A Recorded Debating Dataset

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Abstract

This paper describes an audio and textual dataset of debating speeches, a first-of-a-kind resource for the growing research field of computational argumentation and debating technologies. We detail the process of speech recording by professional debaters, the transcription of the speeches with an Automatic Speech Recognition (ASR) system, their consequent automatic processing to produce a text that is more "NLP-friendly", and in parallel – the manual transcription of the speeches in order to produce gold-standard "reference" transcripts. We release speeches on various controversial topics, each in 5 formats corresponding to the different stages in the production of the data. The intention is to allow utilizing this resource for multiple research purposes, be it the addition of in-domain training data for a debate-specific ASR system, or applying argumentation mining on either noisy or clean debate transcripts. We intend to make further releases of this data in the future.

Keywords: debating technologies, computational argumentation, argumentation mining, automatic speech recognition

1. Introduction

Computational argumentation and debating technologies aim to automate the extraction, understanding and generation of argumentative discourse. This field has seen a surge in research in recent years, and involves a variety of tasks, over various domains, including legal, scientific writing and education. Much of the focus is on argumentation mining, the detection of arguments in text and their classification (Palau and Moens, 2009), but many other tasks are being addressed as well, including argument stance classification (Sobhani et al., 2015; Bar-Haim et al., 2017), the automatic generation of arguments (Bilu and Slonim, 2016), identification of persuasive arguments (Wei et al., 2016), quality assessment (Wachsmuth et al., 2017a) and more. Multiple datasets are available for such research, such as the Internet Argument Corpus (Walker et al., 2012), which consists of numerous annotated political discussions in internet forums, ArgRewrite (Zhang et al., 2017), a corpus of argumentative essay revisions, and the datasets released by IBM Research as part of the Debater Project (Rinott et al., 2015; Aharoni et al., 2014). Lippi and Torroni (2016) list several additional such datasets. Further, Wachsmuth et al. (2017b) have released an argument search engine over multiple debating websites, and Aker and Zhang (2017) have initiated the projection of some datasets to languages other than English, such as Chinese.

All of the above are based on written texts, while datasets of spoken debates, outside of the political domain, are scarce. A spoken debate differs from a written essay or discussion not only in structure and content, but also in style as in any other case of spoken vs. written language. Zhang et al. (2016) made available transcripts from the Intelligence Squared[1] debating television show[2]. The transcripts of the show are available on the show's site, and while they are of high quality, they do not match the audio recordings precisely, requiring substantial additional effort, if one wishes, for example, to use them as ASR training data.

With this paper we release an initial dataset of 10 audio speeches recorded specifically for debating research purposes. We describe in detail the process of producing these speeches and their automatic and manual transcripts. This is a first batch of a larger set of recordings we intend to produce and release in the future.

2. Recording the Speeches

We recorded short speeches about debatable topics, with experienced speakers. This section describes the recording process.

Recruiting and training the speakers Our team of speakers are all litigators or debaters, fluent or native English speakers, experienced in arguing about any given topic. The recruitment and training of the speakers included several steps. First, we interviewed potential speakers to evaluate their ability to argue about a topic when given only a short time to prepare. Then, we provided candidates with an essay to read aloud and record. Candidates were given technical guidelines to ensure high recording quality, including microphone configuration instructions and recording best-practices such as to record in a quiet environment, to use an external microphone and to maintain a fixed distance from the microphone while speaking. After listening to these recordings, we provided the speakers with feedback and repeated the process until the essay recordings were of good quality for the naked ear. Next, we provided each candidate with two motions (e.g. "we should ban boxing") and asked them to record a spontaneous speech supporting each motion, after a 10 minute preparation.

All recordings – three per candidate (one reading and two spontaneous speeches) – were processed through Automatic Speech Recognition (ASR) and were sent to manual transcription, as described in the next sections. We accepted candidates whose Word Error Rate (WER, the sum of substitution, deletion and insertion error rates) was be-

[1]http://www.intelligencesquaredus.org

[2]http://www.cs.cornell.edu/~cristian/debates

low a pre-defined threshold of 10%.

The recording process All speakers received a list of motions, each with an ID and a short name (to be easily identified by human readers), and background information extracted from Debatabase[3] or Wikipedia. The speakers were guided to spend up to 10 minutes reviewing the motion's topic, and then immediately start recording themselves arguing in favor of it for 4-8 minutes. The speakers were instructed not to search for further information about the topic beyond the provided description. The idea is to prevent multiple debaters who record a speech about the same topic from reaching the same resources (in particular debating websites), which may reduce the diversity of the ideas presented in the speeches. Example 1 shows a part of background information for the topic "doping in sports".

