FOUR-IN-ONE: A JOINT APPROACH TO INVERSE TEXT NORMALIZATION, PUNCTUATION, CAPITALIZATION, AND DISFLUENCY FOR AUTOMATIC SPEECH RECOGNITION

Sharman Tan, Piyush Behre, Nick Kibre, Issac Alphonso, Shuangyu Chang

Microsoft Corporation

ABSTRACT
Features such as punctuation, capitalization, and formatting of entities are important for readability, understanding, and natural language processing tasks. However, Automatic Speech Recognition (ASR) systems produce spoken-form text devoid of formatting, and tagging approaches to formatting address just one or two features at a time. In this paper, we unify spoken-to-written text conversion via a two-stage process: First, we use a single transformer tagging model to jointly produce token-level tags for inverse text normalization (ITN), punctuation, capitalization, and disfluencies. Then, we apply the tags to generate written-form text and use weighted finite state transducer (WFST) grammars to format tagged ITN entity spans. Despite joining four models into one, our unified tagging approach matches or outperforms task-specific models across all four tasks on benchmark test sets across several domains.

Index Terms— automatic speech recognition, multi-task learning, inverse text normalization, spoken-text formatting, automatic punctuation

1. INTRODUCTION
Automatic Speech Recognition (ASR) systems produce unstructured spoken-form text that lacks the formatting of written-form text. Converting ASR outputs into written form involves applying features such as inverse text normalization (ITN), punctuation, capitalization, and disfluency removal. ITN formats entities such as numbers, dates, times, and addresses. Disfluency removal strips the spoken-form text of interruptions such as false starts, corrections, repetitions, and filled pauses.

Spoken-to-written text conversion is critical for readability and understanding [1], as well as for accurate downstream text processing. Prior works have emphasized the importance of well-formatted text for natural language processing (NLP) tasks including part-of-speech (POS) tagging [2], named entity recognition (NER) [3], machine translation [4], information extraction [5], and summarization [6].

The problem of spoken-to-written text conversion is complex. Punctuation restoration requires effectively capturing long-range dependencies in text. Techniques have evolved to do so, from n-gram and classical machine learning approaches to recurrent neural networks and, most recently, transformers [7]. Punctuation and capitalization may vary across domains, and prior works have examined legal [8] and medical [9] texts. ASR errors and production resource constraints pose additional challenges [10].

ITN often involves weighted finite state transducer (WFST) grammars [11] or sequence-to-sequence models [12]. Punctuation, capitalization, and disfluency removal are approached as machine translation [13] or, more commonly, sequence labeling problems. Sequence labeling tags each token in the spoken-form text to signify the desired formatting. The translation approach is attractive as an end-to-end solution, but sequence labeling enforces structure and enables customization for domains that may only require partial formatting. Recent works have used pre-trained transformers to jointly predict punctuation together with capitalization [14] and disfluency [15]. Prosodic features have also proven helpful for punctuation early on [16] and have since been used for punctuation and disfluency detection [17, 18]. Despite these joint approaches, no work thus far has completely unified tagging for all four tasks.

We frame spoken-to-written text conversion as a two-stage process. The first stage jointly tags spoken-form text for ITN, punctuation, capitalization, and disfluencies. The second stage applies each tag sequence and outputs written-form text, employing WFST grammars for ITN and simple conversions for the remaining tasks. To our knowledge, we are the first to jointly train a model to tag for the four tasks.

We make the following key contributions:

- We introduce a novel two-stage approach to spoken-to-written text conversion consisting of a single joint tagging model followed by a tag application stage, as described in section 2
- We define text processing pipelines for spoken- and written-form public datasets to jointly predict token-level ITN, punctuation, capitalization, and disfluency tags, as described in sections 3 and 4
- We report joint model performance on par with or exceeding task-specific models for each of the four tasks on a wide range of test sets, as described in section 5
2. PROPOSED METHOD

In this section, we describe our two-stage approach to formatting spoken-form ASR outputs. Figure 1 illustrates the end-to-end workflow of our proposed method.

