

What did you Mention? A Large Scale Mention Detection Benchmark for Spoken and Written Text*

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Abstract

We describe a large, high-quality benchmark for the evaluation of Mention Detection tools. The benchmark contains annotations of both named entities as well as other types of entities, annotated on different types of text, ranging from clean text taken from Wikipedia, to noisy spoken data. The benchmark was built through a highly controlled crowd sourcing process to ensure its quality. We describe the benchmark, the process and the guidelines that were used to build it. We then demonstrate the results of a state-of-the-art system running on that benchmark.

Keywords: Mention Detection, Knowledge Base, Benchmark, Speech

1. Introduction

Extracting semantic information from text is a fundamental task in various NLP (Natural Language Processing) applications such as Information Retrieval, Question Answering, Text Similarity, Argument Construction, and more. The task, referred to as Mention Detection (or Entity Linking or Wikification) links terms (i.e., a single token, or a consecutive sequence of tokens) from unstructured text to nodes (i.e., entities) in a Knowledge Base, such as e.g., DBpedia¹. A Mention is thus a tuple (t, s, u) where t is a term that appears in span² s in the given text, and u is an entity in the Knowledge Base.

In general, entities in a Knowledge Base can be divided into two main types. Well-defined *named entities* such as persons, organizations, and locations; and all other entities. Consider for example the annotated Text 1 below. The term “Attorney General Edwin Meese” is mapped to the person entity *uri:Edwin.Meese*, while “proximity” is mapped to the general entity *uri:Distance*.

Attorney General Edwin Meese determined that the *headquarters* had to be located in close *proximity* to the *Attorney General’s office*.

Text 1

Most of the existing Mention Detection tools focus on extracting named entities, probably since this task is more easily defined. The task of linking all types of entities is more vague (Ling et al., 2015) and requires clear guidelines on what to annotate, how to deal with nested terms, and how to resolve specificity of entities.

However, extracting all types of entities, not only named entities, is crucial for semantic understanding of text. Consider for example the task of semantic similarity. It is easy to see that Text 1 and Text 2 are quite similar though the

wordings are quite different. Such a similarity can be inferred thanks to the mapping of *proximity* and *distance* to the same general entity and the mapping of *headquarters* and *base of operation* to the same general entity.

Attorney General Edwin Meese determined that the *base of operation* was located in close *distance* to the *Attorney General’s office*.

Text 2

We illustrate now the difficulties in building a benchmark for all types of entities. Regarding the issue of what to annotate, consider again Text 1. Shall one link the general term “that” to *uri:That*? Similarly, shall one link “determined” to *uri:Determinacy* and will this contribute anything to the semantic understanding of the text?

Another issue to consider is the nesting of Mentions. In Text 1, should we link “office” to *uri:Office* even though it is nested within the Mention (“Attorney General’s office”, *uri:United.States.Attorney.General*)?

The *empire* ended in 1889, when *Pedro II* was *deposed* ...

Text 3

The last issue with general entities is the specificity of Mentions. Consider Text 3. Should the term “empire” be linked to the general entity *uri:Empire* or to the more specific entity *uri:Empire.of.Brazil*?

Thus, building a benchmark for the evaluation of Mention Detection tools for all types of entities, requires carefully crafted guidelines. Moreover, all existing benchmarks annotate relatively clean and well-phrased text taken from Wikipedia or from newspapers. To the best of our knowledge there is no Mention Detection benchmark for spoken data, which naturally is more noisy and thus poses new challenges for Mention Detection.

Furthermore, NLP applications would work better if they

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¹<http://dbpedia.org>

²A span is the begin and end offsets of the term in the text

can exploit Mentions that are found all over the given texts. Wikipedia for example, contains hyperlinks only in the first appearance of a Mention while other appearances in a document are not hyperlinked. The current benchmark contains a full coverage of Mentions all over the annotated texts and thus it enables evaluation of Mention Detection tools that require such property.

In this paper we present a comprehensive benchmark data covering both named entities as well as general entities, for both written-text data as well as noisy, spoken data.

