the same year, the entity is considered correct. If the post text does not reference the year that the entity name does, the entity link is removed.

Entity types are identified to express topic elements with a relevant object property defined in Topico. In the prototype, locations, persons and temporal expressions are the main focus for type identification. In location identification, schema:Place, dbo:PopulatedPlace, dbo:Place, dbo:Location, dbo:Settlement, geo:SpatialThing, and umbel:PopulatedPlace are considered location related types.

Person identification

Mentioning well known persons in tweets via their user handles is very common. DBpedia resources related to these people are also commonly available. However, these resources typically do not include the user handles. However, Wikidata does include both Twitter user handles as well as references to the Wikipedia pages of known persons. (i.e. @HillaryClinton and http://en.wikipedia.org/wiki/Hillary_Clinton are given as properties of the resource of Hillary Clinton in Wikidata). Converting Wikipedia URLs to DBpedia URIs is straightforward. Therefore, Wikidata is utilized to identify the DBpedia resources of well known persons.

Alternatively, well-known persons may be referred to textually in the post. These references can be identified by querying the results of the entity linker with a SPARQL query to the DBpedia endpoint. This enables checking the type of the entity (rdf:type), which is considered to be a person if it is either foaf:Person or dbo:Person.

Replacing the user handles with the real names people provides a richer context for the entity linker, which in turn, resolves other entities more accurately. Thus, in implementation, first, the mentions are resolved, then the entities are linked, and finally the types of entities are determined.

Temporal expression identification

The identification of references to the day of the week, month, year, seasons, and relative temporal expressions such as tomorrow, now, and tonight are implemented through a look up approach. The spots of these references are linked to the corresponding semantic Web resources in Topico (see
Semantic topic instantiation

Expressing semantic topics is straightforward once the cliques are obtained. For each clique, an instance of topico:Topic class is created in memory of the running process. Each vertex is considered a topic element. The property between a topic element and a topic instance is determined based on the type of the element the vertex is representing. For example, if the element is identified as a person, temporal expression or a location, the property topico:hasPerson, topico:hasTemporalExpression, or topico:hasLocation is selected respectively (see Person identification, Temporal expression identification, and Location identification sections for details). For all other element types the topico:isAbout property is selected. Meta information such as the topic observation interval is added by creating a time:Interval instance via the relationship topico:observationInterval. The topic creation time is added with the data property topic:topicCreatedAt. After all these operations, the instance in the memory is output as RDF to be loaded into a data store which can run a reasoner and allows SPARQL queries such as Fuseki.

Experiments and results

The evaluation of S-BOUN-TI topics is challenging since the proposed approach has no precedence and is significantly different from other approaches in terms of the representation as well as content. The process of manual evaluation is complex and highly time consuming since it involves examining large sets of tweets while determining if they relate to semantic topics that consist on several Linked Data resources. Since the main goal of this work is to examine the utility and feasibility of using LOD to make sense of collections of temporally recent social media content, we considered it important to use current and real data to assess our approach.

In order to evaluate the proposed approach, semantic topics generated from sets of tweets are manually evaluated. They are also compared with topics generated from the same datasets using BOUN-TI [16], which is an earlier topic identification approach we proposed. The quality and utility of the generated topics as well as the approach itself are examined by:

- inspecting the characteristics of topics to gain insight regarding the elements (Semantic topic characteristics section),
- manually annotating topics to assess their relevancy (Semantic topic evaluation section),
- performing semantic queries and reasoning over topics to assess their utility and comparing them with WLB topics in this regard (Topic processing with S-BOUN-TI vs. WLB topics section),
- comparing the S-BOUN-TI topics with those generated by our previous topic identification approach BOUN-TI [16] (S-BOUN-TI vs. BOUN-TI section).

An overview of the evaluation is provided in the Evaluation summary section.

Datasets

In order to evaluate the proposed approach, various datasets were collected during events that generated significant activity on Twitter which are accessible at [24]. The Twitter streaming API filter endpoint [56] that supports the continuous retrieval of tweets that match a given query was used for this purpose.

Table 1. The datasets used to create S-BOUN-TI topics.

| ID   | Explanation                                      |
|------|--------------------------------------------------|
| PD1  | 2016 First presidential debate                   |
| PD2  | 2016 Second presidential debate                  |
| PD3  | 2016 Third presidential debate                   |
| VP   | 2016 Vice presidential debate                    |
| BA   | The divorce of Angelina Jolie and Brad Pitt     |
| CF   | The death of Carrie Fisher                       |
| CO   | Tweets related to the keyword concert            |
| ND   | North Dakota demonstrations                      |
| TB   | Toni Braxton became trending                     |
| IN   | Inauguration of President Trump                  |
| PUB  | A sample of public English tweets                |
A decision for selecting the tweets from which an area will be generated was required. Since the aim of this model is to capture collective topics, tweets that are likely to have some subject alignment are chosen (Table 1). The queries for collecting tweets were aligned with issues of significant interest during the development of this work. Semantic topics were extracted from 11 datasets of 1,076,657 tweets in total. Table 2 provides more information about the datasets.

### Table 2. The queries to fetch the datasets from Twitter and information about the collections

| Set id | Twitter Query                                      | Start time (UTC) | Δt (m) | Posts (#) | # | (%)  |
|--------|----------------------------------------------------|------------------|--------|-----------|----|------|
| PD1    | election2016, 2016election, @HillaryClinton, @realDonaldTrump, #trump, #donaldtrump, #trumpence2016, hillary, hillaryclinton, hillarykaine, @timkaine, @mike_pence, #debates2016, #debatenight | 2016-09-27T01:00:00Z | 90     | 259,200  | 206,827 | 79   |
| PD2    | same as [PD1]                                      | 2016-10-10T01:00:00Z | 90     | 259,203  | 187,049 | 72   |
| PD3    | same as [PD1]                                      | 2016-10-20T01:00:00Z | 90     | 258,227  | 181,436 | 70   |
| VP     | keywords in [PD1], #vpdebate2016, #vpdebate       | 2016-10-05T01:00:00Z | 90     | 256,174  | 135,565 | 52   |
| BA     | #Brangelina                                        | 2016-09-20T23:38:38Z | 21     | 5,900    | 4,777   | 79   |
| CF     | Carrie Fisher                                      | 2016-12-28T13:59:50Z | 15     | 7,932    | 6,753   | 85   |
| CO     | concert                                            | 2016-12-02T19:00:00Z | 60     | 5,326    | 4,743   | 89   |
| ND     | north dakota                                       | 2016-12-03T06:59:48Z | 14     | 7,466    | 6,231   | 83   |
| TB     | Toni Braxton                                       | 2017-01-08T07:08:56Z | 765    | 5,948    | 4,506   | 75   |
| IN     | #inauguration Trump @realDonaldTrump               | 2017-01-21T20:41:44Z | 6      | 5,809    | 5,425   | 93   |
| PUB    | (no keyword)                                       | 2016-12-02-20T29:53Z | 8      | 5,472    | 5,365   | 98   |

The largest datasets were collected during the debates of the 2016 US election. The debates were chosen with the expectation of obtaining a sufficient quantity of interesting tweets. The percentage of unique contributors is greater than 70% (with the exception of [VP]). This is important since this model aims to capture topics from a collective perspective.

Throughout the remainder of this paper, specific datasets are referenced with their ids and each interval within a dataset is denoted with \([t_s, t_e]\) to indicate the interval from \(t_s\) until \(t_e\). For example, dataset [PD1] \([10, 12]\) refers to the tweets posted between 10th to 12th minutes of [PD1].

### Experiment setup

S-BOUN-TI topics are generated with the prototype implementation described in the [Prototype] section using the datasets described in the [Datasets] section.

### Table 3. The values of thresholds for generating topics

| Value | Description                  |
|-------|------------------------------|
| \(\tau_p\) | 0.15 entity link confidence   |
| \(\tau_p\) | 0.35 spot confidence           |
| \(\tau_{\text{min}}\) | 0.001 weak edge pruning weight |
| \(\tau_{\text{min}}\) | 0.0005 minimum edge weight for clique merge |
| \(\tau_{\text{loc}}\) | 0.01 weight of location entities with preposition |
| \(\tau_{\text{2-clique}}\) | 0.01 2-clique removal          |
| \(\tau_{\text{mer}}\) | 0.8 clique merge similarity     |

The prototype uses various thresholds as defined in Table 3. The thresholds \(\tau_p\) and \(\tau_p\) correspond to confidence values of linked entities and spots.
returned by the TagMe API (see the Entity linking section). Higher values for these thresholds yields fewer results. For \( p \), TagMe suggests values between 0.1 and 0.3 for better accuracy. In order to capture higher number of entities a low threshold is preferable. When the lower recommended value of \( p = 0.1 \) was used, we discovered quite a few incorrect entities. Since the accuracy of entities, thus topic elements, is significant a slightly higher value of 0.15 is used – as we observed that this value improved the results considerably. With the same motivations and validated by manual inspections \( p \) is set to 0.35. The S-BOUND-TI prototype considers entity links that satisfy \( p > p \) \& \( p > p \) to be candidate topic elements.

The strategy for processing the element co-occurrence graph is to retain the elements with high frequencies and eliminate the weak ties prior to identifying the topics. The thresholds for processing the graph, namely for pruning and determining topics, were determined based on inspecting the characteristics of the entities and relations in the graph. The graph pruning threshold is set as \( p = 0.0001 \). Higher values result in fewer edges and vertices leading to fewer number of topics (\( p = 0.1 \), for dataset [PD\(_1\)] [0-2] results in only 1 rather general topic consisting of elements [Donald Trump, Hillary Clinton, Debate, Tonight] and for \( p = 0.2 \) results in no topics). On the other hand, lower thresholds result in more topics, such as [Donald Trump, Hillary Clinton, Debate, Middle class, Trickle-down economics, Tax, Americans] and [Donald Trump, Bashar al-Assad, Vladimir Putin, Moscow, Now, Debate]. A \( p = 0 \) would result in any tweets with co-occurring elements to yield a topic, which would not represent collective contributions. For a set of 6,000 posts, 0.001 corresponds to six posts. We assume that this is a sufficient duplication amount for an edge to be kept.

To inspect whether two cliques are similar, the threshold \( c \) is set to 0.8. For \( c = 0 \), any pair of cliques that has any common vertex is considered similar, whereas \( c = 1 \) considers them similar only when all vertices are common. Since maximal cliques are unique, the latter is not possible. Therefore, a value close to 1.0 is selected.

Note that, being similar is a necessary but not sufficient condition for merging two cliques. All vertices must have resulted from co-occurrence in posts, thus the weight of all edges must exceed \( e \) (See the Identifying topics section). Naturally, \( e \leq p \) and was set to \( e = 0.0005 \). For a set of 6,000 posts, this corresponds to them having co-occurred in at least in 3 posts.

To decide how many elements should be in a clique \( c \) is used. In practice, many small cliques emerge from posts, since it is not uncommon for small number of elements to co-occur in small number of posts. A condition that is also linked to retweets. Thus, \( c = 0.01 \) is used to filter such cases. This requires that vertices from a higher number of posts in comparison to those in larger cliques.

Similarly, \( c = 0.01 \) is used as a frequency occurrence threshold representing confidence for locations. Lower values the number of topics that have a location, but with less collective significance.

As is often observed in collective contribution platforms, the frequencies of the entities within tweets exhibit a long tail, with few items having relatively high frequencies and many items having low frequencies.

Fig 6 shows a co-occurrence graph resulting from the first 2016 US presidential debate ([PD\(_2\)]) – a dataset is dominated by posts related to the debate. This graph shows highly interconnected entities including many temporal references. The thickness of edges indicate the weight of the co-occurrence. In this graph there are six dominant topic elements (Debate, Donald Trump, Hillary Clinton, year:2016, Tonight, and Now) that co-occur with numerous other elements. Their normalized weighted degrees are 0.12, 0.11, 0.11, 0.10, 0.07, 0.03 respectively.

