The Aligned Multimodal Movie Treebank:
An audio, video, dependency-parse treebank

Adam Yaari
MIT CSAIL–CBMM
Jan DeWitt
MIT CSAIL–CBMM
Henry Hu
MIT CSAIL–CBMM
Bennett Stankovits
MIT CSAIL–CBMM

Sue Felshin
MIT CSAIL–CBMM
Yevgeni Berzak
Technion
Helena Aparicio
Cornell University
Boris Katz
MIT CSAIL–CBMM
Ignacio Cases*
MIT CSAIL–CBMM
Andrei Barbu*
MIT CSAIL–CBMM

Abstract

Treebanks have traditionally included only text and were derived from written sources such as newspapers or the web. We introduce the Aligned Multimodal Movie Treebank (AMMT)†, an English language treebank derived from dialog in Hollywood movies which includes transcriptions of the audio-visual streams with word-level alignment, as well as part of speech tags and dependency parses in the Universal Dependencies (UD) formalism. AMMT consists of 31,264 sentences and 218,090 words, that will amount to the 3rd largest UD English treebank and the only multimodal treebank in UD. We find that parsers on this dataset often have difficulty with conversational speech and that they often rely on punctuation which is often not available from speech recognizers. To help with the web-based annotation effort, we also introduce the Efficient Audio Alignment Annotator (EAAA)‡, a companion tool that enables annotators to significantly speed-up their annotation processes.

Keywords: multimodal, video, audio, treebank, Universal Dependency parsing

1 Introduction

Treebanks are fundamental resources in Natural Language Processing (Nivre et al., 2016). Despite their central role, most existing treebanks are derived from single-modality texts such as newspapers, blogs, and other online communities. The vocabulary, syntax, and statistics of spoken and written language can be quite different from one another (Caines et al., 2017). To complement these datasets and aid the advent of multimodal conversational agents, we have created a new dataset, the Aligned Multimodal Movie Treebank, AMMT, the content of which is derived from language spoken in Hollywood movies. AMMT is released publicly under an open source license and will be contributed to the Universal Dependencies (UD) (Nivre et al., 2020) treebanks.

Speech based treebanks have proven to be a resource of enormous importance to the NLP research community (Ahrenberg, 2007; Nivre et al., 2006). We find Treebank-3 of the Penn Treebank (Marcus et al., 1993), which includes the Penn Treebank Switchboard corpus (Godfrey et al., 1992), to be the closest existing dataset to AMMT. This corpus contains nearly one million transcribed words from Switchboard annotated with part of speech tags, dysfluencies, and parse trees, and it also in-

Figure 1: An overview of AMMT, our novel multimodal dataset, consisting of transcriptions and parses for 21 movies aligned at the millisecond level. EAAA is a new transcription and alignment tool introduced below.
cludes alignment between words and audio. However, there are several key differences between this dataset and our own. AMMT provides alignment to visual as well as audio data; it is annotated with UD rather than Penn Treebank dependencies; and conversations are much shorter (Switchboard was designed to have long 10 minute conversations between strangers on the phone discussing one of a preselected list of topics). While conversations in AMMT can still be considered as prepared speech, topics are way less constrained. AMMT also includes many more speakers and its audio quality allowed us to recover almost all spoken words. For practical experiments, AMMT is significantly more entertaining for subjects, a key feature for researchers aiming to study the neuroscience of language via neural imaging. Finally, with this contribution, AMMT is being made open to the whole research community and not restricted to LDC members.

Our contributions are: 1. AMMT is the first large-scale treebank to include alignment to both audio and video. 2. AMMT includes fine-grained millisecond-level word boundaries. 3. AMMT is parsed in the UD framework and is the 3rd largest English UD treebank. 4. A new tool, Efficient Audio Alignment Annotator (EAAA), for rapid word boundary annotation in large corpora.

2 Dataset

The AMMT dataset is an English language treebank based on 21 Hollywood movies that provides transcriptions with word-level alignment to the audio-visual stream, as well as part of speech tags and dependency parses in the UD formalism. Annotations for speaker identification will be included at the time of release. Due to copyrighted source material, AMMT provides multiple 1-second-long audio-visual sample clips from every movie, and a tool chain allowing users to obtain their own copies and verify alignment with the dataset.

