

CASCADING AND DIRECT APPROACHES TO UNSUPERVISED CONSTITUENCY PARSING ON SPOKEN SENTENCES

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ABSTRACT

Past work on unsupervised parsing is constrained to written form. In this paper, we present the first study on *unsupervised spoken constituency parsing* given unlabeled spoken sentences and unpaired textual data. The goal is to determine the spoken sentences' hierarchical syntactic structure in the form of constituency parse trees, such that each node is a span of audio that corresponds to a constituent. We compare two approaches: (1) cascading an unsupervised automatic speech recognition (ASR) model and an unsupervised parser to obtain parse trees on ASR transcripts, and (2) direct training an unsupervised parser on continuous word-level speech representations. This is done by first splitting utterances into sequences of word-level segments, and aggregating self-supervised speech representations within segments to obtain segment embeddings. We find that separately training a parser on the unpaired text and directly applying it on ASR transcripts for inference produces better results for unsupervised parsing. Additionally, our results suggest that accurate segmentation alone may be sufficient to parse spoken sentences accurately. Finally, we show the direct approach may learn head-directionality correctly for both head-initial and head-final languages without any explicit inductive bias.

Index Terms— Unsupervised constituency parsing, unsupervised word segmentation, self-supervised speech representations

1. INTRODUCTION

Unsupervised constituency parsing is a long-standing research challenge in natural language processing [1, 2, 3, 4] that aims to automatically determine the syntactic constituent structure of sentences without access to any training labels. It sheds light on how children are able to learn high-level linguistic information, such as syntax and grammar, without expert supervision. Additionally, constituency parse trees have also been shown to improve and provide greater interpretability to a variety of downstream tasks such as semantic role labeling [5], word representation learning [6], and speech synthesis [7, 8, 9].

To the best of our knowledge, syntactic parsing on speech was done exclusively in a supervised manner, using paired text transcripts and syntactic labels for training. However, these approaches cannot be applied to low-resource languages without paired data. This motivates us to explore a more realistic setting where only raw speech and limited unpaired textual data are available.

With no speech-text pairs or tree-text pairs, the first approach to unsupervised spoken constituency parsing is to cascade unsupervised ASR with an unsupervised parser. We compare training the parser on limited unpaired text and ASR transcripts and find that training on ASR transcripts does not help the model parse ASR transcripts of the same domain.

We also propose a framework to directly parse spoken input without any intermediate textual form. First, we split an utterance into word-level segments, and transform each segment into a continuous embedding. Then we directly use this sequence of segment embeddings as input for our unsupervised parser. We refer to this as the direct approach.

Contributions. (1) We perform the first investigation of unsupervised constituency parsing on spoken sentences using only raw speech and unpaired text. (2) We demonstrate that for parsing ASR transcripts, training on limited unpaired text is still better than training on ASR transcripts, and we quantify the effects of ASR errors on unsupervised parsing. (3) We propose a framework to directly parse continuous speech without intermediate lexical unit discovery. (4) We show that our direct approach may induce parse trees with the correct branching direction for different spoken languages.

2. RELATED WORK

2.1. Unsupervised Constituency Parsing

Previous studies in unsupervised constituency parsing focus on obtaining constituency tree structures from large unannotated text corpora, usually by encouraging neural models to follow syntactic structure [4, 10, 11], or parameterizing linguistic models with neural networks [12, 13, 14].

A recent line of work in visually-grounded grammar induction leverages paired images to improve unsupervised constituency parsing [15, 16, 17]. We consider AV-NSL [18] in particular to be most relevant to our work, as they extend this approach to audio-visual learning and attempt to learn constituency parse trees from raw speech and image pairs. Unlike AV-NSL, our work does not rely on paired visual grounding data.

2.2. Parsing Speech with Supervision

Past works on syntactic parsing of speech address topics such as disfluency detection [19, 20], or incorporating prosodic cues [21, 22]. However, most previous works require oracle transcripts, which is an unrealistic setting. Yoshikawa et al. [23] shows that it is possible to build a supervised dependency parser that jointly detect disfluencies and ASR errors, and Pupier et al. [24] build an end-to-end supervised dependency parser for French that jointly predicts transcription and dependency tree from raw speech signals. Both works show an improvement over cascading baseline systems.

Additionally, prosodic features are shown to be closely related to syntax [25, 26] and beneficial for both constituency parsing [27, 28] and dependency parsing [29], even under the presence of ASR errors [30]. These works motivate us to explore ways of using speech features to improve unsupervised constituency parsing of spoken data.