Example 1 (Topic background information)

At least as far back as Ben Johnson's steroid scandal at the 1988 Olympics, the use of performance-enhancing drugs in sports had entered the public psyche. Johnson's world record sprint, his win, and then, the stripping of his gold medal made news around the world. However, performance-enhancing drugs in sports do not begin with Johnson ...

3. Automatic Speech Processing

Every recorded speech was automatically transcribed by a speaker-independent deep neural network ASR system. The system's acoustic model was trained on over 1000 hours of speech from various broadband speech corpora including broadcast news shows, TED talks[4] and Intelligence Squared debates[5]. We used a 4-gram language model with a vocabulary of 200K words, trained on several billion words that include transcripts of the above speech corpora and various written texts, such as news articles.
The ASR system we used is similar to those described in (Soltau et al., 2013; Soltau et al., 2014). We trained speaker-independent convolutional neural network (CNN) models on 40 dimensional log-mel spectra augmented with delta and double delta features. Each frame of speech is also appended with a context of 5 frames. The first CNN layer of the model has 512 nodes attached with 99 filters. Outputs from this layer are then processed by a second feature extraction layer, also with 512 nodes and a similar set of 43 filters. The outputs from the second CNN layer are finally passed to 5 fully connected DNN layers with 2048 hidden units each, to predict scores for 7K context dependent states. This speaker-independent ASR system performs on average at 8.4% WER on the speeches we release with this paper.

Once a speech has been automatically transcribed, we obtain a text in the format shown in Example 2. Each token (including sentence boundary and silence markers <s>, <s/>, ~SIL) is followed by the start and end time of its utterance, in seconds, relative to the beginning of the recording segment. As shown in the example, the stream is divided into multiple numbered lines. The split occurs automatically when a silence of μ milliseconds is detected (we used $\mu = 1000$). Such relatively long pauses may correlate with the end of one sentence and the beginning of another; we have found, however, that the length of the pause is highly speaker-dependent and results in inaccurate splits; hence we ignore it as a signal for sentence splitting, and resort to employ an LSTM for this task, as described below.
This format is the basis for two versions of the data that we release for each speech: an automatically processed ASR version, and a manually transcribed one. The steps for obtaining the former are described in Section 3.1. The production of manual transcripts is described in Section 4.

Example 2 (Raw ASR output)

```
1: <s>[0.000,0.510] the[0.510,0.680]
question[0.680,1.280] of[1.280,1.410]
whether[1.410,1.700] it's[1.700,1.870]
better[1.870,2.200] to[2.200,2.350] fully
[2.350,2.730] assimilate[2.730,3.500] ~SIL
[3.500,3.530] or[3.530,3.700] be
[3.700,3.850] distinguished[3.850,4.550]
from[4.550,4.710] the[4.710,4.800] majority
[4.800,5.270] population[5.270,6.150] ~SIL
[6.150,6.370] is[6.370,6.550] very
[6.550,6.810] subjective[6.810,7.510]
2: <s>[0.000,0.500] first[0.500,0.840]
argument[0.840,1.530] ~SIL[1.530,2.060] we
[2.060,2.210] say[2.210,2.390] that
[2.390,2.560] culture[2.560,3.100] is
[3.100,3.340] a[3.340,3.430] form
[3.430,4.040] ~SIL[4.040,4.070] of
[4.070,4.430] ~SIL[4.430,4.460] expression
[4.460,5.240] </s>[5.240,5.520] culture
[5.520,6.060] </s>[6.060,6.090] sometimes
[6.090,6.710] also[6.710,7.270] </s
>[7.270,7.390] shapes[7.390,8.120] ~SIL
[8.120,8.150] one's[8.150,8.580] thought
[8.580,9.120]
```

3.1. ASR transcripts

To obtain a "clean" version of the raw ASR output stream, we preprocess it, as detailed below. After this processing, the text in Example 2 is converted to a text as in Example 3.

- **Removal of timing information**, including line numbers, and merging of all lines.
- **Removal of non-textual tokens:** Silence markers, ~SIL, appear whenever a relatively long pause has been detected in the speech; sentence boundary tags, <s> and </s>, denote predicted beginnings and ends of sentences. These are the result of the fact that the ASR language model was trained – in addition to spoken language transcripts – also on written texts that contain punctuation marks. We have experimentally determined that these predictions are not reliable enough to be utilized for sentence splitting on their own and used a dedicated method for this purpose, as mentioned. We also remove tags such as

[3]http://idebate.org/debatabase

[4]https://www.ted.com/

[5]We semi-automatically aligned the transcripts and the audio, to overcome the inconsistency problem mentioned in Section 1.