AMMT consists of 31,264 sentences, 218,090 words, 8,541 lemmas and 10,805 unique tokens. The counts of POS tags and dependencies are shown in appendix A. The 21 movies from which the dataset is derived are listed in table 4 along with their unique identifiers and relevant statistics.

Movies were chosen to be appropriate for many ages, with the highest rating being PG-13. They belong to a variety of movie genres (including action, adventure, animation, comedy, drama, fantasy, family, and sci-fi, according to IMDb’s categorization), and their release dates range from 1995 to present. They were selected to have verbose scripts, in the top 50% of randomly sampled movies. Movies which included extensive singing such as musicals were omitted. Copies of the movies were obtained and extracted in full including opening and closing credits. Special features and after-credits scenes were omitted.

2.1 Transcription pipeline

The audio track was originally transcribed using the Google Cloud Speech-to-Text API (Google, 2020). It was then corrected by annotators, hired from rev.com and happyscribe.com depending on the movie, and then further extensively corrected by 7 expert annotators. Transcription followed a set of guidelines to deal with problematic audio segments and to enforce coherence. Manual transcription was performed simultaneously with word-boundary annotation using a new tool developed for this purpose, EAAA (see section 4), which was also subsequently used by annotators to perform sentence segmentation and fixing capitalization.

Transcription was verbatim without any corrections for dysfluencies or mistakes. Instructions were provided to the annotators to standardize the transcripts and eliminate problematic audio segments. Foreshortened words (‘round vs around) were transcribed as they were said including the foreshortening. Abbreviations were always expanded (dr. vs doctor). Cardinal and ordinal numbers were spelled out, while long numbers were written as spoken including conjunctions such as and (e.g., five hundred and five).

<table>
<thead>
<tr>
<th>Aligned Multimodal Movie Treebank</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>sentences</td>
<td>31,264</td>
</tr>
<tr>
<td>tokens</td>
<td>218,090</td>
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<td>8,541</td>
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<td>types</td>
<td>10,805</td>
</tr>
<tr>
<td>num. movies</td>
<td>21</td>
</tr>
</tbody>
</table>

Table 1: Basic statistics of the dataset

Manual transcription was carried out simultaneously with word boundary annotation using a purpose-built tool, EAAA (see section 4). EAAA presented annotators with a spectrogram for 4 second segments of a movie, along with the ability to replay and slow down any sub-segment and seek throughout the movie. As the audio was played, a line marked the location of the audio sample in...
the spectrogram in real time. In some cases, annotators could hear specific words but could not clearly identify in the spectrogram where those words occurred (e.g. short words like to). Annotators were instructed to annotate what they heard regardless of the spectrogram, sometimes leading to such short words having zero-length intervals. Foreign sentences (e.g., Elvish in the movie The Lord Of The Rings) were marked but not included in the corpus, although one-off foreign words in English sentences were transcribed. All cases of singing, unintelligible speech, and multiple speakers overlapping were noted and eliminated from the dataset. Transcripts are as spoken, without correction, even when the speaker erred omitting a word or using a word inappropriately.

After transcription and word boundary alignment, the text was segmented into sentences. Annotators marked the end of each sentence manually and fixed capitalization (of both proper nouns and sentences as needed). Throughout this process, some critical punctuation was introduced as annotators saw fit.

2.2 Dependency parsing pipeline, annotation and validating annotator performance

We parsed all transcriptions with Stanza (Qi et al., 2020) using the standard English model.

<table>
<thead>
<tr>
<th>Metric</th>
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<th>Recall</th>
<th>F1 Score</th>
<th>AligndAcc</th>
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</thead>
<tbody>
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<td>100.00</td>
<td>100.00</td>
<td>N/A</td>
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<td>96.74</td>
<td>96.70</td>
<td>96.72</td>
<td>96.70</td>
</tr>
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</table>

Table 2: Inter-annotator agreement bound of AMMT syntactic annotations.

The AMMT dataset was entirely annotated by an in-house expert annotator over the course of a year. Edge cases were discussed with other three team members with strong background in linguistics and Universal Dependencies in particular. In this period of time, the expert annotator performed a total of three sequential passes over the full dataset with the idea of promoting internal consistency.