Thresholds were set to prune weak topic elements and relations. To study the impact of pruning, we traced the topics back to the original posts from which they were extracted. Table 4 shows the percentage of tweets in the post sets that produce the vertices (topic elements), edges (co-occurring elements), and topics.

| Set  | Vertices Before | Pruned | Topic | Edges Before | Pruned | Topic |
|------|-----------------|--------|-------|--------------|--------|-------|
| [PD\(_1\)] | 71 | 63 | 59 | 37 | 27 | 23 |
| [PD\(_2\)] | 71 | 65 | 61 | 38 | 30 | 24 |
| [PD\(_3\)] | 67 | 57 | 51 | 34 | 23 | 16 |
| [VP] | 71 | 61 | 55 | 37 | 26 | 20 |
| [BA] | 42 | 30 | 26 | 17 | 13 | 8 |
| [CF] | 77 | 74 | 69 | 43 | 38 | 24 |
| [CO] | 87 | 83 | 78 | 64 | 52 | 35 |
| [ND] | 92 | 86 | 75 | 64 | 60 | 51 |
| [TB] | 43 | 41 | 32 | 25 | 22 | 18 |
| [IN] | 81 | 74 | 69 | 52 | 42 | 33 |
| [PUB] | 47 | 10 | 0 | 20 | 2 | 0 |

After pruning, the cliques that are highly similar are merged in order to reduce repetitive topics. This was done by examining the similarity
Fig 6. A sample entity co-occurrence graph from the dataset [PD1].
between topics in terms of k-cliques so long as there has been some degree relation among them prior to pruning. In other words, after the pruning process a few of those cases are revisited to associate them. The initial pruning, is nevertheless important to render the computation feasible due to large number of posts. And, this case is not all that common. Among the k-cliques (k ≥ 3), this results in a decrease of 14% in cliques.

Finally, a decision for how to group the posts to be processed was required. This is relevant from the perspective of processing time given our resources. Furthermore, there is the consideration of the temporal nature of tweets, which is very related to present moment. This is specifically true during events of high public interest. The experiments we conducted were mostly during high traffic times where present moment was relevant. For these cases 2 minute intervals were set, corresponding to approximately 5,800 tweets. Generating the topics took approximately 4 minutes. Different sets could be partitioned differently so as they maintain a meaningful collection and the response time required.

Semantic topic characteristics

This section examines the characteristics the generated S-BOUN-TI topics from 11 datasets. Table 5 summarizes the topics according to their elements. Most topics have persons, which is not surprising, since tweeting about people is quite common. Topics including people emerged regardless of whether the query used to gather the dataset itself included people. Temporal expressions occurred more frequently in topics from datasets where time is more relevant, such as concerts ([CO]). However, there are errors due to ambiguities in the names of months and seasons.

To gain some insight regarding topics extracted from datasets without any search criteria, tweets from the public streams were collected ([PUB]). Although entities were identified in the tweets, no topics were identified. This is due to weak ties between entities. In public datasets collected during major events, such as earthquakes and terrorist attacks, the strength of ties could be strong enough to yield topics.

Table 5. The frequencies of the types of topic elements

| Set      | Topic | Person | Location | Temp. | isAbout |
|----------|-------|--------|----------|-------|---------|
| [PD1]    | 1,221 | 1,121  | 91       | 8     | 0.6     | 808    | 66     | 1,129  | 92     |
| [PD2]    | 1,220 | 1,068  | 87       | 32    | 2       | 559    | 45     | 1,010  | 82     |
| [PD3]    | 1,214 | 1,130  | 93       | 11    | 0.9     | 265    | 21     | 1,118  | 92     |
| [VP]     | 1,511 | 1,377  | 91       | 50    | 3       | 395    | 26     | 1,380  | 91     |
| [BA]     | 9      | 6      | 66       | 0     | 0       | 7      | 77     | 7      | 77     |
| [CF]     | 35     | 34     | 97       | 0     | 0       | 18     | 51     | 27     | 77     |
| [CO]     | 31     | 7      | 22       | 2     | 6       | 19     | 61     | 29     | 93     |
| [ND]     | 43     | 5      | 11       | 40    | 93      | 11     | 25     | 43     | 100    |
| [TB]     | 46     | 46     | 100      | 0     | 0       | 1      | 2      | 43     | 93     |
| [IN]     | 32     | 29     | 90       | 8     | 25      | 11     | 34     | 29     | 90     |
| [PUB]    | 0      | 0      | 0        | 0     | 0       | 0      | 0      | 0      | 0      |

To better understand the topic elements, the linked entities that led to them are examined. We denote linked entities as [spots] [uri], where spots corresponds to a comma separated list of spots in lowercase form and uri is the link to an entity. For example, [north dakota, n. dakota] [dbr:North_Dakota] represents the two spots north dakota and n. dakota that are linked to dbr:North_Dakota. The two spots may occur in a number of tweets in a set of tweets.

Fig 7 shows a topic from dataset [PD1] [50-52]. The posts at the top of the figure are among the tweets that contribute to this topic. The linked entities that ended up being the elements of this topic are:

- [donald, trump, donald trump, donald j. trump, donald j.trump] [dbr:Donald_Trump]
- [stop and frisk, stopandfrisk, stop-and-frisk] [dbr:Terry_stop]
- [lester, lester holt] [dbr:Lester_Holt]
- [racial divide, racial profiling, racial profile, racial segment, racial violence] [dbr:Racial_profiling]

The variety of spots in these examples illustrate how topics represent collective posts.

Some topic elements were not identified because they were not represented in DBpedia. For example, in the tweet MSNBC reports WH has confirmed Flynn did speak to Russian ambassador re sanctions. That means Flynn lied to Pence & admin misled public, the spot Flynn (referring to the former National Security Adviser of U.S., Mike Flynn) was not identified at all. As the LOD resources improve, the issue of missing data will reduce.

As social media is often used for purposes of dissemination, it is important to be able to track if and how their audience is impacted by such messaging. Around the 86th minute of the 2016 US vice presidential debate, the candidates were talking about abortion and its regulation. Topics from dataset [VP] [86–88] include those about Tim Kaine and Mike Pence regarding law, faith, and religion. This reflects that this issue engaged the debate watchers. On the other hand, the topics identified from dataset [PD3] [68–70] where related to Hillary Clinton and Donald Trump regarding
illegal immigration and income tax, while at that time the candidates were debating about Isis, Iraq, and the position of United States in the middle east. In this case topics that were of more relevance to the users overtook the issues being addressed in the actual debate.

Topics include many known people, such as:

- [Trump] ➞ [dbr:Donald_Trump]
  from @thehill ok but why is the North Dakota senator meeting with trump over energy secretary when he owns #nodapl stock???,

- [Mark Ronson] ➞ [dbr:Mark_Ronson]
  from Musicians including Mark Ronson sign open letter to Barack Obama over North Dakota pipeline protests https://t.co/4CyCbuTw9w, and the somewhat surprising, and

- [Naked Cowboy] ➞ [dbr:Naked_Cowboy]
  from tweets like WATCH: North Dakota Sen. Heidi Heitkamp boards Trump Tower elevator with the Naked Cowboy #TCOT
  #WakeUpAmerica #MAGA ....

The topics from the [tn] dataset were about the inauguration of Donald Trump as the US President as well as the Women's March event that took place the day after. The query related to this set was about inauguration and had nothing to do with women's march. Alas, the tweets related to the inauguration were strongly engaged in the women’s march. Topics include people like Madonna and Michael Moore who were very active in the women’s march. Also, the locations London, France and Spain appeared in topics from tweets expressing support for the march.

Semantic topic evaluation

In order to evaluate the proposed approach, topics generated from sets of tweets are manually evaluated. Manually assessing the relevance of topics identified by S-BOUN-TI is highly labor intensive, since it requires examining the topics in detail as well as the tweets from which they were generated (approximately 5,800). Furthermore, some tweets and topic elements may require further investigation to be understood, such as in the case of Terry stop or Naked Cowboy. This tedious task can take several minutes per topic. The level of effort and diligence as well as the resources required to evaluate topics through surveys or services like Amazon Mechanical Turk [57] that rely on human intelligence was deemed prohibitive. Therefore, the manual evaluation was conducted by the authors of this work with much scrutiny.

A web application was developed to evaluate the relevancy of topics for a given interval (Fig 8). With this application, the evaluator can annotate a topic as very satisfied, satisfied, minimally satisfied, not satisfied, or error. Error is marked in cases when tweets or URIs are no longer accessible. Optional comments may be provided for each annotation to express an observation or pose a question regarding a topic. To assist the evaluation process, the user is provided with the options of viewing the tweets from which the topics were generated, a word cloud of the tweets, and the list of linked entities and temporal expressions extracted from the tweets. Furthermore, the topics generated by S-BOUN-TI and BOUN-TI are juxtaposed for comparison purposes. The evaluation of BOUN-TI topics is addressed in S-BOUN-TI vs. BOUN-TI section.

For evaluation purposes, 10 topics from randomly selected 9 intervals (Table 6) from each debate (36 in total) were annotated using this application. Two annotators evaluated 24 intervals, 12 of which were identical in order to compute the inter-annotator agreement rate. As S-BOUN-TI topics are not ranked, topics with higher number of elements were chosen for evaluation. Topics with higher numbers of elements are likely to have resulted from many different tweets, making them more significant to evaluate. The annotators were shown 2 topics of size 2, 87 of size 3, 147 of size 4, 162 of size 5, 66 of size 6, 13 of size 7, and 3 of size 8.

Fig 7. A topic extracted from dataset [PD] [50,52] that is related to Lester Holt and Donald Trump regarding racial profiling and terry stop. Automatic enumeration gave the topic number 23 to this topic.
Fig 8. Various fragments of the topic inspection and evaluation tool for semantic topics. Here topics generated from interval \([68-70)\) of \([VP]\) are shown. The left side shows the topics generated by BOUN-TI and the right side from S-BOUN-TI. The See tweets and See word cloud links show the related tweets and a word cloud generated from them. The Entity frequencies link shows the list of linked entities and their frequencies.
For each interval, the evaluators manually inspect (1) the tweet set from which the topics are generated and (2) each topic generated for that interval to determine if it is related to the tweet set. A topic is examined by evaluating all of its elements by visiting their corresponding DBpedia pages to determine they are related to the tweet set in the context of other elements. If an element is related to the tweet set, but not in the context of the other elements of the topic being examined, it is deemed irrelevant. The evaluator annotates a topic as: very satisfied only if all of the topic elements are valid; satisfied only if one of the topic elements is incorrect; minimally satisfied if more than one element is incorrect while retaining significantly valuable information; and not satisfied if several topic elements are incorrect (i.e. relative temporal expression may be true but not convey sufficiently useful information). Note that the evaluation was performed in a fairly strict manner, where a penalty is given for any kind of dissatisfaction – regardless of where the source may stem from. For example, if a web resource on DBpedia has incorrect information (which happens), this resulted in a reduced satisfaction for that topic. This was done to avoid subjective and relative evaluation as well as serve as an assessment of the appropriateness of the resources being utilized towards the final goal.

The precision of the annotations is computed in two manners, once for when topics are annotated as Very Satisfied or Satisfied and once for when annotated as Very Satisfied only, which resulted in 81.0% and 74.8% with the inter-annotator agreement rate ($F_1$) scores of 93.3% and 92.4% respectively. The $F_1$ scores (computed as defined by Hripcsak and Rothschild [58]) indicate a high degree of agreement among annotators.