2.1. Joint labeling of ITN, punctuation, capitalization, and disfluency

Stage 1 addresses ASR formatting as a multiple sequence labeling problem. We first tokenize the spoken-form text and then use a transformer encoder [7] to learn a shared representation of the input. Four task-specific classification heads – corresponding to ITN, punctuation, capitalization, and disfluency – predict four token-level tag sequences from the shared representation. Each classification head consists of a dropout layer followed by a fully connected layer.

We use the cross-entropy ($CE_i$) loss function and jointly optimize all four tasks by minimizing an evenly weighted combination of the losses as shown in

$$CE_{\text{joint}} = \frac{CE_i + CE_p + CE_c + CE_d}{4} \quad (1)$$

where $CE_i$, $CE_p$, $CE_c$, and $CE_d$ are the cross-entropy loss functions for ITN, punctuation, capitalization, and disfluency, respectively. Our task-specific experiments, described in Section 4, optimize just the loss for the single task at hand.

2.2. Tag application

Stage 2 uses the four tag sequences to format the spoken-form ASR outputs as their written form. Since the tag sequences are token-level, we convert them to word-level for tag application.

To format ITN entities, we extract each span of ITN tokens that are consecutively tagged as the same ITN entity type and span. Then, we apply WFST grammar for that entity type to generate the written form.

ITN formatting may change the number of words in the sequence, so we preserve alignments between the original spoken-form tokens and the formatted ITN entities. When multiple spoken-form tokens map to a single WFST output, we only apply the last punctuation tag and the first capitalization tag. For punctuation, we append the indicated punctuation tags to the corresponding words. For capitalization, we capitalize the first letter or entirety of words, as tagged.

To remove disfluencies, we simply remove the disfluency-tagged words from the text sequence.

Although we compare task-specific and joint models for our experiments, using four independent task-specific models in real scenarios may result in undesirable conflicts between features. For instance, predicted punctuation may not line up with predicted beginning-of-sentence capitalization. The joint model’s shared representations encourage predictions for ITN, punctuation, capitalization, and disfluency to be consistent, avoiding such conflicts later in the tag application stage.

3. DATA PROCESSING PIPELINE

3.1. Datasets

We use public datasets from various domains as well as additional sets specifically targeting ITN and disfluency. Table 1 shows the word count distributions by percentage among the sets.

**OpenWebText** [19]: This dataset consists of web content extracted from URLs shared on Reddit with at least three upvotes.

**Stack Exchange**[^1]: This dataset consists of user-contributed content on the Stack Exchange network.

**OpenSubtitles2016** [20]: This dataset consists of movie and TV subtitles.

**Multimodal Aligned Earnings Conference (MAEC)** [21]: This dataset consists of transcribed earnings calls based on S&P 1500 companies.

[^1]: https://archive.org/details/stackexchange
NPR Podcast: This dataset consists of transcribed NPR Podcast episodes.

Switchboard (SWB) & Fisher: SWB [22] is a large multi-speaker corpus of telephone speech consisting of about 2500 conversations by 500 speakers across the United States. Fisher [23] is also a large conversational telephone speech corpus containing about 2000 hours of transcriptions. Neither set contains disfluency annotations.

Switchboard Dialog Act Corpus (SwDA) [24]: This dataset consists of transcribed human-human conversational telephone speech and extends the Switchboard-1 Telephone Speech Corpus, Release 2 with turn- and utterance-level dialog-act tags.

Web-crawled ITN & Conversational Disfluency: In addition to the above sets, we also use web-crawled ITN entities (e.g., addresses, URLs, phone numbers, and numeric quantities) as well as conversational transcriptions containing disfluencies.

| Dataset                      | Distribution |
|------------------------------|--------------|
| OpenWebText                  | 22.8%        |
| Stack Exchange               | 13.6%        |
| OpenSubtitles2016            | 3.3%         |
| MAEC                         | 2.9%         |
| NPR Podcast                  | 0.6%         |
| SwDA + SWB + Fisher          | 0.3%         |
| Web-crawled ITN              | 56.4%        |
| Conversational Disfluency    | 0.1%         |

Table 1. Data distribution by number of words per dataset

3.2. Data processing of written form

Apart from SwDA, SWB, and Fisher, all of our corpora are written-form text containing ITN, punctuation, and capitalization. To jointly train a single model to predict tag sequences corresponding to ITN, punctuation, capitalization, and disfluency, we process each of our sets to contain token-level tags for each of the four tasks.