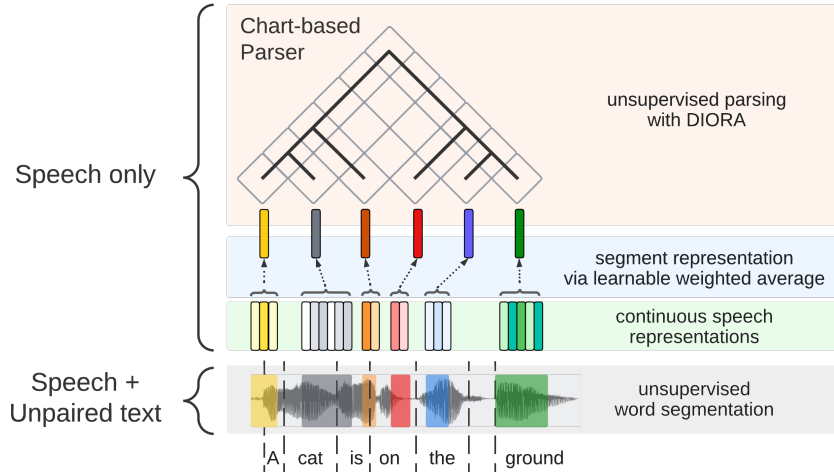


Fig. 1. Diagram of our proposed direct approach to unsupervised spoken constituency parsing, using only raw speech and unpaired text. Textual transcripts of the input sentence are only shown for illustrative purposes.

2.3. Unsupervised Spoken Language Modeling

Unsupervised spoken language modeling [31] aims to learn a spoken language model that simultaneously learns different levels of linguistic structure from raw speech signals with little or no textual data. The ZeroSpeech Challenge 2021 [32, 33] proposes to evaluate such a model at the acoustic, lexical, syntactic, and semantic levels. They find that while current spoken language models excel at the acoustic and lexical levels, higher levels of linguistic structure are much more difficult to model. They only require their models to be able to determine how grammatical a sentence is, while our work aims to solve the more challenging problem of producing the exact constituency structure of a sentence.

3. METHOD

3.1. Background

Constituency parsing is usually formulated under the binary setting in order to reduce computation complexity. [34] This setting entails that for a sentence with n words $\{x_1, x_2, \dots, x_n\}$, each constituent spanning $x_{i:j}$ is composed of two constituents spanning $x_{i:k}$ and $x_{k+1:j}$ for some k such that $i \leq k < j$. Our unsupervised parser follows the chart-based Deep Inside-Outside Recursive Autoencoder (DIORA) framework proposed by [12] to produce binary parse trees without using any syntactically labeled data.

3.1.1. Chart-based Constituency Parsing

Chart-based parsers find the optimal tree out of all valid binary parse trees by filling the upper-triangular portion of an $n \times n$ chart with a score $s_{i,j}$ for each cell. For $1 \leq i < j \leq n$, the score in cell (i, j) represents how likely the span $x_{i:j}$ is a constituent. The CKY dynamic programming algorithm [35, 36] is then used to determine the parse tree with the highest total score.

3.1.2. Unsupervised Parser Architecture: DIORA

DIORA consists of an encoder and a decoder, and operates similarly to masked language models. The framework recursively encodes all

but one of the words from the input sentence as a vector, and optimizes that vector to reconstruct the missing word. The core assumption is that the most efficient weights to produce such an encoding can be used as scores for chart-based constituency parsing. DIORA initially represents the input sentence with pretrained ELMo character embeddings, but subsequent work [17] shows that the framework can also be used with randomly initialized word embeddings.

3.2. Cascading Parsing with Unsupervised ASR

A straightforward approach to unsupervised spoken constituency parsing is to obtain word-level transcripts from unsupervised ASR, then represent each word with a randomly initialized vector. An unsupervised parser can then produce parse trees using these vector sequences as input.

Our unsupervised ASR system adopts the wav2vec-U framework [37]. wav2vec-U first phonemizes unpaired text data, then performs a series of preprocessing steps on unlabeled speech to produce higher-level features with length similar to phoneme sequences. They use adversarial training to train a model to predict phoneme sequences from speech features. A weighted finite-state transducer (WFST) trained on the unpaired text data is then used to decode the output into words. Further improvements are obtained through Hidden Markov Model (HMM) self-training. The phoneme output of the HMM achieves a lower phone error rate and can be decoded into more accurate word-level transcripts.