The evaluation revealed that several topics are quite similar (overlapping topic elements) that primarily differ in their temporal expressions (i.e. now and tonight). Such topics could be merged, although it may be useful to retain the temporal aspect as it reflects an aspect of the contributions. For example, contributions including the temporal term now are more often seen during times of excitement and relevance, such as in the beginning of an event or an issue that suddenly gains relevance. Incorrect topic elements, such as dbr:Time_(magazine) (in the interval [VP][84,86], the term “time” is incorrectly linked to dbr:Time_(magazine)) arise from lack of sufficient context in a tweet and errors such as dbr:Penny result from ambiguity (instead of vice presidential candidate dbr:Mike_Pence the element dbr:Penny is returned by entity linker). Several topics were noted to be interesting. This typically occurred when topics included elements that were very relevant to the context of the dataset (i.e. special prosecutors investigating Hillary Clinton, crime and police brutality, stop and frisk, racism, and African Americans) or when topics with unexpected elements emerged (i.e. pumpkin in regards to the color of Donald Trump’s face, the pantsuit of Hillary Clinton, and Naked Cowboy with Senator Heidi Heitkamp).

While the results of the evaluations of S-BOUND-TI appear to be inferior to those of BOUND-TI, we find that the S-BOUND-TI topics to provide more interesting potentials with finer grained topics with elements interlinked to LOD. These points are elaborated throughout section S-BOUND-TI vs. BOUND-TI.

**Topic processing with S-BOUND-TI vs. WLB topics**

In this section we present the benefits offered by our approach by introducing several tasks of different levels of complexity. We presume the presence of repositories that provide access to the topics with appropriate query support. In other words, the following tasks consider the effort to accomplish a task given that the topics have already been generated. More than 5K S-BOUND-TI topics generated from all of the datasets are used in the semantic processing. The topics are loaded to Fuseki to provide a SPARQL endpoint. We show how S-BOUND-TI can accomplish each task and indicate the effort required to perform the same task for word list based (WLB) topics, such as LDA and NMF. Table 7 lists various supporting functions to help accomplish tasks. At the end of this section, we summarize the effort required by S-BOUND-TI and WLB approaches (Table 5).

**Table 6. The intervals within the datasets that were used for evaluating topics.**

| Set id | Intervals |
|-------|-----------|
| [PD1] | [8-10), [18-20), [26-28), [38-40), [48-50), [68-70), [70-72), [74-76), [84-86), [86-88) |
| [PD2] | [18-20), [24-26), [32-34), [36-38), [56-58), [74-76), [76-78), [80-82), [84-86), [86-88) |
| [PD3] | [0-2), [2-4), [14-16), [32-34), [48-50), [54-56), [62-64), [68-70), [86-88) |
| [VP]  | [8-10), [14-16), [22-24), [36-38), [40-42), [60-62), [74-76), [84-86), [86-88) |

**Table 7. Function to support topic related tasks.**

| Function | Description     |
|----------|----------------|
| EI       | Entity identification |
| TR       | Type resolution   |
| EX       | External resource utilization |
| TI       | Time of contribution |
| RD       | Rule definition   |
| LI       | Location identification |
| QO       | Query optimization |
| SA       | Semantic analysis |
**Listing 1** Query: Persons related to Hillary Clinton.

```sparql
SELECT ?person (COUNT(?topic) AS ?C) WHERE {
  ?topic topico:hasPerson dbr:Hillary_Clinton .
  ?topic topico:hasPerson ?person .
  FILTER (?person NOT IN (dbr:Hillary_Clinton ) )
} GROUP BY ?person ORDER BY DESC(?C)
```

**Listing 2** Query: When did women’s issues emerge?.

```sparql
SELECT DISTINCT ?startTime ?endTime WHERE {
  ?topic topico:observationInterval ?interval.
  ?interval time:hasBeginning ?begin.
  ?interval time:hasEnd ?end.
  ?begin time:inXSDDateTime ?startTime.
  ?end time:inXSDDateTime ?endTime.
  {?topic topico:isAbout dbr:Rape .}
  UNION {?topic topico:isAbout dbr:Abortion .}
  UNION {?topic topico:isAbout dbr:Women\'s_health .}
}
```

A basic query (**Task-1**)

“Show the people that occur with Hillary Clinton.”

The simplest of tasks is to only query topic elements. Since our approach has identified people and represented them with Topico, Task-1 is easily achieved with a simple query (Listing 1). Among the 56 results, the first three are: dbr:Donald_Trump, “4606”^^xsd:integer, dbr:Bill_Clinton, “3468”^^xsd:integer, and dbr:Tim_Kaine, “768”^^xsd:integer.

Whereas for WLB topic representations, there is a need to analyze the words to determine if they represent people and to determine which of them are in the same topic with Hillary Clinton. Therefore, even ignoring the contextual aspects of relatedness, type resolution (TR) is needed. For type resolution, a list of persons will be needed for which an external resource (EX) such as LOD would have to be utilized.

Aggregating topic elements (**Task-2**)

“Show time intervals when women’s issues were discussed.”

Some tasks require the aggregation of information from several topics. Listing 2 shows a query for Task-2 considering that for the given task, abortion, rape, and women’s health are of relevance. This query returned 23 intervals corresponding to 166 topics.

The linked spots are [rape, raped, rapist, rapists, raping, sexual violence, serial rapist] ⇨ [dbr:Rape], [abortion] ⇨ [dbr:Abortion] and [women’s health] ⇨ [dbr: Women’s_health] for this task. Whereas for WLB case, words or phrases indicating women’s issues, and the time intervals (TI) of the topics that are containing these words and phrases must be identified to achieve this task.

This is a good example of the impact of entity linking that captures the concept expressed in a multitude of manners. This example also demonstrates how the temporal aspects are handled. In the context of streaming content, just when certain topics occur, whether they trend, persist, or diminish can be of significance. S-BOUN-TI topics capture this information that is readily usable in queries.

**Topic emergence (**Task-3**)

“Show the top 50 elements of topics that include Donald Trump and Hillary Clinton and when they occurred.”

Considering the intense preparation of political campaigns for the election debates, campaigners would be very interested in how their messaging resonates with the public. Listing 3 shows a federated query to fetch information about which elements emerged and when they did. This query consists of two subqueries. The first subquery selects the 50 topmost elements related to either of the candidates (Hillary Clinton and Donald Trump). The second subquery retrieves the time intervals, the persons, and the isAbout elements of the topics. Finally, the two results are joined on equal topico:isAbout elements, yielding 5,338 results. For example, 2016-09-27T02:08:00Z“^^xsd:dateTime dbr:Patient_Protection_and_Affordable_Care_Act dbr:Donald_Trump.

Whereas for WLB case, words indicating Hillary Clinton and Donald Trump and the identification of words related to the issues (EI) discussed in debates is needed. To identify words related to issues, external resources (EX) is needed. Topmost 50 of these words must be selected according to the number of occurrences of them in topics. Then, the time intervals of topics must be identified (TI), along with whom the words are occurring within the topics.

To illustrate the utility of the query in Listing 3, the results of these topics are summarized in Fig 9 by showing the issues that occurred along with Hillary Clinton and/or Donald Trump. The symbols □, ▤, □ indicate that the issues that co-occurred with Hillary Clinton only, Donald Trump only, or both respectively. The co-occurrence is reported for two minute intervals of each 90 minute debate. Some issues common to both candidates
Listing 3  Query: When did the topmost 50 issues related to Hillary Clinton and Donald Trump emerge during the debates?

```sparql
SELECT ?time ?issueOfInterest ?person {
  SERVICE <http://193.140.196.97:3030/topic/sparql> {
    SELECT ?issueOfInterest (COUNT(?topic) AS ?C)
    WHERE {
      ?topic topico:isAbout ?issueOfInterest.
      ?topic topico:observationInterval ?interval.
      {?topic topico:hasPerson dbr:Hillary_Clinton} UNION
      {?topic topico:hasPerson dbr:Donald_Trump}
      GROUP BY ?issueOfInterest
      ORDER BY DESC(?C) LIMIT 50
    }
  }
  SERVICE <http://193.140.196.97:3030/topic/sparql> {
    SELECT ?time ?about ?person
    WHERE {
      ?topic topico:hasPerson ?person.
      ?topic topico:isAbout ?about.
      ?topic topico:observationInterval ?interval.
      ?interval time:hasBeginning ?intervalStart.
      ?intervalStart time:inXSDDateTime ?time.
      FILTER(?person IN (dbr:Hillary_Clinton, dbr:Donald_Trump))
    }
    GROUP BY ?time ?about ?person
    FILTER (?about=?issueOfInterest)
  }
}
```

and seemed less relevant (i.e. `dbr:Debate`, `dbr:Question`, `dbr:Answer`, and `dbr:President_of_the_United_States`) were removed from the table to highlight issues with differences and to conserve space.

The elements that occur with Hillary Clinton and/or Donald Trump were examined to validate the relations among the co-occurring elements. The transcripts of the debates revealed that racism was mostly discussed in the second half of the first presidential debate and first half of third debate. The identified topics also relate to racism during the same periods, as seen in the rows labeled `White_people` and `Black_people`. Furthermore, the topics relate to both candidates. An inspection of the tweets show this issue arose in both pro-republican and pro-democrat contexts. The topic of `Tax` is only related to Donald Trump in the [48,50)th minute of the vice presidential debate and [80,82)th minutes of the third presidential debate. An inspection of the tweets at that time confirmed that this issue is related only to Donald Trump in those minutes. Two tweets about `Tax` refer to Hillary Clinton in the third debate, which were below the thresholds and did not get represented in a topic related to her.

**Querying topics in conjunction with LOD (Task-4)**

“Show the politicians who were mentioned in the debates.”

Some tasks require acquiring information from external resources, for example the persons whose occupation is “politician” may be available in LOD. At the time of processing these tasks Wikidata was found to provide such information, which is linked to DBpedia resources. The point of utilizing LOD is precisely for the fact that the links can lead to desired information. Task-4 is handled with three SPARQL queries to three distinct endpoints (Listing[4]. First, all persons are retrieved from S-BOUN-TI topics (Query 1). Then, the DBpedia SPARQL endpoint is queried to obtain the Wikidata identifiers for these persons (Query 2). Finally, the persons whose occupation is `Politician` (wikidata:Q82955) are retrieved (Query 3). This task is performed by optimizing the queries (Q) issuing in an order that the one which most restricts the results come first. Some of the results from this query are: `dbr:Abraham_Lincoln`, `dbr:Bill_Clinton`, `dbr:Colin_Powell`, `dbr:Bernie_Sanders`, and `dbr:Saddam_Hussein`.

Whereas for WLB case, performing this task needs identification (EI) of words that indicate politicians (TR) which requires external resource (EX).

**Locations of topics (Task-5)**

“Show the groups of and locations of rock concerts.”

This task requires the determination of concerts of a particular type and its location as well as the band’s name. Here, again an external resource is required to identify the type of concert. For this, DBpedia resources are utilized. Relevant S-BOUN-TI topics come with location(s). Listing[5] shows a query for retrieving this information. This query returns `dbr:Guns_N'_Roses`, `dbr:Mexico_City`. When the query is revised to fetch Country music concerts by replacing `dbc:Rock_music_genres` with `dbc:Country_music_genres`, we get `dbr:Luke_Bryan`, `dbr:Nashville_Tennessee`. While the locations of various concerts originate in tweets, the genres of music groups typically are not.

Whereas for WLB case, the identification of words that indicate music groups (TR), music genres (TR), and locations are needed. To resolve the music group type and the genres, external resources (EX) are needed. To decide if a word or phrase is a location type, location identification task (LI)
Fig 9. The time intervals of topic elements that co-occur with Donald Trump (▯), Hillary Clinton (▮), or both (◽).