We filter and clean the datasets by preserving natural sentences or paragraphs as rows and removing characters apart from alphanumeric, punctuation, and necessary mid-word symbols such as hyphens.

To generate the spoken-form equivalents of the written-form datasets, we use WFST grammar-based text normalization. During text normalization, we preserve alignments between written- and spoken-form ITN entities to generate ITN tags for each token. Capitalization and punctuation tags come directly from the written form. The written-form datasets do not contain conversational disfluencies, so we assign them all non-disfluency tags.

We reserve 10% or at most 50 thousand rows from each set for validation and use the rest for training.

3.3. Data processing of spoken form

SwDA, SWB, and Fisher are spoken-form conversational transcriptions and thus do not contain ITN, capitalization, or punctuation. Therefore, we convert the data into written form by applying a commercial formatting service. Then, we generate ITN, capitalization, and punctuation tags using the same process as written-form datasets.

SwDA already contains dialog act annotations, so we translate these to token-level disfluency tags. Since SWB and Fisher are not annotated for disfluencies, we follow [25] by self-training with the unannotated SWB and Fisher corpora. Specifically, we finetune an uncased BERT base model [26] with a top-level disfluency token classification layer on the SwDA training set and use this model to generate disfluency tags for SWB and Fisher.

We randomly split SwDA into training, validation, and test sets using a 90%, 7%, 3% split, and we use all of SWB and Fisher for training. All sets are represented as byte-pair encoding (BPE) tokens for training and evaluation.

3.4. Tag classes

ITN: We tag each token as one of 5 entity types (alphanumeric, numeric, ordinal, money, time) or ‘O’ representing non-ITN. Since we apply WFST grammars on each spoken-form ITN entity span, we signify each ITN entity span by tagging the first token as the entity tag and prepending an underscore (‘_’) character to the remaining tags in the span. For example, “four thirty p m” is tagged as “time _time _time _time” as illustrated in Figure 1.

Punctuation: We define 4 tag categories: comma, period, question mark, and ‘O’ for no punctuation. Each punctuation tag represents the punctuation that appears appended to the corresponding token of text.

Capitalization: We define 3 tag categories: all uppercase (‘U’), capitalize only the first letter (‘C’), and all lowercase (‘O’).

Disfluency: Following SwDA annotations [24, 27, 28], we define 7 tag categories: correction of repetition (‘C_RT’), reparandum repetition (‘R_RT’), correction (‘C’), reparandum (‘R’), filler word (‘F’), all other disfluency (‘D’), and non-disfluency (‘O’).

4. EXPERIMENTS

4.1. Test sets

We evaluate our task-specific and joint models on public and private test sets.

IWSLT 2011 TED Talks²: The IWSLT 2011 ASR and reference test sets each consists of one continuous stream of

²http://iwslt2011.org/doku.php?id=06_evaluation
text with ground truth punctuation. Because our models expect sentence- or paragraph-level input, we convert the ASR and reference sets into sentences and then form paragraphs of at most 200 words, keeping sentences intact. This results in 322 paragraphs. We generate spoken-form inputs for our model evaluation using text normalization.

**DeepMind Q&A CNN and DailyMail stories** [29]: Each of these sets consists of 10,000 written-form paragraphs extracted from randomly selected stories. Each paragraph is well-formed, at least 3 sentences long, and does not contain extraneous symbols such as quotation marks or parentheses. We generate spoken-form inputs for our model evaluation using text normalization.

**NPR Podcasts** [3]: This set consists of written texts aligned with the original audio files to generate corresponding spoken-form ASR outputs.

**Google TN** [30]: This set consists of written texts aligned with the original audio files to generate corresponding spoken-form ASR outputs.

**SwDA** [24]: We randomly selected 6,445 examples from SwDA as our disfluency test set.

**Conversational Disfluency**: This set consists of 1,646 lines of conversational spoken-form text in which 23.6% of tokens are disfluencies.

**Dictation**: This internal set consists of 100 utterances of long-form dictation ASR outputs and human labeled transcriptions.