Each dataset contains 1000 sentences that were annotated through a carefully controlled crowd sourcing process. Each sentence was labeled by two rounds of *detection* and *confirmation*, done by 10 labelers each, resulting in about 6500 Mentions in each of the two datasets. We describe the process that was used to build the benchmark and further present a simple Mention Detection tool that surprisingly performs better than state-of-the-art systems over the described data.

The paper is organized as follows. We describe related benchmarks in Section 2 and the new benchmark in Section 3. Then in Section 4 we report the performance of a state-of-the-art system on the benchmark. We conclude with summary in Section 5.

2. Related Work

There are several annual Mention Detection challenges that publish benchmarks, such as the TAC-KBP (Text Analytic Conference - Knowledge Base Population (McNamee and Dang, 2009))³, the Microspots NEEL (Named Entity Recognition and Linking)⁴ and ERD (Entity Recognition and Disambiguation (Carmel et al., 2014)). In addition there are benchmarks published by specific research groups such as AIDA (Hoffart et al., 2011), AQUAINT (Milne and Witten, 2008), MSNBC (Ratinov et al., 2011) and more.

The Gerbil project (Usbeck et al., 2015) is a framework for the evaluation of Mention Detection tools. It defines formats and APIs for adding new benchmark data and new Mention Detection tools. The project contains 19 datasets, among them the above mentioned AIDA and AQUAINT.

Most of those benchmarks focus on named entities probably as those entities are well defined. Few benchmarks such as (Milne and Witten, 2008; Ratinov et al., 2011) cover also general entities, but they are relatively small, containing only few hundred Mentions. Moreover, all existing benchmarks refer to written text only.

In contrast, the benchmark data described in this work covers both named entities and more general entities, with respect to written Wikipedia text as well as relatively noisy spoken data.

3. The Benchmark

The benchmark was built using the CrowdFlower platform.⁵ This platform enables relying on high quality workers by integrating hidden test questions within the annotation task, and considering only the work done by annotators who correctly answered a pre-determined fraction of these.

For building the benchmark, we employed a two stage process – a detection task, followed by a confirmation task.

In the detection task, labelers were presented with a text (usually a single sentence) and were asked to link terms in the text to a Wikipedia page.⁶

Then, in the confirmation task, the labelers were presented with the text and the union of all Mentions identified in the detection task, and were asked to confirm or reject each Mention.

To accommodate the issues of generality (what to annotate), nesting of Mentions, and specificity, we employ the following measures. First, each text was associated with a related general *topic*. The topics were selected at random from Debatbase⁷. For example, Text 3 above was associated with the topic *We should abolish the Monarchy*. Overall, we selected 81 topics. We then defined the following guidelines for the labelers.

1. Generality - General terms that clearly have no relation to the topic, should not be marked.
2. Nesting - The longest phrase that corresponds to a single Wikipedia title should be marked.
3. Specificity - The selected Wikipedia title should clearly match the meaning of the marked term, in the context of the provided topic.

The full guidelines of the two tasks can be found in Appendix 8 below. Figures 1 and 2 show the User Interface of the detection and confirmation tasks. In the detection, the labelers were instructed to enter the detected Mentions into a field, each Mention in a separate line in the form of `<term>#<link>`.

Topic: We should embrace open source software

Sentence:
The free and open source software gives users the freedom to use, to alter and to share it.

Enter Mentions for the sentence above using term#links

free#https://en.wikipedia.org/wiki/Free_software

open source software#https://en.wikipedia.org/wiki/Open-source_software

Enter each term#link in a separate line.

Figure 1: The detection UI

Topic: We should embrace open source software

Sentence:
The free and open source software gives users the freedom to use, to alter and to share it.