Listing 4 Query: Fetch the politicians in the topics, which performs three queries the S-BOUN-TI DBpedia, and Wikidata-DBpedia endpoints.

```
SELECT DISTINCT ?person WHERE {
  ?topic topico:hasPerson ?person
}

SELECT ?DbPediaPerson ?wikidataPerson WHERE {
  ?DbPediaPerson owl:sameAs ?wikidataPerson .
  FILTER (?DbPediaPerson IN
    ("http://dbpedia.org/resource/Donald_Trump",
     "http://dbpedia.org/resource/Lester_Holt",
     ...)).
  FILTER regex(str(?wikidataPerson),".*wikidata.\.d*$")
}

SELECT ?person WHERE {
  ?person dbp-owl:occupation wikidata-dbp:Q82955 .
  FILTER (?person IN
    ("http://wikidata.dbpedia.org/resource/Q22686",
     "http://wikidata.dbpedia.org/resource/Q6294",
     ...)).
}
Listing 5 Query: Who are the artists of the rock music concerts, and where are the concerts located?

```
SELECT ?musicGroup ?location {
SERVICE <http://193.140.196.97:3030/topic/sparql>{
    SELECT ?topic ?musicGroup ?location WHERE {
    ?topic topico:isAbout dbr:Concert .
    ?topic topico:hasLocation ?location .
    {?topic topico:isAbout ?musicGroup .}
    UNION
    {?topic topico:hasPerson ?musicGroup .}}}
SERVICE <http://dbpedia.org/sparql>{
    SELECT ?musicGroup2 WHERE {
    ?musicGroup2 rdf:type schema:MusicGroup .
    ?musicGroup2 dbo:genre ?musicGenre .
    ?musicGenre dct:subject dbc:Rock_music_genres }}
FILTER (?musicGroup = ?musicGroup2)
```

Listing 6 Query: Find the common elements in topics including Barack Obama during the 2012 and the 2016 US election debates. This is a federated query that queries two endpoints, one for each debate.

```
SELECT ?about1 {
SERVICE <http://193.140.196.97:3031/topic/sparql>{
    SELECT DISTINCT ?about1 WHERE {
    ?topic1 topico:isAbout ?about1 .
    ?topic1 topico:hasPerson dbr:Barack_Obama}}
SERVICE <http://193.140.196.97:3032/topic/sparql>{
    SELECT DISTINCT ?about2 WHERE {
    ?topic1 topico:isAbout ?about2 .
    ?topic1 topico:hasPerson dbr:Barack_Obama}}
FILTER( ?about1=?about2)}
```

is needed which requires external resources (EX) and inspection of context of posts (similar to what is explained in Location identification section). Searching is needed among music groups for each genre in references in topics.

Finding similar topics (Task-6)

“Show the similar topics in 2012 and 2016 US Presidential debates.”

Some tasks make use of multiple topic data stores. This task is concerned with determining issues that have persisted across two debates. The tweets collected during the 2012 and 2016 US Presidential debates are deployed on distinct Fuseki stores. The 2012 US Presidential dataset is available from [59]. Listing 6 shows a query to fetch the common topic elements regarding Barack Obama from both the 2012 and 2016 debates. This query resulted in the elements dbr:Debate, dbr:President_of_the_United_States, dbr:Debt, dbr:Question, dbr:Tax, dbr:Tax_cut, dbr:Golf, dbr:Economy, dbr:Black_people, dbr:Racism, dbr:Violence, dbr:Birth_certificate, dbr:Lie, dbr:Muslim, dbr:Barack_Obama_presidential_campaign_2008, dbr:Russia, dbr:Iraq, dbr:Immigration, dbr:Blame, and dbr:Central_Intelligence_Agency. One might be surprised to see golf in this list, as playing golf seems to be a matter of public interest with respect to United States presidents. As such, it is not surprising to find dbr:Golf related to Barack Obama during both debates. An inspection of corresponding tweets confirms that indeed Barack Obama’s golfing was being discussed.

In WLB case, only a program that selects the common words in topics of 2012 and 2016 is needed. The results would differ of course, since they would be word based instead of entities. For more conceptual results, keyword extraction or entity identification (EI) methods could be used.

Topics with specific types (Task-7)

“Show the topics related to religious and ethnic issues in the 2012 and the 2016 US debates.”

Sometimes there is a need for querying topics with specific type of elements, where the type is defined in an external resource. Task-7 requires finding information about religions and ethnicity. Although, DBpedia includes many resources related to religion and ethnicity, their instances are not directly available, since DBpedia ontology has not classified them as such. However, Wikidata does and accessing their corresponding Wikipedia resources is straightforward. Listing 7 shows the stub of a query to achieve this task. Query 1 retrieves all religions. A similar query is used to retrieve ethnic groups. Query 2 retrieves the topics that include any of the items fetched in Query 1. A program (QO) that optimizes this query by feeding the output of Query 1 to Query 2 is used for this task.

When this query was run on the 2012 US election debates endpoint, only dbr:Catholicism was returned. For the 2016 US election debates endpoint, the same query returns dbr:Islam in the United States, dbr:Islam, and dbr:Sunny Islam. A manual inspection of tweets confirms the
Listing 7 Query 1: Get the religions from Wikidata, where the property P279* means all subclasses and Q9174 is the identifier for the religion class. Query 2: Get the topics that include religions.

```sql
PREFIX wdt: <http://www.wikidata.org/prop/direct/>
PREFIX wd: <http://www.wikidata.org/entity/>
SELECT DISTINCT ?item ?article
WHERE {
  ?item wdt:P279* wd:Q9174 .
  ?article schema:about ?item .
FILTER (SUBSTR(str(?article),9,17)="en.wikipedia.org/") .}
SELECT ?about (COUNT(?about) as ?C)
WHERE {
  ?topic topico:isAbout ?about .
  FILTER (?about in (dbr:Buddhism, dbr:Jainism, ...
  dbr:Tapa\_Gaccha, dbr:Zen)))
GROUP BY ?about
ORDER BY DESC(?C)
```

difference in reference to religion between the posts in these two elections. While, in 2012, the topics on Catholicism are mostly related to abortion, the topics in 2016 that refer to Islam are in the context of the Iraq war and the 9/11 terrorist attacks.

The very similar query performed for ethnic issues, also differ between the 2012 and 2016 US Presidential debates. In 2012 the elements are dbr:African-Americans, dbr:Massachusett, dbr:Russians, dbr:Egyptians, dbr:Jews, dbr:Mexican-Americans, dbr:Arabs, and dbr:Israelis. In 2016 they are dbr:African-Americans, dbr:Russians, dbr:Hispanic, dbr:Asian-Americans, dbr:Chinese-Americans, dbr:Hispanic_and_Latino-Americans, dbr:Mexican-Americans, and dbr:Mexicans. Furthermore, the topic elements co-occurring with dbr:African-Americans also vary. For example, the elements dbr:Police and dbr:Racism only occurred in the 2016 topics.

In WLB case, to accomplish this task, identification of religions (TR) which requires an external resource (EX), and a program that searches religions in topics needed.

**Define new relations (Task-8)**

“Declare that a topic that has two persons are related with vcard:hasRelated.”

In this case, the desire is to relate co-occurring persons in a topic using an existing relation that is external to Topico. For this purpose reasoning is utilized with a rule written in Semantic Web Rule Language (SWRL) [60] as follows:

```
Topic(?topic) ~
hasPerson(?topic, ?person1) ~
hasPerson(?topic, ?person2)
-> vcard:hasRelated(?person1, ?person2)
```

which defines a vcard:hasRelated relation between two people in the same topic. VCard ontology [61] specifies relationships among people and organizations. vcard:hasRelated property is used to specify a relationship between two entities.

Due to computational constraints, the reasoner is run on a subset of topics that are extracted from the first presidential debate, which infers the vcard:hasRelated relationship among dbr:Donald_Trump, dbr:Hillary_Clinton and dbr:Lester_Holt. Such relations typically persist and extend the ontology with domain specific inferences. It is easy to imagine that there would be many interesting rules in the case of political campaigns. Reasoning also allows subjective inquiries through introducing rules of interest.

In WLB case, persons in topics must be identified (TR) which requires external resources (EX). If this relation is to be persisted, it must be stored.

**Topic Enrichment (Task-9)**

This task aims to enrich topics with information in external resources. S-BOUN-TI topics can be enriched using categories defined in DBpedia. DBpedia resources are linked to their categories with dct:subject property (a property from the widely used Dublin Core vocabulary). Enriching topics in such a manner makes them accessible to better queries and processing. For example, dbr:Job has the category dbc:Employment. The s-BOUN-TI topics with the dbr:Job are indirectly related to dbc:Employment. The following SWRL rule associates the categories of every topic element with their DBpedia category with the topico:isAbout property:

```
Topic(?topic) ~
isAbout(?topic, ?element) ~
```
Table 8. The subtasks required to perform various tasks by WLB and S-BOUN-TI topics.

| Task | WLB topics | S-BOUN-TI topics |
|------|-------------|------------------|
| 1    | TR, EX      | –                |
| 2    | TI          | –                |
| 3    | EI, TI, EX  | –                |
| 4    | TR, EX, EI  | EX (2), QO       |
| 5    | TR (2), LI, EX (2) | EX         |
| 6    | –           | –                |
| 7    | TR, EX      | EX, QO           |
| 8    | TR, EX      | RD               |
| 9    | SA, EX      | RD, EX           |
| 10   | –           | EI               |

dct:subject(?element, ?category) -> isAbout(?topic, ?category)

When the reasoner is active the following query returns all topics with elements with category dbc:Employment, those including dbr:Job.