**Voicemails**: This internal set consists of 400 voicemail ASR outputs and human labeled transcriptions.

**Web-crawled ITN test set**: This manually curated set of ITN entities is designed to comprehensively evaluate model performance on each ITN entity category.

### 4.2. Experimental Setup

We hypothesize that the joint model will perform at least on par with task-specific models, as the joint model may better leverage synergies in language between ITN, punctuation, capitalization, and disfluencies.

To test our hypothesis, we train one task-specific model for each of the four tasks and one joint model. To directly compare task-specific and joint models, we train the models with the same training and validation sets, using the same model architecture and hyperparameters. Each model is trained to convergence.

Both task-specific and joint models are 12-layer transformers with 16 attention heads, 1024-dimension word embeddings, 4096-dimension fully connected layers, and 8-
dimension projection layers between the transformer encoder and the decoder that maps to the tag classes. The joint model contains four parallel projection layers, one for each of the tasks. From here, we refer to the task-specific models collectively as TASK and the joint model as JOINT.

Because the joint model only has a quarter of the parameters of the four task-specific models combined, we also compare JOINT to smaller task-specific models TASK-SMALL with 512-dimension word embeddings and 2048-dimension fully connected layers. TASK-SMALL in total trains about 204 million parameters, compared to JOINT which trains about 171 million parameters.

Disfluency-specific training data makes up just 0.4% of the total training data, so we also train a task-specific model on just the conversational datasets (SwDA, SWB, Fisher). We refer to this disfluency detection model as TASK-DISF.

### 5. RESULTS

We measure performance of each task on test sets using word-level precision (P), recall (R), and F1 scores. Table 2 presents punctuation results on all relevant test sets. JOINT performance is consistently on par with TASK, achieving similar F1 scores across sets and tag classes. In the period and question mark categories, JOINT outperforms both task-specific models on several sets. Across the test sets, JOINT mostly maintains or improves upon TASK precision, sometimes sacrificing some points in recall. In customer scenarios such as long-form dictation, a tilt towards precision is often preferable to avoid over-punctuation.

From Tables 3 and 5, we see that JOINT almost always achieves the best capitalization and ITN F1 across the board, matching or outperforming both task-specific models. Punctuation improvements in detecting sentence boundaries contributed to some gains in beginning-of-sentence capitalization. Jointly training to predict ITN entities helped JOINT to correctly capitalize difficult entities such as addresses and alphanumeric codes.

Table 4 shows results from evaluating the models on the SwDA test set and an internal conversational test set containing disfluencies. On both sets, we see that JOINT significantly outperforms TASK, achieving 44% higher F1 on SwDA and 69% higher F1 on the Disfluency test. JOINT matches the performance of TASK-DISF, which is trained only on Swd, SWB, and Fisher corpora.

This disparity between TASK and TASK-DISF performance reflects TASK’s training skew towards fluent rather than disfluent data; understandably, TASK achieves low recall. Even though we train JOINT on the same imbalanced data as TASK, we see that JOINT achieves performance on par with TASK-DISF. While the F1 scores of TASK-DISF and JOINT suggest the two perform similarly, qualitative evaluation on out-of-domain test cases reveals important differences.
Table 2. Punctuation results