Confirm or reject the following Mentions for the sentence above

Mention	URI	Confirm
free	https://en.wikipedia.org/wiki/Free_software	<input type="radio"/> Yes <input type="radio"/> No
open source software	https://en.wikipedia.org/wiki/Open-source_software	<input type="radio"/> Yes <input type="radio"/> No

Figure 2: The confirmation UI

³<https://tac.nist.gov//2016/KBP/>

⁴<http://microposts2016.seas.upenn.edu/challenge.html>

⁵<https://www.crowdflower.com/>

⁶We use DBpedia and Wikipedia interchangeably as one is a reflection of the other

⁷<http://idebate.org/deATABASE>

Since the labelers were instructed to select all valid pages for a given term, the ground truth can contain multiple correct pages for some of the terms (as long as they were confirmed by the majority of the annotators as described above). Furthermore, to have a full coverage of the text, the labelers were instructed in both jobs to detect and confirm all repeating occurrences of the same term. Thus, for a given text the same term can appear multiple times in Mentions (either with the same span but linked to different entities, or with different spans in the text).

The ground truth was then defined as Mentions that were confirmed by the majority of the annotators (i.e., at least six out of ten) in the confirmation task.

The full benchmark consists of 1000 sentences from Wikipedia and 1000 sentences of spoken data. The sentences were selected as follows. For the Wikipedia sentences, we selected Wikipedia articles that discuss the above 81 topics, and then we picked 1000 sentences at random from those articles. We refer to this dataset by *Wiki*. The spoken data sentences were taken from professional speakers discussing some of those topics. The spoken data has two forms: the output of an Automatic Speech Recognition (ASR) engine; and a cleansed manual transcription of it. The generation of the spoken data is described in (Mirkin et al., 2017). The 1000 sentences of the spoken data were selected at random from those speeches. We refer to the two flavors of the spoken data by *ASR* and *Trans*, where the former is the output of the ASR engine without any editing, and the latter is the output of the manual transcription.

The *Trans* data is naturally cleaner than the *ASR* data, and therefore the labeling of the spoken data and the generation of the ground truth was done on *Trans*. However, since for applications that work directly with speech, only *ASR* output will be available, we projected the ground truth of *Trans* to *ASR*, resulting in the *ASR* benchmark which enables the evaluation of models for Mention Detection in spoken data.

The projection of the ground truth of *Trans* to *ASR* was done as follows. Given a pair of corresponding sentences (T, A) where T is from *Trans* and A is from *ASR*, we create a mapping from each offset (i.e., character) in T to a corresponding offset (i.e., character) in A , by using minimum Edit distance with backtracking (Hall and Dowling, 1980). Then given a labeled Mention (t, s, e) in T , we use the above mapping to find the corresponding span s' in A and define the corresponding Mention in A as (t', s', e) , where t' is the text in span s' in A .

An example of the projection is illustrated in Text 4. Note the distorted “*jewish refute. these*” that is linked to [uri:Jewish_refugees](#). The *ASR* data poses therefore an additional challenge for Mention Detection over the base task.

Trans: [Jewish refugees](#) were turned away from the [UK](#)
ASR: [jewish refute. these](#) were turned away from the [u_k](#)

Text 4

Overall, the *Wiki* dataset has 6375 Mentions, out of which

only 486 are named entities and the rest are general entities. Each of the *ASR* and *Trans* has 6239 Mentions, out of which only 84 are named entities. The low number of named entities compared to general entities, is an evidence to the importance of Mention Detection benchmarks such as the one described in this paper.

Note that on average there are about 6.2 Mentions per sentence in each of the datasets. Given an average sentence length of 20 tokens, and given that some Mentions cover more than one token, this is quite a robust coverage of the text.

The average pair-wise kappa(Cohen, 1960) of the detection task was 0.3 for *Wiki* and 0.34 for *Trans*. The average kappa for the confirmation task was 0.47 for *Wiki* and 0.54 for *Trans*. Since different labelers labeled different number of sentences, the kappa for each pair of labelers was calculated by considering the sentences they both labeled. The average kappa over all pairs of labelers was taken as a weighted average of their kappa, where the weight of each pair was the total number of Mentions in their shared sentences.

The relatively low kappa in the detection task is attributed to the fact that this task is naturally more open ended compared to the confirmation task in which annotators simply need to confirm or reject candidates out of a fixed list of candidate Mentions. Moreover, dealing with general entities adds to the inherent complexity of the detection task. Note that the goal in the detection sub-task was to obtain a high coverage of Mentions whose union is then used in the confirmation sub-task. The low kappa in the detection, indicates a divergence between labelers and thus a high coverage of candidate Mentions.