```sql
SELECT ?topic WHERE
{ ?topic topic:isAbout dbc:Employment }
```

Similarly, if instead of dbc:Employment, topics about dbc:Law_enforcement_operations_in_the_United_States is queried, the resulting topics include those with the element dbr:Stop-and-frisk_in_New_York_City.

Similar enrichment in WLB case requires additional functionality as there are no syntactic similarity among the terms. Statistical approaches have been proposed to enrich topics with keywords from external sources [62–64]. Thus, it will require semantic analysis (SA) of topics and external resources (EX) which may require considerable programming. In this case, topics with semantic representation populated using LOD are quite conveniently utilized.

**Document classification (Task-10)**

In the topic detection field, a well known approach is to represent topics as sets of keywords (topic models) that are related to a semantic theme, and associate relatedness of documents with these topic models. LDA, NMF, and LSA fall into this category. These approaches are unsupervised clustering methods. These topic models can be used to understand a document's general theme. After further, possibly manual investigation on clusters, they could be labeled with their themes such as arts, science, and news and they can be used in classification task. With these methods, a new document can be classified to one or more of the topics (theme) by comparing its words. For example, a document may be related to news and science topics. The drawback of this approach is that, a new document may have completely different semantic themes than the existing topic models. This results in a low comparison score. In other words, the new document is not related to any existing topic. An alternative is adding the new document to the original corpus, and restarting the topic detection process. This approach requires no further processing for document classification, but, there is an overhead of re-processing. To overcome re-processing, approaches have been proposed [65,66] for environments where new documents arrive. S-BOUN-TI does not fall into the category of topic identification approaches that output topic models that represent a semantic theme as keywords or phrases. Therefore, a document classification, in the conventional way such as described above can not be applied with S-BOUN-TI. However, a document could be compared with an existing topic just like a document could be compared with an existing topic model of LDA, NMF, or LSA. The semantic similarity of documents with topics could be identified. Identifying similar topics provides the semantic theme of the documents. This information can be utilized in identifying the temporal and spatial relatedness, such as identifying when the similar topics are talked about, or where the topic is related to. To accomplish this, entities in documents must be identified (EI). Then, documents become comparable with the semantic topics. The advantage of comparing semantically represented topic elements with semantically represented documents is that it allows variety in similarity computations. For example, documents and topics could be compared after semantic enrichment described in Task-9. This allows classification (comparing topics with documents) in an abstract level such as the DBpedia categories.

**S-BOUN-TI vs. WLB summary**

Utility of S-BOUN-TI and WLB topics is tabulated in Table 8 based on the above task requirements. The effort required to perform the tasks are expressed with the abbreviations that was shown in Table 7. For effort descriptions that require several functionalities of the same type are indicated with a parenthesized number following the type. For example, TR(2) indicated two functions for type resolution (i.e. person and music group). Since S-BOUN-TI topics readily support SPARQL queries are taken for granted and not shown in the table. Likewise basic functionality, such as string, set, list operations are considered low level functionality that is common to all processing.
S-BOUN-TI vs. BOUN-TI

A comparison of the S-BOUN-TI approach with other approaches is quite challenging, since the representations and methods used to identify topics differ significantly. Nevertheless, a high level comparison to inspect how our previous topic identification approach BOUN-TI [16] capture topics is useful.

BOUN-TI [16] is a topic identification approach that produces human readable topics, where topics correspond to Wikipedia page titles. Essentially, BOUN-TI identifies a ranked list of topics by comparing tf-idf vectors corresponding to the content of the microblog posts and Wikipedia pages using cosine similarity. BOUN-TI topics are produced for human interpretation, whereas S-BOUN-TI topics are intended for machine processing.

The relevancy of BOUN-TI topics are assessed through manual annotation, similar to how it was done for S-BOUN-TI topics. A web application is used to annotate the top ten BOUN-TI topics in a manner similar to how the relevancy of S-BOUN-TI topics were annotated (as described in the Semantic topic evaluation section). Topics are evaluated by annotating them as very satisfied if the topic is completely related to a tweet set, such as Christianity and abortion when tweets are related to abortion and Christianity. Topics that are not quite correct but are related are marked as satisfied, such as for the topic History of women in the United States when the tweets are about women’s rights and violence against women in the United States. Topics that are significantly distant but still have some relevancy are marked as minimally satisfied; such as Hillary Clinton presidential primary campaign, 2008 when the tweets are about Hillary Clinton’s 2016 US presidential campaign. Topics that are totally wrong are annotated as not satisfied, such as the topic Laura Bush in a set of tweets where she is never mentioned.

The results are examined in two ways: for topics marked either very satisfied or satisfied (assuming general satisfaction) and for topics annotated exclusively as very satisfied. Table 9 shows the precision scores resulting from the evaluation of the BOUN-TI and S-BOUN-TI topics. The scores of S-BOUN-TI are somewhat lower. The nature of the topics as well as the annotation criteria are important to keep in mind while interpreting these results. BOUN-TI topics are human readable rather encyclopedia titles. As they tend to be more general, they are more likely to be marked satisfied. For example, in the case of presidential debates, BOUN-TI identified numerous topics related to presidential debates, some being historical (i.e. “Hillary Clinton presidential primary campaign, 2008”). All of them are likely to be annotated as relevant, albeit being somewhat repetitive. In contrast, the S-BOUN-TI approach strives to identify a variety of topics.

It should be noted that the evaluation criteria of S-BOUN-TI topics is somewhat harsher since they are annotated as very satisfied only when all of the topic elements are correct. Since, S-BOUN-TI topics are produced for machine processing, the accuracy of topic elements is more crucial, making a harsher criteria is reasonable. It is also easier to identify mistaken elements in contrast to assessing a whole document as an error.

Table 9. User Evaluation of BOUN-TI and S-BOUN-TI topics.

|          | Very satisfied | Very satisfied or Satisfied |
|----------|----------------|-----------------------------|
| BOUN-TI  | Precision      | F₁                          |
|          | 79.3           | 89.0                        |
|          | 88.9           | 94.0                        |
| S-BOUN-TI| 74.8           | 92.4                        |
|          | 81.0           | 93.3                        |

BOUN-TI is based on bag of words that can match articles that are not in line with the intent of the tweets. For example, the topic Barack Obama citizenship conspiracy theories matches the words Barack and citizen present in tweets, where the context of word citizen was in the tweet text: Hillary is easily my least favorite citizen in this entire country. S-BOUN-TI topics are not similarly impacted, since it relates entities that occur in individual tweets — a highly local context. It considers both the wider context of collections to capture the collective contributions while associating topic elements based on a the context individual posts. For example, for the interval [26-28], BOUN-TI produces topics for Donald Trump, Hillary Clinton, Bill Clinton, Barack Obama’s Citizenship, and Laura Bush (several topics related to Hillary and Bill Clinton). Whereas, S-BOUN-TI produces topics that include dbr: Hillary Clinton and dbr: Donald Trump and issues such as dbr: Debate, dbr: ISIS (terrorism), dbr: Fact (fact checking), dbr: Lester Holt (the moderator of the debate), dbr: Interrupt (high levels of interruptions during the debate), dbr: Watching, and dbr: Website (fact checking website, specifically Hillary Clinton’s). While both produce relevant topics, S-BOUN-TI produces a greater variety of and more granular topics. On the other hand, BOUN-TI topics are human friendly as well as useful, especially when tweet sets match detailed Wikipedia pages (which certainly exist thanks to prolific contributors), the result is very satisfactory for human consumption.

We observe that, in general BOUN-TI captures more well defined and higher level human readable topics, while S-BOUN-TI picks up on lower level elements of forming a greater variety of machine processable topics.

Evaluation summary

In order to assess the proposed approach, S-BOUN-TI topics were generated from sets of tweets and examined by inspecting their characteristics, using them in processing tasks, and comparing them with topics generated from BOUN-TI. Our main inquiry was to assess the viability of generating topics from collections of microblog posts with use of resources on LOD. We found that considerable links between tweets and LOD resources were identified and that identifying topics from the constructed entity co-occurrence graph yielded relevant topics. With semantic queries and reasoning, we saw that it was possible to reveal information that is not directly accessible in the original source (tweets), which could be very useful for those (i.e. campaign managers, marketers, journalists) who are following information from social media.

The proposed approach is a straightforward one aimed to gain a basic understanding of the feasibility of mapping sets of tweets to semantically related entities. If possible, this would facilitate a vast number of applications that harvest the richly connected web of data. Our observations lead
us to believe that this is possible. Furthermore, this approach would improve by enhancing the techniques used to identify and relate topic elements, refining the topic representation, and with the increasing quality of data on LOD which have been improving in terms of quantity and quality during the span of this work, which is most encouraging. Potential improvements are elaborated in Discussion and future work section.

Discussion and future work

The overall results have been encouraging, leaving us with many potential future research directions to pursue. It is worth noting that, the proposed approach intended to explore the viability of such a direction. Various aspects of the proposed approach such as entity linking, topic representation, and processing have been straightforward with the intent of serving as a baseline. Each of these aspects are worth further developments.

Improvements to semantic topics can be achieved by improving: (1) the topic elements, (2) the topic identification algorithm, and (3) the ontology. The remainder of this section describes general observations regarding the proposed approach and potential improvements.

Working with the Linked Open Data

While cross-domain queries (federated queries) with LOD provide interesting results, their performance can be quite inefficient due to the distribution of data resources. Therefore, careful query planning is required for reasonable response times, which can be dramatically different based on the ordering of subqueries. Generally, executing more restrictive queries first in order to restrict the search space is a good idea.

One of the issues that impacts our approach are mistakes in the data on LOD. For example, during this work, the entity dbr:Women’s_righs had rdf:type dbr:Person, which seems incorrect. This leads to this issue being treated as a person, which propagates to the generated topic as a topic:Person. We expect such errors to occur in LOD and that they will be corrected in time. Our observations are that the quality of information on LOD is steadily improving. As data improves, so will resulting topics. However, additional effort to validate elements by cross-checking with alternative resources may be pursued.

Finally, ongoing work in W3C working groups, such as Social Web Protocols are promising regarding increased opportunities for LOD.

Improving topic elements

S-BOUN-TI uses references to entities in LOD to form topics. Most of the inspected topics were satisfactory, whereas some of them were unsatisfactory due to entity linking issues. S-BOUN-TI improves some of the incorrect links through relinking. It takes the social signals from the crowd to decide on the entities that are most likely. There are cases when the same spot is linked to different entities in the same tweet set. However, we have observed that this occurs rarely, most likely since the tweet sets are retrieved according to a query that tends to create a shared context. For example, the spot birth certificate is linked to dbr:Birth_certificate in the tweet text "AND THERE’S THE BIRTH CERTIFICATE MENTION #debatenight. The same spot is linked to dbr:Barack_Obama_citizenship_conspiracy_theories in the tweet text I was the one that got #Obama to produce the birth certificate - #Trump. This happens because the latter provides a context (who is Obama). The first linking is correct if only one tweet is taken into account. However, when the tweet set is taken into account, the context is about Barack Obama’s birth certificate. In this case, the spot is re-linked to the second entity which is dbr:Barack_Obama_citizenship_conspiracy_theories, which is more relevant.