| Test Set       | Model       | COMMA | PERIOD | Q-MARK | OVERALL |
|----------------|-------------|-------|--------|--------|---------|
|                |             | P     | R     | F₁    | P      | R     | F₁    | P      | R     | F₁    |
| Ref. CNN Stories | TASK-SMALL  | 84    | 80    | 82    | 90     | 83    | 86    | 85     | 83    | 84    |
|                | TASK        | 84    | 82    | 83    | 91     | 84    | 87    | 86     | 85    | 85    |
|                | JOINT       | 84    | 81    | 82    | 90     | 84    | 87    | 86     | 83    | 85    |
| Ref. DailyMail Stories | TASK-SMALL | 76    | 79    | 77    | 90     | 88    | 89    | 82     | 71    | 76    |
|                | TASK        | 77    | 80    | 79    | 92     | 90    | 91    | 88     | 78    | 83    |
|                | JOINT       | 77    | 79    | 78    | 91     | 89    | 90    | 84     | 74    | 78    |
| ASR IWSLT 2011 TED | TASK-SMALL | 66    | 31    | 43    | 73     | 68    | 71    | 59     | 42    | 49    |
|                | TASK        | 68    | 33    | 44    | 75     | 68    | 72    | 56     | 45    | 50    |
|                | JOINT       | 70    | 20    | 31    | 75     | 67    | 71    | 80     | 26    | 39    |
| Ref. IWSLT 2011 TED | TASK-SMALL | 78    | 61    | 69    | 81     | 88    | 85    | 80     | 85    | 82    |
|                | TASK        | 79    | 67    | 72    | 84     | 88    | 86    | 71     | 90    | 80    |
|                | JOINT       | 79    | 63    | 70    | 82     | 87    | 85    | 80     | 85    | 82    |
| ASR NPR Podcasts | TASK-SMALL  | 71    | 60    | 65    | 83     | 77    | 80    | 80     | 68    | 74    |
|                | TASK        | 71    | 62    | 67    | 84     | 78    | 81    | 80     | 68    | 74    |
|                | JOINT       | 71    | 60    | 65    | 83     | 77    | 80    | 82     | 69    | 75    |
| ASR Dictation  | TASK-SMALL  | 69    | 54    | 61    | 72     | 78    | 75    | 48     | 94    | 64    |
|                | TASK        | 70    | 57    | 63    | 73     | 79    | 76    | 44     | 94    | 60    |
|                | JOINT       | 70    | 56    | 62    | 73     | 80    | 76    | 50     | 81    | 62    |
| Ref. Dictation | TASK-SMALL  | 73    | 59    | 65    | 82     | 76    | 79    | 71     | 92    | 80    |
|                | TASK        | 73    | 61    | 66    | 83     | 78    | 80    | 65     | 100   | 79    |
|                | JOINT       | 73    | 61    | 66    | 85     | 77    | 81    | 72     | 100   | 84    |

Table 3. ITN results

| Test Set       | Model       | ITN   |
|----------------|-------------|-------|
|                |             | P     | R     | F₁    |
| Ref. CNN Stories | TASK-SMALL  | 88    | 87    | 88    |
|                | TASK        | 88    | 87    | 88    |
|                | JOINT       | 89    | 88    | 88    |
| Ref. DailyMail Stories | TASK-SMALL | 84    | 84    | 84    |
|                | TASK        | 84    | 84    | 84    |
|                | JOINT       | 85    | 84    | 85    |
| ASR NPR Podcasts | TASK-SMALL  | 76    | 58    | 66    |
|                | TASK        | 77    | 59    | 66    |
|                | JOINT       | 77    | 59    | 67    |
| Ref. Wikipedia | TASK-SMALL  | 65    | 69    | 67    |
|                | TASK        | 63    | 68    | 66    |
|                | JOINT       | 64    | 69    | 66    |
| ASR Dictation  | TASK-SMALL  | 75    | 59    | 66    |
|                | TASK        | 74    | 58    | 65    |
|                | JOINT       | 76    | 60    | 67    |
| Ref. Dictation | TASK-SMALL  | 84    | 62    | 72    |
|                | TASK        | 83    | 62    | 71    |
|                | JOINT       | 84    | 63    | 72    |
| Ref. Web-crawled ITN | TASK-SMALL | 82    | 76    | 79    |
|                | TASK        | 85    | 75    | 78    |
|                | JOINT       | 82    | 76    | 79    |

Table 4. Disfluency results

| Test Set       | Model       | DISFLUENCY |
|----------------|-------------|------------|
|                |             | P         | R     | F₁    |
| Ref. SwDA      | TASK-DISF   | 95        | 84    | 89    |
|                | TASK        | 89        | 47    | 62    |
|                | JOINT       | 94        | 85    | 89    |
| Ref. Conv. Disfluency | TASK-DISF | 78        | 44    | 56    |
|                | TASK        | 72        | 20    | 32    |
|                | JOINT       | 76        | 42    | 54    |

In the example voicemail in Table 6, TASK-DISF incorrectly tags “oh” as disfluency, while JOINT correctly detects that it is part of a phone number. In real customer scenarios, tagging and removing “oh” as disfluency would completely alter the phone number and render it unusable. By jointly training on a wide range of non-disfluency data, we generalize well to other domains and avoid critical false positives in production environments.