3.3. Direct Parsing on Speech Segments

The direct parsing approach extends the DIORA framework by training on continuous word-level speech embeddings instead of ELMo embeddings. Using continuous segment representations allows our parser to benefit from continuous information in speech, in comparison to the discretization approach recently proposed in spoken language modeling [31]. This design choice is supported by AV-NSL [18], which finds that continuous segment representations outperforms discrete representations for audio-visual parsing.

From each spoken utterance, we prepare (1) frame-level features, and (2) word-level segments. Frame-level features can ex-

tracted from a pretrained self-supervised speech model such as XLSR-53 [37], and word-level segments can be determined with unsupervised word segmentation models [38, 39]. Mirroring AV-NSL, we represent each segment with a continuous embedding parameterized by a simple weighted average of frame-level features. Weights are determined by a learnable two-layer MLP that is jointly optimized with the parser. This sequence of word-level segment embeddings is then directly used as input for our parser, then jointly optimized with the reconstruction loss proposed in DIORA [12].

4. EXPERIMENTS

4.1. Datasets, Preprocessing, and Hyperparameters

Experiments are mainly conducted on the SpokenCOCO dataset [40], a 742h English read-speech dataset produced by 2.3k speakers reading the captions in MSCOCO [41]. Each image in MSCOCO corresponds to 5 captions on average. Following [16], we use the spoken captions of the 83k/5k/5k image split for training, validation, and testing respectively. The textual captions of the remaining 31k images are used as unpaired text data for unsupervised ASR. We focus on the more practical setting of unsupervised spoken constituency parsing using speech and unpaired text data only, hence we do not utilize the image data.

Additional experiments in Korean are done on the Zeroth-Korean corpus¹, which contains 51.6hrs of audio spoken by 105 speakers for training, and 1.6hrs by 10 different speakers for testing. We use the utterances of 10 speakers in the original training set for validation.

We note that due to a lack of labelled spoken sentences, we are limited to experimenting on high-resource languages. Following [15, 16], ground-truth parse trees are obtained from the outputs of an off-the-shelf parser [42] on the normalized text captions. Punctuation is removed from the trees, and we run forced alignment using the Montreal Forced Aligner [43] to obtain oracle word boundaries.

For all experiments, we use the same hyperparameters as the randomly initialized DIORA experiment in [17], with a batch size of 32 and learning rate of $5e-3$. We perform unsupervised model selection with the reconstruction loss of DIORA on the validation set. Our cascading and direct systems are trained for 10 epochs and 2000 batches respectively, as we found our direct systems to converge much faster. Further details are available in our training code².

4.2. Evaluation

Unsupervised constituency parsing on text is typically evaluated with F_1 score of constituents, where a match is only counted if a predicted constituent and a oracle constituent consist of the exact same words. However, erroneous word segmentation or ASR may introduce mismatch in the number of word-level leaves between model predictions and ground truth parse trees. Therefore, we match the constituents first by calculating an alignment between our word-level segments and oracle text, similar to SParseval [44].

We use forced alignment to determine the spans of audio that correspond to each word in the oracle sentence. We then compute the optimal one-to-one mapping that maximizes total span overlap between oracle segmentation and our proposed word segmentations³.

¹<https://github.com/goodatlas/zeroth>

²<https://github.com/roger-tseng/speech-parsing>

³This mapping is determined via bipartite weight mapping, where the nodes are speech segments and the weights are given by the overlap duration across nodes.

This allows us to first match nodes between predicted and ground truth parse trees, and calculate an F_1 score that jointly considers segmentation and parsing performance. We include whole sentence spans in our evaluation, in order to compare to AV-NSL [18]. For all experiments, we evaluate fully unsupervised parsing with this proposed F_1 score, and report the average and standard deviation of corpus-level F_1 of the best model before convergence over five different random seeds.

4.3. Results of Cascading Systems

We train two unsupervised ASR models to observe how varying accuracy of ASR may affect parsing performance. The two models are trained with and without self-training following the original setup of wav2vec-U. They are denoted as ASR-ST and ASR respectively. We use a 100-hour subset of speech from the training set, and 150k unpaired text sentences as our training data. Word-level transcriptions for the entire SpokenCOCO dataset are decoded from the phoneme output sequences of the ASR models. Word error rate of training set transcripts is 13.15% and 28.25% for ASR-ST and ASR.