Among the incorrect entity linkings, what we typically encounter more frequently is that a spot is linked to multiple entities with different meanings. For example, the spot Trump being linked from different tweets to dbr:Trump (card games) and dbr:Donald_Trump. Here, the latter is the correct one and relinking corrects the former error. Thus, making use of the wisdom of the crowd approach meaningful in this context.

One reason of incorrect entity linking is the name of songs, movies, albums and books. These types might match any text piece since they are too numerous and are often commonly used words and phrases in everyday language. For example the word nation could be linked to a book named The Nation. For these types, and for the unlinked spots, a method that considers entities from other knowledge resources such as Yago [67] and Google knowledge graph [68] could be used to address some of these problems. Specialized databases could be used for specific type of entities such as songs and albums. For example, MusicBrainz [59], another database that provides artists, albums, songs and their relations in the semantic Web, could be used for entity linking.

The behavior of the entity linker TagMe has a very significant impact. In the early phases of this work, we experimented with DBpedia spotlight [70]. No significant difference was observed between the results of these linkers. TagMe used Wikipedia and DBpedia Spotlight used DBpedia as resources for entity linking. There is a clear mapping between Wikipedia to DBpedia. Thus, the results they produce are very similar. DBpedia Spotlight requires a local installation to be deployed, whereas TagMe offers a well documented and reliable RESTful API with fast response times. Thus, to avoid adding the overhead of maintaining another piece of software, we opted TagMe. Based on the encouraging results we obtained from our experiments, it is worthy to experiment with alternative entity linkers to explore improvements in entity detection. For example, WAT [71] which is a successor of TagMe could be adapted. This requires setting more number of parameters to tune, which requires a more detailed manual analysis of entity linking results with the datasets. In a production system, a local entity linker could be used and tuned for the system to work in real-time conditions. Thus, DBpedia spotlight may be more appropriate.

Although entity linking is very useful to identify text parts, it still needs improvement when used in the context of topic identification. Incorrect linking happens when the entity linker incorrectly suggests a wrong link with high confidence. For example, the spot kaine gets linked to a fictional character dbr:Kaine rather than dbr:Tim_Kaine and Pence to dbr:Pound_sterling (pence which is a currency redirect to this entity) instead of
At first glance, DBpedia does not express any instance of maximal cliques, since in our datasets there are many dominant vertices that tend to connect to lower-degree vertices. The lower-degree vertices representation. Then, it is possible to state “The instance (entity) related to each other but are related to the dominant vertices Maximal cliques successfully group such elements. For example the vertices time, the location, and the cause of death could be sought in tweets. Handling of such events may improve topic element identification. For example, in the case of death, the identification and age of the deceased; the hashtags in the tweets that contribute to elements of the topics. Quality and the quantity of topics. Meta information that indicates variety in terms of the number of words and users that contributed to a topic may be useful to identify a person whose name is Michael. This is under consideration. Finally, sources other than DBpedia on LOD (i.e. Geonames) may be used to detect locations.

Among the temporal expressions, the names of months and seasons are ambiguous. They may be person names (i.e. April, May, and Summer). Examples of other ambiguities are March as in the month vs the verb in women’s march ([IN] dataset)and [May] in May the force be with you ([CF] dataset). Likewise, the season Fall and the verb fall are ambiguous. In datasets that include more context, spots like fall concert, summer festival, Winter Concert, and WinterFest are correctly identified. It is evident that improvements to address such ambiguities is required with use of NLP techniques.

To link unlinked spots, richer NLP techniques are required. Improving location and person identification is particularly significant as they are often of interest to researchers. However, another way to address unlinked spot expression (for spots i.e. conference hall and Michael) is to create an instance of the class owl:Thing for the spot and link the spot to this instance. Frequently referenced unlinked spots could therefore have a representation. Then, it is possible to state “The instance (entity) E that is linked to spot S is observed at time interval ‘startTime-endTime’ and is related to other instances dbr:Instance1, dbr:Instance2, ..., dbr:Instancee. Expressing an unlinked spot as an instance in this way expresses a context for the instance, which could be used to define the spot. If the same spot is encountered again, the previously expressed context could be compared with the spot’s context. If the spot and the contexts are sufficiently similar, then the recently encountered same spot could be linked to the previously expressed instance.

In addition to person type that we focus on this study, under foaf:Agent class, other sub-classes exist such as foaf:Group and foaf:Organization. At first glance, DBpedia does not express any instance of foaf:Group type at the time of writing this article (to retrieve instances of this type see [72]). Therefore, we have not focused on identifying this type. In future work, music bands and any kinds of ad-hoc or persistent group could be represented with this type. On the other hand, foaf:Organization instances exist in DBpedia. However, it is not trivial to identify an organization only by identifying the spot that references it in texts. Organizations often have a location type. Therefore, if an entity with organization indicating type in DBpedia is not identified as a location, it could be represented as an organization. Sophisticated NLP techniques, such as considering the context of a post could be used to identify organizations. This issue is also referred as type ranking. Recent study on type ranking [74] gives insight.

Some topics are quite similar but resulted in distinct topics due to temporal expressions. For example, the first presidential debate was held on a Monday night. Thus, the phrases now, tonight, and Monday night are equivalent in the case they were used at that time. Thus, they can be included in a single topic. This may be addressed with temporal rules that are applied after topics are created or by processing the entity co-occurrence graph by introducing strong links between equivalent nodes (a context dependent task) prior to topic identification to assure they end up in the same clique.

Finally, entity and temporal expression identification would improve if tweets are normalized [75] and hashtag segmentation [76] is performed prior to entity linking since the context and term recognition would improve.

**Improving semantic topics**

S-BOUN-TI topics are intended to represent collective contributions. However, a manual inspection of how the topics are formed revealed that some topics result from few users or mostly from retweets of the same posts. Further investigation is needed to identify these cases and their effect on the quality and the quantity of topics. Meta information that indicates variety in terms of the number of words and users that contributed to a topic may be useful for this purpose. Topics could be rated according to frequencies of relationships and entities, diversity of posters, diversity of words and of hashtags in the tweets that contribute to elements of the topics.

Certain patterns of contribution have emerged during special events, such as the use of RIP, dies and death when someone dies. Special handling of such events may improve topic element identification. For example, in the case of death, the identification and age of the deceased; the time, the location, and the cause of death could be sought in tweets.

Our approach identifies topics using the maximal cliques algorithm which may limit the number of elements in topics. We have chosen to use maximal cliques, since in our datasets there are many dominant vertices that tend to connect to lower-degree vertices. The lower-degree vertices typically represent many aspects related to the dominant elements. These lower-degree vertices are often not related to each other according to posts. Maximal cliques successfully group such elements. For example the vertices dbr:Federal_Bureau_of_Investigation and dbr:Bill_Clinton are not related to each other but are related to the dominant vertices dbr:Hillary_Clinton and dbr:Debate (Fig.6). If the clique criterion were relaxed so as to
allow an element in a group if it is related with a certain percentage of elements in the group, but not all of them, and if this relaxation allows the inclusion of one element, more granular topics would be obtained. If this is applied for the same example, dbr:Federal_Bureau_of_Investigation and dbr:Bill_Clinton would be in the same group resulting in an abstract topic with more number of elements. However, this inclusion would also imply that they are related to each other in a context. An inspection of the posts reveals that they are not in fact mentioned in the same context, but rather that people are talking about Hillary Clinton in the context of FBI. We considered these situations in the design of the approach. In our implementation, we have already relaxed cliques to take into consideration lower weights between two vertices in the graph using $r_{min}$. This relaxation still takes into account the co-occurrence of elements in the same post. However, because of conditions similar to those explained here, in these experiments, we decided not to assign two elements to the same topic if they are not extracted from the same post.

In literature, the quasi-cliques model relaxes the criteria by defining dense subnetworks that are not strictly maximal cliques. An example application by Xiang et al. [77] groups related genes by using edge covering quasi-clique merger (eQCM). They apply a slight modification to the original QCM algorithm [78] which ensures that vertices of edges are assigned to at least one group if the edge weights are greater than a predetermined threshold. This approach computes the edge weights using the Pearson correlations of gene expression profiles. The task of identifying groups of related genes bears similarities with the grouping of entities for topic identification. The edges with weights over a certain threshold must be covered. Our approach similarly considers edges over certain weights to indicate relatedness among relevant vertices (entities) that we identify. The difference is that, eQCM works on weighted undirected graphs, whereas we work on unweighted graphs by disregarding the weights (after pruning, the resulting entities and relations are considered relevant irrespective of their weights). Such approaches for relaxing the computation of cliques is worth be exploring in the future.

**Improving ontology**

*Topico* is a very straightforward ontology developed to test the general approach of representing topics to benefit from semantic querying and processing. The characteristics of streaming microblogs were considered during its definition. The results of this study have been encouraging, thus revisiting the expressibility of *Topico* is warranted. For example, topic sentiments reflecting emotional aspects related to the crowd could be of interest. Twitter jargon could be included [79] and expressed in the semantic Web. Then, topics could include elements referencing these definitions.

Domain specific topics are also of interest. The generation of topics in conjunction with other ontologies such as for events could generate topics specific to events including details of time, places, performer, and much more. For domain specific topics, rules that are significant from a subjective perspective could be added, such as people of certain professions. Assuming the existence of such rules, queries like retrieve topics about politicians, retrieve topics about artists, and retrieve topics about both artists and politicians become possible. To reason over information hosted in external domains such as Wikidata, similar to software that run the federated queries, a federated reasoner is required. This is an active research area from which this work expects to greatly benefit.

**Performance issues**

While performance issues are significant in processing large quantities of data, they have not been a focus in this work. Optimization is needed in the case of heavy Twitter usage and the whole data that Twitter provides, even if external data sources such as Wikipedia, Wikidata, and DBpedia are quickly accessible for the computing process. Several solutions would be applied, including adding more RAM and processing power, and parallelizing processes.

When the system is real-time, several keywords could be tracked using the streaming API, and these Twitter streams could be transformed into topic streams using S-BOUN-TI. After this, the topics could be queried on a stream reasoning knowledge base using C-SPARQL [80].

The post set size was selected considering to the performance of the prototype in condition of heavy posting and the use of the Twitter streaming API. However, in contexts where topics change slower or faster, interval sizes that are larger or smaller may be more suitable. Further investigation regarding the determination of interval size is among our future directions.