Separately, after this annotation process concluded, a subset of AMMT consisting in 300 sentences of length 5 through 20 uniformly sampled across movies were reannotated by an expert annotator. This expert annotator has a strong background in linguistics and did not contribute to the dataset otherwise. The length of these sentences was selected to avoid the effect of very short or very long sentences (see table 2).

The inter-annotator agreement of the annota-
tions was with 99.53% on correct POS tagging, 98.95% on correctly placing dependencies (UAS), and 98.31% on correctly identifying the type of a dependency relation. MLAS ties together POS and LAS into a single number, 96.72%, which measures the inter-annotator agreement of the annotations (Straka, 2018).

Note that the inter-annotator score presented in table 2 is thus a measure, for this particular subset of the dataset, of the disagreement between the original expert annotator and the external expert annotator. As such it should only be considered as a bound on the actual disagreement between the two annotators.

We found word-boundary inter-annotator agreement to be remarkably high, with less than 15ms on average for all words in a single movie, *Lord Of The Rings*, annotated by 5 annotators.

### 2.3 Performance of existing parsers

We compared our annotations against those produced by Stanza (Qi et al., 2020) in fig. 3. Stanza was the original parser used to initialize the treebank before extensive human correction. This likely biases the results toward Stanza in subtle ways (Berzak et al., 2016) which we do not investigate here beyond section 2.2.

Note that performance on short sentences, fewer than 3 words, and long sentences, with more than 20 words, is far worse than average-case performance (see fig. 5 for the distribution of sentences in AMMT). This trend is not observed in other corpora such as the English Web Treebank (EWT) (Silveira et al., 2014), where performance increases for short sentences (although these are very infrequent) while the performance drop for long sentences is half or less than that seen in AMMT. While the distributions of POS in both corpora are slightly different (cf. appendix A), the performance drop for short sentences appears to be driven by POS tag errors, see the relative drop in POS accuracy between fig. 3(a,b,c) — perhaps such sentences require more context to be correctly interpreted. The performance drop for long sentences appears to be driven by incorrectly identified relationships, see the relative drop in UAS between fig. 3(a,b,c).

### 3 Multimodal feature analysis

Exploring the utility of the corpus as a multimodal resource for grounded language and vision tasks, we quantified the co-occurrence of nouns and their corresponding objects (i.e. objects that are verbally mentioned as they appear on screen). As an approximation, we considered the 80 object classes of the Microsoft COCO dataset (Lin et al., 2014). We extracted all nouns corresponding to a COCO class (580 nouns across all movies) and manually reviewed the middle frame of a word utterance. We find an average of 36.5% noun-object agreement rate (212 co-occurring objects) across all movies ($\mu = 23.7\%$, $\sigma \approx 17.5\%$ per movie); see fig. 4.

Considering noun-object agreements across both object classes and movie types reveals variable distributions. Some nouns are highly likely to appear on screen as their corresponding noun is uttered, like Person (94.4%), types of vehicles (Car: 59.7%, Bicycle: 68.3%) and animals (Giraffe: 100%, Cow: 100%), while others have not co-occurred once despite being uttered multiple times. Moreover, unambiguous nouns (e.g. Laptop: 50%, TV: 42.8%, Toilet: 33.3%) tend to have a significantly higher agreement rate scores than words with multiple POS (e.g. Bear: 2.5%, Orange: 0%, Remote: 0%). Some movie categories are also more likely to have high noun-object agreement, such as movies aimed for a younger audience (educational and animation genres), perhaps to enable language learning.

![Figure 3](image-url)
through multimodality. For example, *Cars-2* and *Sesame Street* present 79.2% and 74.3% agreement rate respectively, while *The Lord Of The Rings 1* and 2, and *Avengers Infinity War* score only 17.6%, 14.2% and 5.9% respectively; see fig. 6.

Figure 4: COCO classes noun-object agreement across the corpus (sorted by agreement rate). All nouns corresponding to one of the 80 COCO classes (orange) vs their corresponding objects in the video during the noun utterance (blue). Objects were manually detected in the middle frame of a word utterance.