The training set transcripts are then used to train our parser. We follow [16] and use the 10,000 most commonly occurring words in their respective training set transcripts as the vocabulary set for the parser. Since we assume the availability of unpaired text data in the cascade scenario, we also consider training a parser from the unpaired text data alone.

	Training split	Training	Testing	F_1
(A)	Entire train set	oracle	oracle	57.15 ± 2.09
(B)	Unpaired text	oracle	ASR-ST	44.08 ± 1.64
(C)	Entire train set	ASR-ST	ASR-ST	40.53 ± 1.65
(D)	Unpaired text	oracle	ASR	34.97 ± 1.32
(E)	Entire train set	ASR	ASR	31.01 ± 1.17

Table 1. F_1 score of our cascading systems. The leftmost column lists whether training data comes from the unpaired text split or the training split. We also list the F_1 score obtained by training and testing our parser on oracle transcripts in row (A) as a topline.

Effect of ASR errors on parsing. When comparing results across different blocks, we can see that parsing accuracy is heavily degraded when ASR errors are present. Additionally, one might expect that training a parser on ASR transcripts would allow it to better handle text with ASR errors during inference. However, by comparing rows (B)/(C) and rows (D)/(E), we see that training our parser on unpaired oracle text is consistently better than training on ASR transcripts. We note that this occurs in spite of the training set being nearly 3x larger than the unpaired text set. We hypothesize that this is partially caused by the decoding process of wav2vec-U. Uncommon words rarely get decoded by the WFST language model. As a result, the ASR transcripts contain fewer types of words compared to the original vocabulary, and parser trained on imperfect transcripts deal with more out-of-vocabulary words. The training set transcripts from the ASR-ST model only use 8.2k words out of the original 16k words present in the ground truth captions.

4.4. Results of Direct Systems

For direct systems, only speech features and word boundaries are required. We extract frame-level speech features from the 14th layer of XLSR-53 [45], a publicly available wav2vec 2.0 model pretrained on 53 languages. For word boundaries, we naively split all utterances into 0.5-second segments, to encompass approximately one word in each segment⁴.

Since this method of segmentation is very inaccurate, the parsing results are similarly poor (Table 2 row (D)). However, when provided with ground truth segmentation during testing (Table 2 row (C)), the parser trained on fixed length segments is able to achieve a performance similar to the parser trained on ground truth. This suggests that our direct system is limited by segmentation accuracy during inference.

4.5. A Hybrid Approach: Segmenting speech with word boundaries determined by unsupervised ASR

	Approach	Segmentation		F_1
		Training	Testing	
(A)	AV-NSL	ground truth	ground truth	55.51
(B)	Ours	ground truth	ground truth	57.11 \pm 0.00
(C)	Direct	every 0.5 sec.	ground truth	57.10 \pm 0.01
(D)	Direct	every 0.5 sec.	every 0.5 sec.	3.88 \pm 0.00
(E)	Hybrid	AST-ST	AST-ST	40.44 \pm 1.72
(F)	Hybrid	ASR	ASR	28.49 \pm 0.57

Table 2. F_1 score of direct and hybrid systems. We include F_1 scores obtained by training and testing using oracle segmentation in rows (A) and (B) as toplines.

We compare our systems with AV-NSL under oracle segmentation settings in rows (A) and (B). We find that our parser outperforms AV-NSL despite not using any visual grounding information. This suggests that the DIORA framework may be better suited for unsupervised spoken constituency parsing.

We experimented with a speech-only unsupervised word segmentation method [46], but found it to be suboptimal. Therefore, we consider a hybrid approach that uses forced alignment to obtain word boundaries from unsupervised ASR transcripts. We find that when word boundaries are sufficiently accurate, using word boundaries alone can achieve similar accuracy to cascading systems, as shown in Table 1 row (C) and Table 2 row (E). This implies that accurate word segmentation is necessary for unsupervised constituency parsing from speech, which aligns with the findings in AV-NSL.

4.6. On the Inductive Bias and Trivial Tree Structure

Due to the head-initial property of English [47], constituency parse trees tend to be right-branching, especially if punctuation is removed. On the other hand, for head-final languages such as Japanese and Korean, trees are left-branching instead.

In our direct and hybrid systems, we observe that our models tend to converge to producing right-branching trees on Spoken-

⁴As a reference, average word length in SpokenCOCO is about 0.4 seconds, see Appendix of [40].