**Topic browser**

Aside of application-specific processing, it can be desirable simply to browse topics. Fig.10 shows an early prototype [81] of a topic browser that presents a topic from the [ND] dataset. The prototype is available for download at [82]. Here topics are shown in a human readable format by utilizing entity information such as depictions and abstracts. The user can upload sets of tweets, from which S-BOUN-TI topics will be generated and deployed to a Fuseki service. Three types of querying is supported: (1) keyword that matches the label of an entity, (2) faceted to search according to element types, and (3) semantic to pose SPARQL to the Fuseki SPARQL endpoint. Numerous improvements are planned, such as supporting rules to facilitate more sophisticated retrieval and origin tracking to reveal the original source of the topics.

**Related work**

The approaches that have been proposed for making sense of content generated by microblog users differ in terms of whether they process a single microblog post, or multiple microblog posts, whether they use external data resources such as Wikipedia or not, their methods and how the topics are expressed. We refer to the related work in the context of these criteria.
Methods have been proposed [16,17] to identify topics of microblog post sets for human consumption. The method by Sharifi et al. [17] builds a summarizing phrase by recognizing common consecutive words. **BOUN-TI** [16] seeks similar Wikipedia pages with microblog post set content, and outputs titles as topics. A section compares S-BOUN-TI and BOUN-TI in detail. The main aspect of S-BOUN-TI is that it aims to extract machine interpretable topics.

Some approaches link entities in a variety of domains such as DBpedia, Wordnet, and MusicBrainz to text fragments of microblog posts. Approaches [18–20] have been proposed that use Wikipedia page titles, connections among pages, page contents, and anchor texts of links in pages to decide whether a fragment of text is suitable to be linked to a Wikipedia article. External data resources such as Wikipedia, MusicBrainz, City DB, Yahoo! Stocks, Chrome, and Adam have been utilized for entity linking [19]. Other approaches [27–31] link parts of a single post to resources in DBpedia. **S-BOUN-TI** focuses on determining topics of multiple microblog posts from multiple users, and does not implement entity linking. However, it utilizes an existing implementation, TagMe [18], to extract some of the elements of the structured topics. Alternatively, the approach by Kapanipathi et al. [83] identifies entities related to users using Zemanta which is an entity linker no longer active. The Wikipedia categories of these entities are considered as user interests and used to provide recommendations. Mansour et al. [84] proposes domain specific approach to augment information about local businesses with content from tweets. The entities are extracted based on the information they poses on local businesses. The terms chosen to augment the business entities are selected based on their term frequencies.

Semantic tagging and semantic information extraction has been applied on mediums other than microblogs such as news documents, meeting reports and blogs [26,85,86]. Approaches have been proposed that defines an ontology or use existing vocabulary or ontologies to represent the information they extract. Some approaches [87,88] semantically annotate news documents and express the extracted information in the semantic Web. Another approach by semantically annotates meeting reports of The European Parliament [89]. The annotations are linked to DBpedia, GeoNames, and Eurovoc thesaurus. It automatically links by seeking matching strings of the labels in DBpedia. The links are manually controlled and fixed by a human if necessary. Another approach based on LDA extracts words, terms, and concepts from documents, and expresses them using SKOS, OWL, and RDFS structures [90]. LOD, Wordnet, and DBpedia resources are used to represent terms and concepts. It analyzes the output of LDA topics with the input documents, forms related terms and nouns from LDA topics and expresses them in the semantic Web. These approaches work on semi-structured documents such as meeting reports, and plain text documents such as news and blogs.

While some approaches semantically tag parts of single posts, other approaches process single posts to extract information by using keywords to decide if a post indicates the state of the user such as mood and sickness. For example, one approach [91] manually defines keywords for four different classes of moods. If a keyword is found in a post, it is assumed that the post states the user’s mood. In the health domain, words and regular expressions are manually defined [92]. Matching words and regular expressions indicate their corresponding sicknesses. Another approach [93] automatically extracts indicative words of sicknesses from Wikipedia. Then, it identifies those words in microblog posts. Other studies that extract information from a single post often classify posts into groups such as in positive mood, or earthquake reporting post using machine learning techniques. One of these studies [31] classifies whether a post is incident related or not. Incident related tweets are grouped under three different
categories which are crash, fire, and shooting. One approach uses predefined list of words of topics and relates a post to a topic using the matching words. Another approach classifies whether a post reports an earthquake during the time that it is posted. Single post processing approaches can be applied on each post in a post set, and the results can be aggregated to obtain results such as public health trends, public mood changes, earthquake time and location detection. Unlike these approaches where each post is independently processed, S-BOUN-TI processes a post set to obtain topics and uses other posts to resolve issues related to insufficient context of single post processing.

Among the approaches that work on microblog post sets, some of them identify topics by considering temporal properties of posts. Changes in the frequency of words and hashtags indicate topics. The generated topics are formed from either words or representative posts. Other approaches use similarity measures between microblog posts by applying tf-idf or latent semantic analysis (LSA) based vector space models, or by measuring the similarity among words and phrases through other metrics such as the distance between two Wikipedia pages in the Wikipedia link graph, where the pages in the graph are identified by the content of the posts. Other types of approaches that work on microblog post sets are the probabilistic topic modeling approaches. The most widely applied approaches are based on Latent Dirichlet Allocation (LDA) or tf-idf or tf-idf based vector space models. The LDA outputs topics as a collection of related words (WLB topics). The approach in relies on documents that are manually labeled by humans with external concepts. The labels are used to enrich LDA topic models that outputs collection of related words as topics. A comparison of using S-BOUN-TI and word list based (WLB) topics is presented in Section 4.3.1.

S-BOUN-TI is a similar approach to S-BOUN-TI that is based on cliques of entities in scientific documents to identify emerging scientific topics in the embryonic phase. The approach builds co-occurrence network of semantic concepts extracted from documents. Concepts are clustered based on clique detection. The clusters are post-processed to merge similar ones using Jaccard index. The resulting clusters are considered topics. However, S-BOUN-TI identifies topics of microblog posts by utilizing entity linking where the entities are defined in LOD, specifically the encyclopedic resource DBpedia, and is not specific to a domain.

Ontologies have been used to capture and represent the knowledge expressed in textual documents in the domain of health. Approaches that use ontologies for document representation, classification, and retrieval, express each textual document using an ontological representation such as: The research article A contains a reference to gene TNF which is defined in the ontology O. S-BOUN-TI generates topics from collections of posts as aggregate information which can be queried and processed in their own right.

One of the main categories of time linked entities would be events. Event ontologies, and ontologies that include definition of an event have been proposed which mainly express the temporal and spatial dimensions of an event along with its related entities such as agents. Not all topics are related to events. The main difference of topics and events is the way they express temporal information. For example the tweet text On my way to Bertinoro! Excited for the International Semantic Web Research Summer School to start! #isws2018 #semweb, is about an event but the tweet text The semantic Web and LOD are powerful concepts but are rarely implemented. / #DevDiscuss is not about an event. A topic may not be related to any date or time but the time of the posts it is produced from. The posting time is defined as a meta information for a topic. Abstract concepts such as now, and today are bounded with topics which are typical in microposts. These concepts can be further processed to reason about time.

Conclusions

This work investigates the viability of extracting semantic topics from collections of microblog posts via processing their corresponding linked entities that are LOD resources. To this end, an ontology (Topico) to represent topics is designed, an approach to extracting topics from sets of microposts is proposed, a prototype of this approach is implemented, and topics are generated from large sets of posts from Twitter. The resulting topics and their potentials are examined in detail.

The main inquiry of this work is to examine whether an approach based on entity linking microposts to LOD resources could produce satisfactory semantic topics. In other words, would the fast flowing, short, untidy, noisy microblog posts be suitable for entity linking based topic extraction? Based on this work, we demonstrated that entity linking to LOD yields sufficiently interesting results. We are further encouraged by the current efforts in the linking open data activities in providing greater and better resources.

The main goal of producing semantic topics is for their utility through further processing in the context of LOD. Through accomplishing several tasks of different level of complexities with SPARQL queries and SWRL rule definitions, we have observed that interesting information that is not readily available in the original posts can be revealed. A user evaluation of semantic topics (with 81.0% precision and F1 of 93.3%) and our continuous manual inspection show that identified topics are relevant.

In summary, we demonstrated that there are many opportunities in pursuing this direction. We see many directions to improve the topic identification approach as well as to process topics in general and in domain specific manners.

Acknowledgements

We thank Dr. Jayant Venkatathan and Dr. T. B. Dinesh for valuable contributions during the preparation of this work. We are grateful for the feedback received from the members of SosLab (Department of Computer Engineering, Boğaziçi University) during the development of this work. We thank Kasım Bozdağ for the effort in the prototype.
References

1. Internet Live Stats. Twitter statistics; 2018. Available from: http://www.internetlivestats.com/twitter-statistics/
2. Diao Q, Jiang J, Zhu F, Lim EP. Finding Bursty Topics from Microblogs. In: Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Long Papers - Volume 1. ACL ’12. Stroudsburg, PA, USA: Association for Computational Linguistics; 2012. p. 536–544. Available from: http://dl.acm.org/citation.cfm?id=2390524.2390599
3. Ramage D, Dumais S, Liebling D. Characterizing Microblogs with Topic Models. In: Proceedings of the Fourth International AAAI Conference on Weblogs and Social Media. AAAI; 2010. p. 130–137.
4. Yan X, Guo J, Lan Y, Cheng X. A Biterm Topic Model for Short Texts. In: Proceedings of the 22Nd International Conference on World Wide Web. WWW ’13. New York, NY, USA: ACM; 2013. p. 1445–1456.
5. Zhao WX, Jiang J, Weng J, He J, Lim EP, Yan H, et al. Comparing Twitter and Traditional Media Using Topic Models. In: Proceedings of the 33rd European Conference on Advances in Information Retrieval. ECIR’11. Springer-Verlag; 2011. p. 338–349. Available from: http://dl.acm.org/citation.cfm?id=1996889.1996934
6. Mehrotra R, Sanner S, Buntine W, Xie L. Improving LDA Topic Models for Microblogs via Tweet Pooling and Automatic Labeling. In: Proceedings of the 36th International ACM SIGIR Conference on Research and Development in Information Retrieval. SIGIR ’13. New York, NY, USA: ACM; 2013. p. 889–892.
7. Perrier A. Segmentation of Twitter Timelines via Topic Modeling; 2015. Available from: https://alexisperrier.com/nlp/2015/09/16/segmentation_twitter_timelines_lda_vs_lsa.html
8. Ozer M, Kim N, Davulcu H. Community detection in political Twitter networks using Nonnegative Matrix Factorization methods. In: Proceedings of the 2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, ASONAM. Institute of Electrical and Electronics Engineers Inc.; 2016. p. 81–88.
9. Alvanaki F, Michel S, Ramamritham K, Weikum G. See What’s enBlogue: Real-time Emergent Topic Identification in Social Media. In: Proceedings of the 15th International Conference on Extending Database Technology. EDBT ’12. New York, NY, USA: ACM; 2012. p. 336–347.
10. Cataldi M, Di Caro L, Schifanella C. Emerging Topic Detection on Twitter Based on Temporal and Social Terms Evaluation. In: Proceedings of the Tenth International Workshop on Multimedia Data Mining. MDMKDD ’10. New York, NY, USA: ACM; 2010. p. 4:1–4:10.
11. Kasiviswanathan SP, Melville P, Banerjee A, Sindhwani V. Emerging Topic Detection Using Dictionary Learning. In: Proceedings of the 20th ACM International Conference on Information and Knowledge Management. CIKM ’11. New York, NY, USA: ACM; 2011. p. 745–754.
12. Marcus A, Bernstein MS, Badar O, Karger DR, Madden S, Miller RC. TwitterMonitor: Aggregating and Visualizing Microblogs for Event Exploration. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. CHI ’11. New York, NY, USA: ACM; 2011. p. 227–236.
13. Mathioudakis M, Koudas N. TwitterMonitor: Trend Detection over the Twitter Stream. In: Proceedings of the 2010 ACM SIGMOD International Conference on Management of Data. SIGMOD ’10. New York, NY, USA: ACM; 2010. p. 1155–1158.