4 Tools

To efficiently annotate the alignment between word onsets and offsets and the audio stream, we created a new tool, the Efficient Audio Alignment Annotator (EAAA). EAAA enables annotators to start with a rough transcript and approximate alignment between words and the audio track. Annotators can simultaneously correct the transcript while annotating new words. An overview of the EAAA interface is shown in fig. 2. Tools such as Praat (Boersma, 2001) also allow for annotating audio corpora with word boundaries. Unlike Praat, EAAA is web-based making it easier for annotators to use. Data such as spectrograms and wave files seen by annotators is pre-processed on the server-side, making browsing and accessing movies with EAAA near real-time. Since EAAA is a single-purpose tool meant for transcription and fine-grained alignment, it provides custom features which significantly speed up the annotation process like keyboard shortcuts, the ability to handle audio files of any length, and a streamlined interface. EAAA also handles multiple concurrent annotators, sharing and comparing multiple annotations directly.

EAAA pre-processes movie files into 4 second segments that overlap by 2 seconds and computes spectrograms for each segment with Librosa (McFee et al., 2015). Storage is provided by a local Redis database which is not exposed to the web. In addition, EAAA includes a telemetry server which collects comprehensive information during the annotation process including every transcript change, keyboard shortcut used, and mouse press.

5 Conclusion

AMMT and EAAA are open source and AMMT will be contributed to the UD treebanks. In addition to verbatim transcriptions and a treebank, AMMT provides a tool chain to enable access and alignment to the source video and audio. Most datasets for evaluating and training parsers are focused on written rather than spoken language. With the rise of conversational agents, AMMT can serve as a more predictive benchmark in this domain.

At present, no end-to-end systems – from video-and-audio to parses – exist, even if humans often use visual information to disambiguate and contextualize auditory information. We hope that AMMT and its tooling will support further work on multimodal approaches to conversational agents, end-to-end parsing, as well as psychophysics and neuroscience with language in context.

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Ethics

The AMMT corpus was constructed using Hollywood movies. Many of these movies generated by the US/Western film industry are unbalanced in terms of cultural and sociolinguistic diversity and oftentimes rely on stereotypes. As such, the distributions of gender, race, age, socioeconomic status, etc. appearing in this corpus are biased as they are sampled from this pool.

Annotators, both in lab and online, contributed significant effort to the development of this dataset. The vast majority of the annotation effort was carried out in lab, with only limited bootstrapping from online services, due to both ethical and quality concerns. Using state-of-the-art models like speech recognizers significantly sped up every stage of the annotation, for example, making transcription only slightly slower than real time. In lab annotators were paid over $18/hour.

Limitations

Movies in AMMT were selected to be appropriate and entertaining for many ages with the highest rating being PG-13. This selection criterion limits the genres and topics covered. Also, speech in movies is prepared speech. While prepared speech is often meant to seem similar to natural speech, it limits the applicability of the corpus. Similarly, the relationships, social situations, and actions taken by agents, are constructions designed with a purpose (e.g. discoursive, entertainment) rather than examples of actual social dynamics, conflict, or growth.

Effort was made to make transcriptions verbatim to maintain the regional or cultural variation in speech present in the original movies, e.g., by directly including foreshortened words. However, such variation is generally selected against in the creation of Hollywood movies and so is poorly represented in this dataset.

The current version of the corpus is monolingual (English) although two Spanish movies were partially processed and may be included in a future version.

References


A Appendix

Figure 5: Distribution of sentence lengths in AMMT. Most sentences are quite short. The mean sentence length is 6.97 words long. Compare to standard corpora derived from written sources like the English Web Treebank (15.33 words/sentence) long and the Penn Treebank (23.73 words/sentence in the test set).

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<th>Dependencies</th>
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</tbody>
</table>

Table 3: The distribution of POS tags (left), and the most common dependencies (right). There is a long tail of dependencies.

Figure 6: COCO classes noun-object agreements per movie (sorted by number of nouns). All nouns corresponding to one of the 80 COCO classes (orange) vs their corresponding objects in the video during the noun utterance (blue) per movie.

Figure 7: Comparing POS frequency in EWT, a treebank derived from text on the web, and AMMT, our new benchmark derived from spoken language. Among many differences, note that in AMMT, nouns are much less common and pronouns are far more common.
Table 4: Name, unique identifier (IMDb ID), and statistics for the 21 movies from which AMMT is derived. Movies were selected to be appropriate for most ages enabling a wide range of experiments. Movies are not randomly sampled; they were selected for their verbose scripts and subjects entertainment during experiments. For more on IMDb identifiers, see https://developer.imdb.com/documentation/key-concepts#imdb-ids