COCO⁵. It is worthwhile to note that our framework does not apply any inductive bias that encourages the model to favor right-branching trees; hence, it is non-trivial for such a phenomenon to emerge. We hypothesize that our systems learn a language’s branching direction from continuous spoken input without supervision.

We empirically verify this claim by conducting experiments on Korean, a primarily left-branching language. Over 5 runs with different random seeds, 3 runs converge towards producing some left-branching structures (Fig. 2), supporting our hypothesis.

	English	Korean
<i>Rule-based</i>		
Left branching	24.68	27.15
Right branching	57.11	7.60
<i>Speech only</i>		
0.5 sec. segmentation	57.10 \pm 0.01	18.53 \pm 8.99

Table 3. Results of direct systems trained on English (right-branching) and Korean (left-branching), respectively, using the same setting as Table 2 row (C).

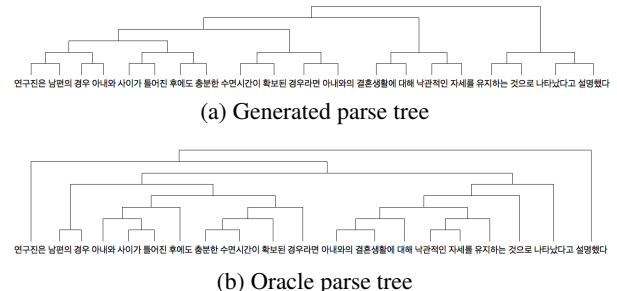


Fig. 2. A sample pair of oracle and generated Korean parse trees. Only textual transcripts are shown for ease of visualization.

5. CONCLUSION

The work investigates cascading and direct approaches to perform constituency parsing on speech input, while only requiring raw speech and unpaired data. For cascading systems, we empirically show that parsers trained on ASR transcripts do not parse ASR transcripts better than parsers trained on unpaired text. For direct and hybrid systems, our results suggest that using segmentation alone may be sufficient to produce unsupervised parse trees.

For future work, we expect to extend our system to end-to-end training to jointly optimize word segmentation and parsing. Additionally, we also plan to investigate whether unsupervised spoken constituency parsing can be improve other speech processing tasks under low-resource scenarios, such as text-to-speech, spoken question answering, or spoken content retrieval.

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⁵We note that right-branching is a difficult baseline even for parsers trained on oracle text. As shown in Table 1 row (A) and [17], unsupervised text parsers only marginally improve on right-branching trees.