%HESITATION, as well as tokens denoting hesitation that were transcribed explicitly, such as ah or um.

- **Abbreviations reformatting:** The ASR-produced underscored abbreviation format (i_b_m) is replaced with the standard all-caps one (IBM).
- **Automatic punctuation and sentence splitting:** The automatically transcribed text contains no punctuation. In downstream tasks, such as syntactic parsing, long texts are often difficult to handle, and we consequently split the stream of ASR output into sentences. Unlike typical sentence-splitting methods, whose main goal is to disambiguate between periods marking end-of-sentence and those denoting abbreviations, here the text contains no periods, hence a different method is required. We employed a bidirectional LSTM (Hochreiter and Schmidhuber, 1997) to predict commas and end-of-sentence periods over the ASR output. This neural network was trained on speeches like the ones we share in this paper, TED talks, and the English side of the French-English parallel corpus from the IWSLT 2015 MT task (Cettolo et al., 2012).

Example 3 (Clean ASR output)

```
the question of whether it's better to
fully assimilate or be distinguished from
the majority population is very subjective.
 first argument we say that culture is a
form of expression culture sometimes also
shapes one's thought.
```

4. Manual Transcription

As mentioned, the ASR process produces texts that on average have a word error rate of about 10%, or about 1 error in 10 words. In order to obtain a "reference" text – a precise transcript of the speech – we employ human transcribers to post-edit the automatic transcript, i.e. correct its mistakes.

Transcribers selection and training We invited 15 candidates to train as transcribers. As a first test we asked them to transcribe the same four speeches, after carefully reading the guidelines. We used their outcomes for creating ground-truth transcripts: for each speech, we compared its transcripts pair-wise, listened carefully to points of differences, and created a "gold-transcript" that resolved all differences between the individual transcripts. Using these four gold-transcripts, we scored the work of the individual transcribers, and accepted as transcribers only 9 of the candidates whose transcript was at least 98% accurate. They were further trained by transcribing 10 speeches each, and getting feedback on them upon our review. Once done, we considered them "experienced transcribers".

Transcription methodology In our experience, starting from initial transcripts produced by ASR can halve the time necessary to produce reference transcripts, while maintaining similar transcript quality. This is particularly true if the ASR is highly accurate since it reduces the number of corrections the human transcriber has to make. One should be aware, however, that this procedure can introduce bias, depending on how conscientious the human transcriber is. An inexperienced or less conscientious transcriber may neglect to correct some ASR mistakes.

It is easier for human transcribers to process shorter segments of speech, especially if they have to listen multiple times to unclear segments. Hence, to speed up the process of human transcription, the audio and transcript are first segmented by cutting them at silences longer than 500ms. Excessively long audio segments are then further divided at their longest silences, which must be at least 100ms. Note that the resulting segments do not necessarily correspond to linguistic boundaries or to where punctuation marks should be placed; often in spontaneous speech, a person may pause in the middle of a sentence when faced with an increased cognitive load, e.g. when trying to recall a word. Similar methods of using ASR output as a basis for manual transcription were applied, e.g., by (Park and Zeanah, 2005) and (Matheson, 2007), for the purpose of transcribing interviews for interview-based research.

The human transcribers use Transcriber[6], a tool for assisting manual annotation of speech signals through a graphical user interface. The tool synchronizes the text with the audio, and allows the human transcriber to review the text while listening to the audio, and easily pause, fix, annotate, and continue listening from a selected segment. On average, the time needed for manual transcription by experienced transcribers is approximately 5 times the duration of the audio file. An example of the input to the tool – the output of the above-mentioned segmentation process – is presented in Example 4. The output of the post-edition, which uses the same format, is shown in Example 5.

The guidelines used for manual transcription explain how to deal with cases such as speaker hesitation, repetitions and utterance of incomplete words, what punctuation to use[7], how to write abbreviations, numbers, etc. The main principles are that the transcripts should be as close to the speech as possible, and that they should maintain a uniform format that can be easily parsed in subsequent processing.[8]

Example 4 (Input for manual transcription)

```
<Sync time="18.020"/>
doping is the use of performance enhancing
drugs
<Sync time="21.290"/>
at what i
<Sync time="22.030"/>
am talking about sports i am of course
referring to
<Sync time="25.015"/>
a competitive sports
<Sync time="26.630"/>
for example the olympics
<Sync time="28.320"/>
or other kinds of competitions
```

---

[6] http://trans.sourceforge.net/en/presentation.php; We used version 1.5.1

[7] Since the ASR does not produce punctuation, initially the human transcribers were not instructed to insert them. Yet, some transcribers felt more comfortable adding punctuation as it made transcripts more readable; the transcription guidelines were accordingly revised. Punctuation also make the texts more accessible for analysis and annotation and may be helpful for some automatic processing tasks.