Our results indicate that jointly labeling ITN, punctuation, capitalization, and disfluency achieves performance on par with four equivalent task-specific models, despite a 75% reduction in parameters. Even when TASK outperforms JOINT, JOINT still achieves equal or better F₁ compared to TASK-SMALL which trains 33 million more total parameters. Therefore, our approach not only maintains or improves task-specific performance but also significantly cuts training and runtime costs for formatting in real scenarios.
Table 5. Capitalization results. Uppercase refers to words longer than 1 letter that are uppercase, Capital refers to words with only first letter capitalized, and Single-case refers to 1-letter words that are uppercase.

Table 6. Example in which TASK-DISF mistakes ‘oh’ as disfluency, while JOINT correctly formats the phone number

6. RELATED WORK

ITN formatting approaches typically involve rule-based systems such as WFST grammars [31] and sequence-to-sequence models [12]. WFST grammars promise accurate results [11], and recent work has explored combining sequence-to-sequence models and WFST grammars for production [32].

While punctuation, capitalization, and disfluency detection tasks have long been addressed as sequence labeling problems, the techniques to solve them have evolved. Unigram and n-gram language models are straightforward but suffer from limited knowledge of surrounding context and lack of scalability as n grows large [2, 33]. Classical machine learning techniques for punctuation and disfluency detection use hidden markov models (HMMs) [34], maximum entropy models [35], and conditional random fields (CRFs) [36]. However, these approaches require manual feature engineering and are cumbersome to train.

These classical techniques gave way to deep neural network approaches such as recurrent neural networks (RNNs), which are easier to train and able to learn more complex features. RNNs and especially long-short term memory (LSTM) models, sometimes combined with CRF layers, have effectively leveraged surrounding context to predict punctuation [17, 37], capitalization [38], and disfluency detection [39, 40]. Most recently, pre-trained transformers have dominated the state-of-the-art in spoken-to-written text conversion.

Multiple sequence labeling approaches have addressed jointly training punctuation with capitalization [14] and disfluency detection [15, 34]. However, we are the first to jointly label all four key components of ASR formatting. Joint learning not only takes advantage of natural correlations in language, but also drastically reduces latency and memory costs in production. Furthermore, our hybrid ITN approach has the best of both worlds – better context-based detection of ITN entities and highly accurate WFST grammars.

7. CONCLUSION

In this paper, we introduced a four-in-one approach to ITN, punctuation, capitalization, and disfluency removal for spoken-to-written text conversion. Our joint transformer tagging model, trained from scratch on spoken- and written-form data, matches or exceeds the performance of task-specific models on all four tasks across test domains – despite training a fraction of the parameters. Our approach can be extended to jointly tag for POS, NER, and other NLP tasks. Future work will explore prosodic cues and multilingual modeling.

8. ACKNOWLEDGEMENTS

We thank Yashesh Gaur and our colleagues at Microsoft for their work on streaming ITN using sequence labeling and WFST grammars, which we built upon in our approach.
9. REFERENCES

[1] Maria Shugrina, “Formatting time-aligned asr transcripts for readability,” in Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics, 2010, pp. 198–206.

[2] Lucian Vlad Lita, Abe Ittycheria, Salim Roukos, and Nanda Kambhatla, “Truecasing,” in Proceedings of the 41st Annual Meeting of the Association for Computational Linguistics, 2003, pp. 152–159.

[3] Dustin Hillard, Zhongqiang Huang, Heng Ji, Ralph Grishman, Dilek Hakkani-Tur, Mary Harper, Mari Ostendorf, and Wen Wang, “Impact of automatic comma prediction on pos/name tagging of speech,” in 2006 IEEE Spoken Language Technology Workshop. IEEE, 2006, pp. 58–61.

[4] Matthias Paulik, Sharath Rao, Ian Lane, Stephan Vogel, and Tanja Schultz, “Sentence segmentation and punctuation recovery for spoken language translation,” in 2008 IEEE International Conference on Acoustics, Speech and Signal Processing. IEEE, 2008, pp. 5105–5108.