6. REFERENCES

- [1] G. Carroll et al., “Two experiments on learning probabilistic dependency grammars from corpora,” Tech. Rep., USA, 1992.
- [2] D. Klein et al., “Corpus-based induction of syntactic structure: Models of dependency and constituency,” in *ACL*, 2004.
- [3] R. Bod, “An all-subtrees approach to unsupervised parsing,” in *COLING-ACL*, 2006.
- [4] Y. Shen et al., “Neural language modeling by jointly learning syntax and lexicon,” in *ICLR*, 2018.
- [5] E. Strubell et al., “Linguistically-informed self-attention for semantic role labeling,” in *EMNLP*, 2018.
- [6] A. Kuncoro et al., “Syntactic structure distillation pretraining for bidirectional encoders,” *TACL*, 2020.
- [7] H. Guo et al., “Exploiting Syntactic Features in a Parsed Tree to Improve End-to-End TTS,” in *Interspeech*, 2019.
- [8] S. Tyagi et al., “Dynamic Prosody Generation for Speech Synthesis Using Linguistics-Driven Acoustic Embedding Selection,” in *Interspeech*, 2020.
- [9] C. Song et al., “Syntactic representation learning for neural network based tts with syntactic parse tree traversal,” in *ICASSP*, 2021.
- [10] Y. Shen et al., “Ordered neurons: Integrating tree structures into recurrent neural networks,” in *ICLR*, 2019.
- [11] Y. Kim et al., “Unsupervised recurrent neural network grammars,” in *NAACL-HLT*, 2019.
- [12] A. Drozdov et al., “Unsupervised latent tree induction with deep inside-outside recursive auto-encoders,” in *NAACL-HLT*, 2019.
- [13] H. Zhu et al., “The return of lexical dependencies: Neural lexicalized PCFGs,” *TACL*, 2020.
- [14] S. Yang et al., “Neural bi-lexicalized PCFG induction,” in *ACL-IJCNLP*, 2021.
- [15] H. Shi et al., “Visually grounded neural syntax acquisition,” in *ACL*, 2019.
- [16] Y. Zhao et al., “Visually grounded compound pcfgs,” in *EMNLP*, 2020.
- [17] B. Wan et al., “Unsupervised vision-language grammar induction with shared structure modeling,” in *ICLR*, 2021.
- [18] C. I. Lai et al., “Textless phrase structure induction from visually-grounded speech,” 2023.
- [19] E. Charniak and M. Johnson, “Edit detection and parsing for transcribed speech,” in *NAACL*, 2001.
- [20] M. Honnibal et al., “Joint incremental disfluency detection and dependency parsing,” *TACL*, 2014.
- [21] J. G. Kahn et al., “Effective use of prosody in parsing conversational speech,” in *HLT/EMNLP*, 2005.
- [22] M. Dreyer et al., “Exploiting prosody for PCFGs with latent annotations,” in *Interspeech 2007*, 2007.
- [23] M. Yoshikawa et al., “Joint transition-based dependency parsing and disfluency detection for automatic speech recognition texts,” in *EMNLP*, 2016.
- [24] A. Pupier et al., “End-to-End Dependency Parsing of Spoken French,” in *Interspeech*, 2022.
- [25] F. Grosjean et al., “The patterns of silence: Performance structures in sentence production,” *Cognitive Psychology*, 1979.
- [26] P. Price et al., “The use of prosody in syntactic disambiguation,” in *Workshop on Speech and Natural Language*, 1991.
- [27] Z. Huang et al., “Appropriately handled prosodic breaks help PCFG parsing,” in *NAACL-HLT*, 2010.
- [28] T. Tran et al., “Parsing speech: a neural approach to integrating lexical and acoustic-prosodic information,” in *NAACL-HLT*, 2018.
- [29] H. Ghaly et al., “Using prosody to improve dependency parsing,” in *International Conference on Speech Prosody*, 2020.
- [30] T. Tran et al., “Assessing the Use of Prosody in Constituency Parsing of Imperfect Transcripts,” in *Interspeech*, 2021.
- [31] K. Lakhota et al., “On generative spoken language modeling from raw audio,” *TACL*, 2021.
- [32] T. A. Nguyen et al., “The zero resource speech benchmark 2021: Metrics and baselines for unsupervised spoken language modeling,” in *NeurIPS SAS Workshop*, 2020.
- [33] E. Dunbar et al., “The zero resource speech challenge 2021: Spoken language modelling,” *arXiv*, 2021.
- [34] D. Jurafsky et al., *Speech and Language Processing (2nd Edition)*, Prentice-Hall, Inc., USA, 2009.
- [35] T. Kasami, “An efficient recognition and syntax-analysis algorithm for context-free languages,” *Coordinated Science Laboratory Report*, 1966.
- [36] D. H. Younger, “Recognition and parsing of context-free languages in time n^3 ,” *Information and control*, 1967.
- [37] A. Baevski et al., “Unsupervised speech recognition,” *NeurIPS*, 2021.
- [38] S. Bhati et al., “Segmental Contrastive Predictive Coding for Unsupervised Word Segmentation,” in *Proc. Interspeech*, 2021.
- [39] H. Kamper, “Word segmentation on discovered phone units with dynamic programming and self-supervised scoring,” *arXiv preprint arXiv:2202.11929*, 2022.
- [40] W. N. Hsu et al., “Text-free image-to-speech synthesis using learned segmental units,” in *ACL-IJCNLP*, 2021.
- [41] T. Y. Lin et al., “Microsoft coco: Common objects in context,” in *ECCV*, 2014.
- [42] N. Kitaev et al., “Constituency parsing with a self-attentive encoder,” in *ACL*, 2018.
- [43] M. McAuliffe et al., “Montreal Forced Aligner: Trainable Text-Speech Alignment Using Kaldi,” in *Interspeech*, 2017.
- [44] B. Roark et al., “Sparseval: Evaluation metrics for parsing speech,” in *LREC*, 2006.
- [45] A. Conneau et al., “Unsupervised Cross-Lingual Representation Learning for Speech Recognition,” in *Interspeech*, 2021.
- [46] T. Fuchs et al., “Unsupervised Word Segmentation using K Nearest Neighbors,” in *Interspeech*, 2022.
- [47] M. C. Baker, *The atoms of language: The mind’s hidden rules of grammar*, Basic books, 2008.