[8] The transcription guidelines are shared with the released data.

```
<Sync time="30.040"/>
like a true the fonts
<Sync time="31.800"/>
and etcetera
```

Example 5 **(Output of manual transcription)**

```
<Sync time="18.020"/>
doping is the use of performance enhancing
drugs .
<Sync time="21.290"/>
uh when i
<Sync time="22.030"/>
am talking about sports i am of course
referring to
<Sync time="25.015"/>
uh competitive sports ,
<Sync time="26.630"/>
for example the olympics
<Sync time="28.320"/>
or other kinds of competitions
<Sync time="30.040"/>
like uh tour de france
<Sync time="31.800"/>
uh etcetera ,
```

4.1. Reference Transcripts

The post-edited transcripts include annotations of disfluencies, for example when the speaker uttered only a part of the word (e.g. "spor-" for a partial utterance of "sports"). Some of the annotations are only necessary for ASR training, e.g. a mispronunciation of a word, while others contain signals that may be useful for downstream text processing. Our approach in producing the reference transcripts was to remove all non-textual annotations, producing a text-only version of the transcription, that can be used as-is, e.g. for argument extraction. From the Transcriber's output, we first remove all SGML tags and merge the lines into a single stream. We then remove incomplete words and mispronounced words (replacing them with the correct pronunciation); similarly to the raw ASR preprocessing, we remove annotations, hesitations and reformat abbreviations. Finally, we detokenize the text, i.e. remove any unnecessary spaces between tokens, for example, before a punctuation mark. Example 6 shows the text segment from Example 5 after going through this cleaning. As can be seen in the example, we apply only minimal truecasing to the text – capitalizing sentences' first letters and occurrences of "I". We have experimented with more sophisticated truecasing tools and abstained from applying them to the released texts due to mixed results.

Example 6 **(Clean reference transcript)**

```
Doping is the use of performance enhancing
drugs.
When I am talking about sports I am of
course referring to competitive sports, for
 example the olympics or other kinds of
competitions like tour de france etcetera,
```

5. Dataset

The dataset we created was generated through the process described in the previous sections. We release all file types, including raw and cleaned versions, to enable research based on various signals, including audio-based ones, such as prosody or speech rate, and to allow performing different preprocessing. Table 1 summarizes the files that are obtained and released for each debatable topic.

Extension	Description
wav	Recorded speeches
asr	Raw automatic transcriptions
asr.txt	Clean automatic transcriptions
trs	Manual transcriptions
trs.txt	Clean manual transcriptions (references)

Table 1: Summary of released file types.

The topics we selected are taken from (Rinott et al., 2015). This initial release includes 10 motions listed in that paper, where each speech was recorded by a different speaker.[9] Table 2 provides details about the specific recordings included in this release.

#	Topic	Length	WER
1	Violent video games	07:37	6.2%
21	One-child policy	05:36	6.7%
61	Doping in sports	06:02	12.9%
101	Affirmative action	07:30	11.6%
121	Banning boxing	03:44	3.1%
181	Multiculturalism	06:00	6.2%
381	Abolishing the monarchy	05:27	8.3%
483	Freedom of speech	05:32	12.6%
602	School vouchers	04:10	3.5%
644	Year round schooling	04:08	9.8%

Table 2: List of speeches in our initial release. Length is in minutes; WER is of the speaker-independent model.

As can be seen in the table, there is a large variance in WER across different debate recordings. The WER of any specific debate can vary depending on the degree of mismatch with the ASR acoustic and language models. Examples of mismatch include differences in speaker voice, speaking style and rate, audio capture (microphone type and placement), ambient noise, word choice and phrasing, etc. By reducing mismatch through model adaptation of speaker-dependent acoustic models, the WER can be significantly reduced. For instance, with adaptation using about 15 minutes of a speaker's data, the WER for the speech of topic 61 is reduced from 12.9% to 8.6% and for topic 483 from 12.6% to 9.7%.

The dataset is freely available for research at `https://www.research.ibm.com/haifa/dept/vst/mlta_data.shtml`.

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[9]Currently, the list contains only a single female speaker; we are making an effort to recruit more female debaters.

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