14. Salatino AA, Osborne F, Motta E. AUGUR: Forecasting the Emergence of New Research Topics. In: Proceedings of the 18th ACM/IEEE on Joint Conference on Digital Libraries. JCDL ’18. New York, NY, USA: ACM; 2018. p. 303–312. Available from: http://doi.acm.org/10.1145/3197026.3197052
15. Sayyadi H, Raschid L. A Graph Analytical Approach for Topic Detection. ACM Trans Internet Technol. 2013;13(2):4–1–4:23. doi:10.1145/2542214.2542215.
16. Yıldırım A, Uskudarli S, Özgür A. Identifying Topics in Microblogs Using Wikipedia. PLoS ONE. 2016;11(3):1–20. doi:10.1371/journal.pone.0151885.
17. Sharifi B, Hutton MA, Kalita JK. Experiments in Microblog Summarization. In: Proceedings of the 2010 IEEE Second International Conference on Social Computing. SOCIALCOM ’10. Washington, DC, USA: IEEE Computer Society; 2010. p. 49–56.
18. Ferragina P, Scaiella U. Fast and Accurate Annotation of Short Texts with Wikipedia Pages. IEEE Software. 2012;29(1):70–75. doi:10.1109/MS.2011.122.
19. Gattani A, Lamba DS, Garera N, Tiwari M, Chai X, Das S, et al. Entity Extraction, Linking, Classification, and Tagging for Social Media: A Wikipedia-based Approach. Proc VLDB Endow. 2013;6(11):1126–1137. doi:10.14778/2536222.2536237.
20. Meij E, Weerkamp W, de Rijke M. Adding Semantics to Microblog Posts. In: Proceedings of the Fifth ACM International Conference on Web Search and Data Mining. WSDM ’12. New York, NY, USA: ACM; 2012. p. 563–572.
21. Sheth A. Citizen Sensing, Social Signals, and Enriching Human Experience. IEEE Internet Computing. 2009;13(4):87–92. doi:10.1109/MIC.2009.77.

22. Auer S. Introduction to LOD2. In: Auer S, Bryl V, Tramp S, editors. Linked Open Data – Creating Knowledge Out of Interlinked Data: Results of the LOD2 Project. Springer International Publishing; 2014. p. 1–17.

23. Schmachtenberg M, Bizer C, Paulheim H. The Semantic Web - ISWC 2014. In: Adoption of the Linked Data Best Practices in Different Topical Domains. Cham: Springer International Publishing; 2014. p. 245–260.

24. Yıldırım A, Uskudarlı S. S-BounTI: Semantic Topic Identification approach from Microblog post sets using Linked Open Data, published datasets; 2018. Available from: https://doi.org/10.6084/m9.figshare.7527476.

25. SoSLab. Explore semantic topics; 2018. Available from: http://soslab.cmpe.boun.edu.tr/sbounti/.

26. Gruetze T, Kasneci G, Zuo Z, Naumann F. CohEEL: Coherent and Efficient Named Entity Linking through Random Walks. Web Semantics: Science, Services and Agents on the World Wide Web. 2016;37(0).

27. Torres-Tramón P, Hromic H, Walsh B, Heravi BR, Hayes C. Kanopy4Tweets: Entity Extraction and Linking for Twitter. In: Proceedings of 6th workshop on ‘Making Sense of Microposts’, Named Entity Recognition and Linking (NEEL) Challenge in conjunction with 25th International World Wide Web Conference (WWW); 2016. p. 64–66.

28. Caliano D, Fersini E, Manchanda P, Palmonari M, Messina E. UniMiB: Entity Linking in Tweets using Jaro-Winkler Distance, Popularity and Coherence. In: Proceedings of 6th workshop on ‘Making Sense of Microposts’, Named Entity Recognition and Linking (NEEL) Challenge in conjunction with 25th International World Wide Web Conference (WWW); 2016. p. 70–72.

29. Greenfield K, Caseres R, Coury M, Geyer K, Gwon Y, Matterer J, et al. A Reverse Approach to Named Entity Extraction and Linking in Microposts. In: Proceedings of 6th workshop on ‘Making Sense of Microposts’, Named Entity Recognition and Linking (NEEL) Challenge in conjunction with 25th International World Wide Web Conference (WWW); 2016. p. 67–69.

30. Waitelonis J, Sack H. Named Entity Linking in #Tweets with KEA. In: Proceedings of 6th workshop on ‘Making Sense of Microposts’, Named Entity Recognition and Linking (NEEL) Challenge in conjunction with 25th International World Wide Web Conference (WWW); 2016. p. 61–63.

31. Schul A, Guckelsberger C, Janssen F. Semantic Abstraction for Generalization of Tweet Classification: An Evaluation on Incident-Related Tweets. Semantic Web. 2016;8(3):353–372.

32. TagMe. TagMe API Documentation; 2018. Available from: https://sobigdata.d4science.org/web/tagme/tagme-help.

33. Brickley D, Miller L. FOAF Vocabulary Specification 0.99; 2014. Available from: http://xmlns.com/foaf/spec/.

34. Dublin Core Metadata Initiative. DCMI: DCMI Metadata terms; 2012. Available from: http://dublincore.org/documents/dcmi-terms/.

35. W3C. WGS84 Geo Positioning: an RDF vocabulary; 2009. Available from: http://www.w3.org/2003/01/geo/wgs84_pos.

36. W3C Semantic Web Interest Group. Basic Geo (WGS84 lat/long) Vocabulary; 2003. Available from: https://www.w3.org/2003/01/geo/.

37. GeoNames. GeoNames Ontology - Geo Semantic Web; 2012. Available from: http://www.geonames.org/ontology/documentation.html.

38. Cox S, Little C. Time Ontology in OWL. W3C; 2017. Available from: https://www.w3.org/TR/owl-time/.

39. Cox SJD. The gregorian months; 2017. Available from: https://www.w3.org/ns/time/gregorian#.

40. Linked Data community. Linked Data | Linked Data - Connect Distributed Data across the Web; 2018. Available from: http://linkeddata.org/.

41. McCrae JP. The Linked Open Data Cloud Diagram; 2018. Available from: http://lod-cloud.net.

42. Bizer C, Lehmann J, Kobilarov G, Auer S, Becker C, Cyganiak R, et al. DBpedia - A Crystallization Point for the Web of Data. Web Semantics: Science, Services and Agents on the World Wide Web. 2009;7(3):154–165. doi:10.1016/j.websem.2009.07.002.

43. Suchanek FM, Kasneci G, Weikum G. YAGO: A Large Ontology from Wikipedia and WordNet. Web Semantics: Science, Services and Agents on the World Wide Web. 2008;6(3):203–217. doi:http://dx.doi.org/10.1016/j.websem.2008.06.001.

44. Guha RV, Brickley D, Macbeth S. Schema.Org: Evolution of Structured Data on the Web. Commun ACM. 2016;59(2):44–51. doi:10.1145/2844544.

45. Schema.org. Home - schema.org; 2018. Available from: http://schema.org/.

46. Vrandečić D, Krötzsch M. Wikidata: A Free Collaborative Knowledgebase. Commun ACM. 2014;57(10):78–85. doi:10.1145/2629489.

47. Wikimedia Foundation. Wikidata; 2018. Available from: https://www.wikidata.org/wiki/Wikidata:Main_Page.
75. Sönmez Ç, Özgür A. A Graph-based Approach for Contextual Text Normalization. In: Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP). Association for Computational Linguistics; 2014. p. 313–324. Available from: http://aclweb.org/anthology/D14-1037

76. Çelebi A, Özgür A. Segmenting hashtags and analyzing their grammatical structure. Journal of the Association for Information Science and Technology. 2018;69(5):675–686. doi:10.1002/asi.23989.

77. Xiang Y, Zhang CQ, Huang K. Predicting Glioblastoma Prognosis Networks using Weighted Gene co-expression Network Analysis on TCGA Data. BMC Bioinformatics. 2012;13(2):S12. doi:10.1186/1471-2105-13-S2-S12.

78. Ou Y, Zhang CQ. A New Multimembership Clustering Method. Industrial and Management Optimization. 2007;3(4):619–624.

79. Beal V. Twitter Dictionary: A Guide to Understanding Twitter Lingo; 2018. Available from: https://www.webopedia.com/quick_ref/Twitter_Dictionary_Guide.asp

80. Barbieri DF, Braga D, Ceri S, Della Valle E, Della Valle M. C-SPARQL: SPARQL for Continuous Querying. In: Proceedings of the 18th International Conference on World Wide Web. WWW ’09. New York, NY, USA: ACM; 2009. p. 1061–1062.

81. Yıldırım A, Uuskudarlı S. The information revealed by processing semantic topics extracted from collective short posts. In: 26th Signal Processing and Communications Applications Conference (SIU). IEEE; 2018. p. 1–4.

82. Yıldırım A. S-BounTI: Semantic Topic Identification approach from Microblog post sets. An application.; 2018. Available from: https://doi.org/10.6084/m9.figshare.5943211

83. Kapanipathi P, Jain P, Venkataramani C, Sheth A. User Interests Identification on Twitter Using a Hierarchical Knowledge Base. In: The Semantic Web: Trends and Challenges. Cham: Springer International Publishing; 2014. p. 99–113.

84. Mansour R, Refaei N, Murdock V. Augmenting Business Entities with Salient Terms from Twitter. In: Proceedings of COLING 2014, the 25th International Conference on Computational Linguistics: Technical Papers. Dublin City University and Association for Computational Linguistics; 2014. p. 121–129. Available from: http://www.aclweb.org/anthology/C14-1013

85. Dornescu I, Or/uni0103san C. Densification: Semantic Document Analysis using Wikipedia. Natural Language Engineering. 2014;20:469–500. doi:10.1017/S1351324913000296.

86. Jovanovic J, Bagheri E, Cuzzola J, Gasevic D, Jeremic Z, Bashash R. Automated Semantic Tagging of Textual Content. IT Professional. 2014;16(6):38–46. doi:10.1109/MITP.2014.85.

87. Kiryakov A, Popov B, Terziev I, Manov D, Ognyanoff D. Semantic Annotation, Indexing, and Retrieval. Web Semantics: Science, Services and Agents on the World Wide Web. 2004;2(1):49–79. doi:http://dx.doi.org/10.1016/j.websem.2004.07.005.

88. Rospocher M, van Erp M, Vossen P, Rigau G, et al. Building Event-centric Knowledge Graphs from News. Web Semantics: Science, Services and Agents on the World Wide Web. 2016;37-38:132–151. doi:10.1016/j.websem.2015.12.004.

89. van Aggelen A, Hollink L, Kemman M, Kleppe M, Beunders H. The debates of the European Parliament as Linked Open Data. Semantic Web Journal. 2017;8(2):271–281.

90. Rocca PD, Senatore S, Loia V. A Semantic-grained Perspective of Latent Knowledge Modeling. Information Fusion. 2017;36:52–67. doi:10.1016/j.inffus.2016.11.003.

91. Lansdall-Welfare T, Lampos V, Cristianini N. Effects of the Recession on Public Mood in the UK. In: Proceedings of the 21st International Conference on World Wide Web. WWW ’12 Companion. New York, NY, USA: ACM; 2012. p. 1221–1226.

92. Prieto VM, Matos S, Álvarez M, Cacheda F, Oliveira JL. Twitter: A Good Place to Detect Health Conditions. PLoS ONE. 2014;9(1):1–11. doi:10.1371/journal.pone.0086191.

93. Parker J, Wei Y, Yates A, Frieder O, Goharian N. A Framework for Detecting Public Health Trends with Twitter. In: Proceedings of the 2013 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining. ASONAM ’13. New York, NY, USA: ACM; 2013. p. 556–563.

94. Eissa AHB, El-Sharkawi ME, Mokhtar HMO. Towards Recommendation Using Interest-Based Communities in Attributed Social Networks. In: Companion Proceedings of The Web Conference 2018. WWW ’18. Republic and Canton of Geneva, Switzerland: International World Wide Web Conferences Steering Committee; 2018. p. 1235–1242.

95. Sakaki T, Okazaki M, Matsuo Y. Earthquake Shakes Twitter Users: Real-time Event Detection by Social Sensors. In: Proceedings of the 19th International Conference on World Wide Web. WWW ’10. New York, NY, USA: ACM; 2010. p. 851–860.

96. Chen Y, Amiri H, Li Z, Chua TS. Emerging Topic Detection for Organizations from Microblogs. In: Proceedings of the 36th International ACM SIGIR Conference on Research and Development in Information Retrieval. SIGIR ’13. New York, NY, USA: ACM; 2013. p. 43–52.

97. Genc Y, Sakamoto Y, Nickerson JF. Discovering Context: Classifying Tweets through a Semantic Transform based on Wikipedia. In: Proceedings of the 6th international conference on Foundations of augmented cognition: directing the future of adaptive systems. FAC’11. Springer-Verlag; 2011. p. 484–492. Available from: http://dl.acm.org/citation.cfm?id=2021773.2021833
98. Petrović S, Osborne M, Lavrenko V. Streaming First Story Detection with Application to Twitter. In: Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics. Association for Computational Linguistics; 2010. p. 181–189.

99. Vitale D, Ferragina P, Scaiella U. Classification of Short Texts by Deploying Topical Annotations. In: Proceedings of Advances in Information Retrieval: 34th European Conference on IR Research, ECIR 2012, Barcelona, Spain, April 1-5. Springer Berlin Heidelberg; 2012. p. 376–387.

100. Montenegro C, Ligutom C III, Orio JY, Ramacho DAM. Using Latent Dirichlet Allocation for Topic Modeling and Document Clustering of Dumaguete City Twitter Dataset. In: Proceedings of the 2018 International Conference on Computing and Data Engineering. ICCDE 2018. New York, NY, USA: ACM; 2018. p. 1–5.

101. Phan XH, Nguyen LM, Horiguchi S. Learning to Classify Short and Sparse Text & Web with Hidden Topics From Large-scale Data Collections. In: Proceedings of the 17th international conference on World Wide Web. WWW ’08. New York, NY, USA: ACM; 2008. p. 91–100.

102. Hingmire S, Chakraborti S. Sprinkling topics for weakly supervised text classification. In: Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers). vol. 2; 2014. p. 55–60.

103. Abulaish M, Dey L. Biological Relation Extraction and Query Answering from MEDLINE Abstracts using Ontology-based Text Mining. Data & Knowledge Engineering. 2007;61(2):228–262. doi:https://doi.org/10.1016/j.datak.2006.06.007.

104. Wei CH, Kao HY, Lu Z. PubTator: a Web-based Text Mining Tool for Assisting Biocuration. Nucleic Acids Research. 2013;41(W1):W518–W522. doi:10.1093/nar/gkt441.

105. Müller HM, Kenny EE, Sternberg PW. Textpresso: An Ontology-Based Information Retrieval and Extraction System for Biological Literature. PLoS Biology. 2004;2(11):1984–1989. doi:10.1371/journal.pbio.0020309.

106. Hur J, Özgür A, Xiang Z, He Y. Development and Application of an Interaction Network Ontology for Literature Mining of Vaccine-associated Gene-gene Interactions. Journal of Biomedical Semantics. 2015;6(1):1–10. doi:10.1186/s13208-014-0041-x.

107. IJntema W, Goossen F, Frasincar F, Hogenboom F. Ontology-based News Recommendation. In: Proceedings of the 2010 EDBT/ICDT Workshops. EDBT ’10. New York, NY, USA: ACM; 2010. p. 16:1–16:6.

108. Ray SK, Singh S. Blog Content Based Recommendation Framework using WordNet and Multiple Ontologies. In: 2010 International Conference on Computer Information Systems and Industrial Management Applications (CISIM); 2010. p. 432–437.

109. Pasin M, Hammond T. Core Ontology; 2015. Available from: http://data.nature.com/downloads/latest/ttl/npg-core-ontology.ttl

110. Shaw R. LODE: An ontology for Linking Open Descriptions of Events; 2010. Available from: http://linkedevents.org/ontology/

111. Raimond Y, Abdallah S. The Event Ontology; 2007. Available from: http://motools.sourceforge.net/event/event.html

112. schema org. Event; 2017. Available from: https://schema.org/Event