[5] Benoit Favre, Ralph Grishman, Dustin Hillard, Heng Ji, Dilek Hakkani-Tur, and Mari Ostendorf, “Punctuating speech for information extraction,” in 2008 IEEE International Conference on Acoustics, Speech and Signal Processing. IEEE, 2008, pp. 5013–5016.

[6] Joanna Mrozinski, Edward WD Whittaker, Pierre Chatain, and Sadoaki Furui, “Automatic sentence segmentation of speech for automatic summarization,” in 2006 IEEE International Conference on Acoustics Speech and Signal Processing Proceedings. IEEE, 2006, vol. 1, pp. I–I.

[7] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin, “Attention is all you need,” Advances in neural information processing systems, vol. 30, 2017.

[8] George Sanchez, “Sentence boundary detection in legal text,” in Proceedings of the natural legal language processing workshop 2019, 2019, pp. 31–38.

[9] Monica Sunkara, Srikanth Ronanki, Kalpit Dixit, Sravan Bodapati, and Katrin Kirchhoff, “Robust prediction of punctuation and truecasing for medical asr,” arXiv preprint arXiv:2007.02025, 2020.

[10] Monica Sunkara, Srikanth Ronanki, Dhanush Bekal, Sravan Bodapati, and Katrin Kirchhoff, “Multimodal semi-supervised learning framework for punctuation prediction in conversational speech,” arXiv preprint arXiv:2008.00702, 2020.

[11] Peter Ebden and Richard Sproat, “The kestrel tts text normalization system,” Natural Language Engineering, vol. 21, no. 3, pp. 333–353, 2015.

[12] Courtney Mansfield, Ming Sun, Yuzong Liu, Ankur Gandhe, and Björn Hoffmeister, “Neural text normalization with subword units,” in Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 2 (Industry Papers), 2019, pp. 190–196.

[13] Junwei Liao, Yu Shi, Sefik Emre Eskimez, Liyang Lu, Ming Gong, Linjun Shou, Hong Qu, and Michael Zeng, “Improving readability for automatic speech recognition transcription,” in arXiv:2004.04438, April 2020.

[14] Raghavendra Pappagari, Piotr Żelasko, Agnieszka Mikolajczyk, Piotr Pężik, and Najim Dehak, “Joint prediction of truecasing and punctuation for conversational speech in low-resource scenarios,” in 2021 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU). IEEE, 2021, pp. 1185–1191.

[15] Qian Chen, Mengzhe Chen, Bo Li, and Wen Wang, “Controllable time-delay transformer for real-time punctuation prediction and disfluency detection,” in ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020, pp. 8069–8073.

[16] Elizabeth Shriberg, Rebecca Bates, and Andreas Stolcke, “A prosody only decision-tree model for disfluency detection,” in Fifth European Conference on Speech Communication and Technology, 1997.

[17] Xiaoyin Che, Cheng Wang, Haojin Yang, and Christoph Meinel, “Punctuation prediction for unsegmented transcript based on word vector,” in Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC’16), 2016, pp. 654–658.

[18] Vicky Zayats, Trang Tran, Richard Wright, Courtney Mansfield, and Mari Ostendorf, “Disfluencies and human speech transcription errors,” arXiv preprint arXiv:1904.04398, 2019.

[19] Aaron Gokaslan and Vanya Cohen, “Openwebtext corpus,” 2019.

[20] Pierre Lison and Jörg Tiedemann, “Opensubtitles2016: Extracting large parallel corpora from movie and tv subtitles,” European Language Resources Association, 2016.
[21] Jiazheng Li, Linyi Yang, Barry Smyth, and Ruihai Dong, “Maec: A multimodal aligned earnings conference call dataset for financial risk prediction,” in Proceedings of the 29th ACM International Conference on Information & Knowledge Management, 2020, pp. 3063–3070.

[22] John J Godfrey, Edward C Holliman, and Jane McDaniels, “Switchboard: Telephone speech corpus for research and development,” in Acoustics, Speech, and Signal Processing, IEEE International Conference on. IEEE Computer Society, 1992, vol. 1, pp. 517–520.

[23] Christopher Cieri, David Miller, and Kevin Walker, “The fisher corpus: A resource for the next generations of speech-to-text,” in LREC, 2004, vol. 4, pp. 69–71.

