Truthfulness Verification System

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1 Introduction

Web has became the most prevalent source of information now a days. However, many information on the web is untruthful. Also because of the widespread reach of web, sometimes web is used to propagate untruthful facts for social and political reasons. Hence with the increasingly use of web as information source, verification of information truthfulness became an important facet to consider.

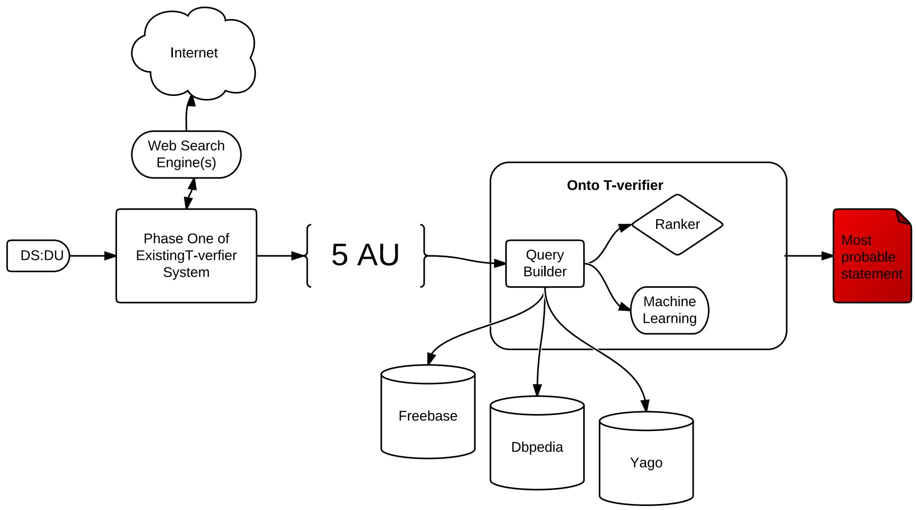
The popular search engines extract information from web based on keywords and metadata without considering the truthfulness of the facts. Also, there have been not much research in this area. To our best knowledge, the most recent work on this area is T-verifier [7], which uses results from search engines to verify truthfulness of statements. T-verifier performs very well on the test-dataset. However, T-verifier has some problems with the overall approach to verify the truthfulness of statements and there is room for improvement. In this work, we will extend the T-verifier system so that it's weaknesses can be resolved to get a more robust truthfulness verification system.

2 Current System

Current system for truthfulness verification is called T-verifier [7], which uses two phase methods for truthfulness verification of statements. Each of these two phases rely heavily on search results returned by popular search engines. T-verifier takes the doubtful statements (DS) as input from the user along with the doubtful unit (DU). Phrase after removing DU from DS is called topic unit (TU).

At the first phase, T-verifier generates alternative statements by supplying TU to search engine and collecting the relevant alternate DU-s. However, from basic web search may result in lot of alternate DUs that are not semantically or logically relevant to the original DS. Hence, T-verifier uses combination of seven features to rank alternate DUs. These features primarily exploit the facts that relevant alternative units frequently co-occur, people often mention both misconception and truthful conception together, data-type matching, and sense-closeness. T-verifier chooses top 5 alternative statements based on top 5 alternate DUs obtained in this phase.

At the second phase, top 5 alternative statements from phase 1 is supplied to the search engine again. Then the returned searched result is ranked by multiple rankers such as Alternative Unit Ranker, Hits ranker, Text-feature Ranker, Domain Authority Ranker etc. Then all those ranks are merged to form an overall ranking among the alternate statements and top statement in this final merged ranking is considered as truthful statement.



(a) System overview

Figure 1: System overview

3 Problems with Current System

Although results from the tested dataset achieves good performance (90% accuracy), failing of T-verifier for some statements shows that it has some inherent problems and there is room for improvement.

First, T-verifier assumes that truthful statements will be more propagated in the web compared to the untruthful statement. However, this may be not true in general because of intended and planned propaganda for establishing some untruthful statements. This kind of propagandas are even becoming more common now a days due to widespread reach of Internet. T-verifier also showed that *"Hillary Clinton is the President of United States"* has more hits than *"Hillary Clinton is the Secretary of State"*. Although T-verifier was able to find the correct statement in this case using multiple ranks together, in general the untruthful statement can be prevalent in the web compared to truthful statements.

Second, T-verifier do not use the reputation of the information source. T-verifier uses only search results returned by the search engine irrespective of the origin and believability of the information origin. Hence there is room for improvement here to give more weight to the information obtained from trustworthy sources such as Wikipedia.

4 Propsed System

4.1 Description of extraction algorithm

For disambiguation among the alternative statements, Wikipedia is generally used as an authoritative source. However, the contents of Wikipedia is not available in the form that is consumable in a programmatic format. To address such difficulties a number of projects Yago, DBpedia, Freebase have organized the massive amount of data in a searchable fashion e.g DBpedia uses SPARQL endpoint, Freebase uses MQL api. Open source implementation of Python wrappers exist for both the interfaces exist and appear to be mature enough for our needs.

4.1.1 Freebase

Freebase has information about approximately 20 million Topics, each one having a unique Id, which can help distinguish multiple entities which have similar names, such as Henry Ford the industrialist vs Henry Ford the footballer. Most of the topics are associated with one or more types[1] (such as people, places, books, films, etc) and may have additional properties like "date of birth" for a person or latitude and longitude for a location. Freebase not only contains data from the Wikipedia but also other sources; users can submit data to the Freebase datastore and expand it in richness. We tinkered with the api[2] and it appeared to be the most viable starting point for the project.