In the confirmation sub-task, whose output determines the gold standard, the union of all detected mentions is shown to the labelers.

The combination of low kappa in the detection task and the relatively high kappa in the confirmation task justifies the two tasks and indicates on a high coverage (in the detection task) and a high quality of Mentions (in the confirmation task).

The full benchmark is available for download at http://www.research.ibm.com/haifa/dept/vst/debating_data.shtml.

4. Evaluation

As described in Section 3 above, our benchmark consists of 1000 labeled sentences from Wikipedia, 1000 labeled sentences of transcribed (*Trans*) spoken data, and 1000 sentences of *ASR* data.

We divided each of the three datasets to two equal parts of training and testing, each with 500 sentences. We refer to them as *Wiki-dev*, *Trans-dev* and *ASR-dev* for development and *Wiki-test*, *Trans-test* and *ASR-test* for testing.

Table 1 shows the results of a state-of-the-art system TagMe (Ferragina and Scaiella, 2012) on the three test datasets. To accommodate guideline 2 (i.e., Nesting of Mentions, as described in Section 3.), we configured TagMe to return the longest phrases and avoid nesting of Mentions.

We can see that the precision and recall on `Wiki` are higher than on the two spoken datasets `Trans` and `ASR`. For example the recall on `Wiki` is 0.523 compared with 0.436 on `Trans` and 0.421 on `ASR`. This is expected as the Wikipedia text is cleaner. We can also see that the performance on the `Trans` dataset is a bit higher than on the `ASR` dataset. This is also expected as the `ASR` data is more noisy.

	Precision	Recall	F1-measure
Wiki	0.584	0.523	0.552
Trans	0.569	0.436	0.494
ASR	0.555	0.421	0.478

Table 1: Performance of TagMe on the test sets

5. Conclusions

We presented a large scale Mention Detection benchmark that contains named entities as well as general entities, annotated on both clean, written text and noisy, speech data. The benchmark contains full coverage of annotations over 1000 sentences from Wikipedia and 1000 sentences of speech data that appear in two forms, one transcribed manually, and the other is the output of an ASR engine. The benchmark was annotated via a high quality and controlled crowd sourcing process, based on clear guidelines indicating what to annotate and how to resolve nesting and specificity of conflicting Mentions. Each of the datasets includes a total of around 6500 Mentions, where the named entities are less than 8% of them and the rest are general entities. The benchmark is robust in terms of the types of annotated Mentions and the coverage of the underling texts, and thus can be used for the evaluation of NLP applications that require semantic understanding of text.

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8. Appendix: Labelers Guidelines

We describe below the guidelines that were given to the labelers in the detection and in the confirmation tasks.

8.1. Detection Task

In this task, you are given a topic and a free text paragraph related to this topic. Your task is to detect terms mentioned in the text, and link those terms to their most relevant Wikipedia title, based on the following guidelines.

1. The longest phrase that corresponds to a single Wikipedia title should be marked. For example, if the text mentions the term “[video games](#)” you should mark this term along with the Wikipedia title [uri:Video_game](#), and not mark the individual terms “[video](#)” (with [uri:Video](#)) nor “[games](#)” (with [uri:Game](#)).
2. Terms should be entered into the text field, in separated rows in the same order as they appear in the original text. Each term should be entered as `<term>#<link>` where `<term>` is the exact original phrase as appears in the text and the link is the URL of the corresponding Wikipedia title.
3. Derivations and/or Redirects should be considered and used. For example, the term “[students](#)” should be linked to its derivation in Wikipedia, [uri:Student](#); the term “[election campaign](#)” should be linked to [uri:Political_campaign](#) since it is redirected in Wikipedia to this title; and so on.