[24] Daniel Jurafsky, Elizabeth Shriberg, and Debra Biasca, “Switchboard SWBD-DAMSL shallow-discourse-function-annotation coders manual, draft 13,” Tech. Rep. 97-02, University of Colorado, Boulder Institute of Cognitive Science, Boulder, CO, 1997.

[25] Paria Jamshid Lou and Mark Johnson, “Improving disfluency detection by self-training a self-attentive model,” arXiv preprint arXiv:2004.05323, 2020.

[26] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova, “BERT: Pre-training of deep bidirectional transformers for language understanding,” in Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), Minneapolis, Minnesota, June 2019, pp. 4171–4186, Association for Computational Linguistics.

[27] Elizabeth Shriberg, Rebecca Bates, Paul Taylor, Andreas Stolcke, Daniel Jurafsky, Klaus Ries, Noah Coccaro, Rachel Martin, Marie Meteer, and Carol Van Ess-Dykema, “Can prosody aid the automatic classification of dialog acts in conversational speech?” Language and Speech, vol. 41, no. 3–4, pp. 439–487, 1998.

[28] Andreas Stolcke, Klaus Ries, Noah Coccaro, Elizabeth Shriberg, Rebecca Bates, Daniel Jurafsky, Paul Taylor, Rachel Martin, Marie Meteer, and Carol Van Ess-Dykema, “Dialogue act modeling for automatic tagging and recognition of conversational speech,” Computational Linguistics, vol. 26, no. 3, pp. 339–371, 2000.

[29] Karl Moritz Hermann, Tomas Kocisky, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom, “Teaching machines to read and comprehend,” Advances in neural information processing systems, vol. 28, 2015.

[30] Richard Sproat and Navdeep Jaitly, “Rnn approaches to text normalization: A challenge,” arXiv preprint arXiv:1611.00068, 2016.

[31] Graham Neubig, Yuya Akita, Shinsuke Mori, and Tatsuya Kawahara, “A monotonic statistical machine translation approach to speaking style transformation,” Computer Speech & Language, vol. 26, no. 5, pp. 349–370, 2012.

[32] Monica Sunkara, Chaitanya Shivade, Srvan Bodapati, and Katrin Kirchhoff, “Neural inverse text normalization,” in ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2021, pp. 7573–7577.

[33] Agustin Gravano, Martin Jansche, and Michiel Bacchiani, “Restoring punctuation and capitalization in transcribed speech,” in 2009 IEEE International Conference on Acoustics, Speech and Signal Processing. IEEE, 2009, pp. 4741–4744.

[34] Yang Liu, Elizabeth Shriberg, Andreas Stolcke, Dustin Hillard, Mari Ostendorf, and Mary Harper, “Enriching speech recognition with automatic detection of sentence boundaries and disfluencies,” IEEE Transactions on audio, speech, and language processing, vol. 14, no. 5, pp. 1526–1540, 2006.

[35] Jing Huang and Geoffrey Zweig, “Maximum entropy model for punctuation annotation from speech,” in Interspeech, 2002.

[36] Wei Lu and Hwee Tou Ng, “Better punctuation prediction with dynamic conditional random fields,” in Proceedings of the 2010 conference on empirical methods in natural language processing, 2010, pp. 177–186.

[37] Jiangyan Yi, Jianhua Tao, Zhengqi Wen, Ya Li, et al., “Distilling knowledge from an ensemble of models for punctuation prediction,” in Interspeech, 2017, pp. 2779–2783.

[38] Hao Zhang, You-Chi Cheng, Shankar Kumar, W Ronny Huang, Mingqing Chen, and Rajiv Mathews, “Capitalization normalization for language modeling with an accurate and efficient hierarchical rnn model,” in ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2022, pp. 6097–6101.

[39] Vicky Zayats, Mari Ostendorf, and Hannaneh Hajishirzi, “Disfluency detection using a bidirectional lstm,” arXiv preprint arXiv:1604.03209, 2016.

[40] Shaolei Wang, Wanxiang Che, and Ting Liu, “A neural attention model for disfluency detection,” in Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics, 2016, pp. 278–287.