Listing 1: Minimal code to Freebase

```
import freebase
import pprint

query = [{
  "a:starring": [{
    "actor": "Meg Ryan"
  }],
  "b:starring": [{
    "actor": "Tom Hanks"
  }],
  "type": "/film/film",
  "*": [],
}]

pp = pprint.PrettyPrinter(indent=4)
result = freebase.mqlread(query)

print "Movie names & their various forms"


for i in result:
```

```
pp.pprint(i["key"])
```

Listing 2: Cleaned Output

```
Movie names & their various forms
[    '158982',
     'You$0027ve_Got_Mail',
     '18171032',

      ...
     'E-m$0040il_f$00FCr_Dich',
     'youve-got-mail']
[    '176489',
     'Joe_Versus_the_Volcano',
     'Joe_Vs$002E_The_Volcano',
     'Brain_Cloud',
      ...
     '2327353',
     'joe-versus-the-volcano']
[    '226198',
     'Sleepless_in_Seattle',
     'Sleepless_In_Seattle',
      ....
     '169146',
     '106482',
     'Insonnia_d$0027amore',
     '62812',
     'Schlaflos_in_Seattle',
     'sleepless-in-seattle'\]
```

The above results show how the three movies starring Tom Hanks and Meg Ryan. When we query Google with Tom Hanks and Meg Ryan, the top result is a page from Answers.com where a user has asked which are the movies where the two actors appear together, and the answer lists these three movies namely - “Joe versus the Volcano”, “ Sleepless in Seatle” and “Youv́e got Mail”. A quick lookup of the Wikipedia and IMDB pages also confirm the same.

4.1.2 Dbpedia

DBpedia is a similar project to Freebase, but it focuses mainly on the content available from Wikipedia. It scores in being precisely importing the data from the info boxes in Wikipedia pages, but at this stage it does not seem to be offering anything additional over Freebase [4]. We are yet to explore its programmatic interface [3].

4.1.3 Yago

YAGO is a semantic knowledge base with over 900,000 entities (like persons, organizations, cities, etc.) and uses Wikipedia and Wordnet as its main source of information. We are yet to explore the programmatic interfaces it provides and how we can use it for the project.

4.2 Truthfulness verification

4.2.1 Building queries from the data supplied by the user

We take the content words from the topic unit(TU), along with each of the alternative units(AU), and plugin the datatype(t) to form a number of queries.

$$q_i = \{TU, AU_i, t_{AU_i}\} \qquad \text{where } i = 1 \cdots n$$

where n is the number of alternative units generated by the first phase of the existing system. By quering the various ontologies described above we will get results which might have the following cases:

$$\begin{aligned} freebase(q_i) &= \phi \\ &= r_i \end{aligned}$$

From what we have explored till now, by quering Freebase we can get the various property, value pairs associated with an entity which is the TU in our case. In case the result is ϕ, it suggests that we do not have information for this particulat combination TU and AU_i. Due to the richness of the information in Freebase we can assume with a considerable degree of confidence that this combination is untrue. This is one way verification, but in case of non-null results, how do we filter and rank the results with the available set of information is something we can not formulate at this stage with out further exploration.

4.2.2 Finding Sense of Words

To classify a statement as true or false we need to get the semantic of sense of the words of the sentences. For example consider the following sentence.

"Tom Hanks was the lead actress in the movie sleepless in Seattle"

Now our query results from ontologies will give us the fact that Tom hanks is a male actor. Now using wordnet we will be able to find that actress means female actor. So by simple inference our system will be able to classify the above example as untruthful.

However, finding sense of words in a complex problem in general and not easy to solve for all cases all the time. For example, consider the following sentence.

"Filipino is the primary language of Philipines"

now Wikipedia has "Filipino is the national language of Philipines". Both sentences have same meaning but it is not easy to relate primary with national because they are not each others synonym as separate words. They become synonym depending on the context they are used such as above example. At this point, we don't have any generic strategy to handle these kind of situations. However, we will explore more to find possible ways to solve these problems. And one possible way may be to use some natural language processing techniques. Specifically, we will look into NLTK library to solve these kind of issues.

4.2.3 Use of Co-reference Program

Totha: please write up two lines here

4.2.4 Application of Machine learning algorithms

Though usage of machine learning algorithm seems to be a good approach at this point. Consider the following example.

"Tom Hanks was the lead actress in the movie sleepless in Seattle"

Now If the algorithm can learn that Tom hanks is a male and so he can't be an actress then our system should be able to classify the above statement as false.

However, we will need to explore more to be sure that we can apply machine learning algorithms successfully. Supervised classifiers might not be beneficial for us due to the limited dataset for training and the potentially unlimited variety of inputs to classify. However, if we can use Graph Based Partially Supervised Learning[5] or Spreading Activation [6] on the information extracted from the rich ontologies is something we plan to explore.

5 Conclusion

It this paper, we described current system for truthfulness verification of statements found in the web called T-Verifier and described the possible improvements to the current system. We will primarily use authentic information sources such as Wikipedia and Ontologies extracted from Wikipedia such as FreeBase, DBPedia, and YOGA to found the truthfulness of doubtful statements.

References

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