4. General terms that clearly have no relation to the topic, should not be marked. In particular, general terms that undoubtedly convey no content related to the pre-specified topic - e.g., “*first*”, “*known*”, “*today*”, “*different*”, “*numbers*”, etc., should not be marked, even though they may have a corresponding Wikipedia title.
5. Disambiguation should be done based on context. If a term can be associated with several Wikipedia titles, you should link it with the title that best matches its meaning, based on the context of the entire text paragraph, and also - if needed - based on the pre-specified topic. For example, in a text discussing wild animals, the term “*Jaguar*” should be linked to the Wikipedia title that describes this animal, and not to a Wikipedia title discussing Jaguar cars.
6. The selected Wikipedia title should clearly match the meaning of the marked term. In case of a term that has both a general title and a more specific context-dependent title, the specific title should be selected. For example in a text that talks about Israel and mentions the term “*air force*”, the term should be linked to [uri:Israeli_Air_Force](#) and not to [uri:Air_force](#).

Technical Guidelines

1. It is recommended to use the flexible search interface of Wikipedia to find the relevant Wikipedia title that matches the term.
2. Names and titles should be marked together, if possible. For example the phrase “*US Secretary of State Hillary Clinton*” should be linked as a whole to [uri:Hillary_Rodham_Clinton](#)
3. The selected Wikipedia title should not correspond to an internal Wikipedia section, nor to a page of type list (such as [uri:List_of_political_scientists](#)) and neither to a page of type disambiguation (such as [uri:Map_\(disambiguation\)](#)).
4. Anaphora and co-references should not be resolved. In particular, pronouns like “*he*”, “*they*”, etc., should not be marked as terms.
5. If a term appears several times in the text with the same meaning, and you decided to link this term to a particular Wikipedia title, then you should make sure to link all its occurrences in the text to the same title.

8.2. Confirmation Task

In this task you are given a topic, a free text sentence related to this topic, and a list of terms mentioned in this sentence, linked to their presumably corresponding Wikipedia titles. Please confirm or reject each suggested term, according to the following guidelines.

1. The marked term should represent the longest phrase that corresponds to a single Wikipedia title. For example, if the term “*video games*” is linked to the Wikipedia title [uri:Video_game](#), and its sub terms “*video*” and “*games*” are linked to Video and Game,

respectively, then you should confirm “*video games*” and reject “*video*” and “*games*”.

2. Derivations and/or Redirects should be considered and used. For example, the term “*students*” should be linked to its derivation in Wikipedia, [uri:Student](#); the term “*election campaign*” should be linked to [uri:Political_campaign](#) since it is redirected in Wikipedia to this title; and so on.
3. General terms that clearly have no relation to the topic, should not be confirmed. In particular, general terms that undoubtedly convey no content related to the pre-specified topic - e.g., “*first*”, “*known*”, “*July*”, “*today*”, “*different*”, “*numbers*”, etc., should not be marked, even though they may have a corresponding Wikipedia title.
4. Disambiguation to a Wikipedia title should be done based on context. If selecting the Wikipedia title associated with a term involves disambiguation, this should be done based on the context of the surrounding text, and also - if needed - based on the pre-specified topic.
5. The selected Wikipedia title should clearly match the meaning of the marked term. In case of a term that has both a general title and a more specific context-dependent title, the specific title should be selected. For example in a text that talks about Israel and mentions the term “*air force*”, the term should be linked to [uri:Israeli_Air_Force](#) and not to [uri:Air_force](#).

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2. The selected Wikipedia title should not correspond to an internal Wikipedia section, nor to a page of type list (such as [uri:List_of_political_scientists](#)) and neither to a page of type disambiguation (such as [uri:Map_\(disambiguation\)](#)).
3. Anaphora and co-references should not be resolved. In particular, pronouns like “*he*”, “*they*”, etc., should not be confirmed as terms.
4. The same term may appear multiple times in a single sentence. For example in the text “As fewer choices are offered to the voters, voters may vote for a candidate ...”, you may see two candidates for “*voters*”: voters(36,42) (where (36,42) is the span of “*voters*” in the text) and for voters(44,50). You should confirm/reject each appearance independently.
5. In addition, in principle a single term may be associated with several Wikipedia titles, as long as the guidelines above are satisfied. For example, in the text “...complained about African marriage customs ...” the term “*customs*” may appear with a link to [uri:Convention_\(norm\)](#) and to [uri:Tradition](#). Both options are valid and can be confirmed.