Text normalization, or the process of transforming text into a consistent, canonical form, is crucial for speech applications such as text-to-speech synthesis (TTS). In TTS, the system must decide whether to verbalize "1995" as "nineteen ninety five" in "born in 1995" or as "one thousand nine hundred ninety five" in "page 1995". We present an experimental comparison of various Transformer-based sequence-to-sequence (seq2seq) models of text normalization for speech and evaluate them on a variety of datasets of written text aligned to its normalized spoken form. These models include variants of the 2-stage RNN-based tagging/seq2seq architecture introduced by [1], where we replace the RNN with a Transformer in one or more stages, as well as vanilla Transformers that output string representations of edit sequences. Of our approaches, using Transformers for sentence context encoding within the 2-stage model proved most effective, with the fine-tuned BERT encoder yielding the best performance.

Index Terms— text normalization, transformers

1. INTRODUCTION

Text normalization is a key component for a wide range of speech and language processing applications. However, depending on the particular application, the requirements for text normalization systems can vary greatly. We examine text normalization in the context of text-to-speech (TTS) synthesis, where written text is read aloud. In this scenario, numbers (e.g., 123), which might typically be mapped to some unified symbol for all numbers (e.g. N) during pre-processing, must instead be translated into their spoken form (e.g., one hundred twenty three) as part of the front-end of the TTS system. Numbers are just one instance of non-standard words [2] that have different pronunciations depending on the context. We can further categorize these non-standard words into semiotic classes [3], such as measures, dates, and URLs.

Early works on text normalization in speech were largely based on hard-coded rules [4, 5, 6] and later, a combination of hand-written grammars [7] and machine learning for specific semiotic classes: [8] for letter sequences, [9] for abbreviations, [10] for cardinals, and [11] for URLs. More recently, there has been increased interest in neural models due to their promise of better accuracy for less maintenance compared to grammars [12, 13, 14, 15, 16, 17].

[12] first presented a variety of RNN-based architectures for text normalization along with an open-sourced corpus of written text paired with its spoken form. A subsequent study [13] concentrated on the attention-based sequence-to-sequence (seq2seq) model based on [18] that outperformed the other models along with a finite-state transducer (FST)-based filter to mitigate the unrecoverable errors produced by the RNN alone (e.g., 50 ft → fifty inches). [1] further improved upon this work by presenting neural architectures with increased accuracy and efficiency and covering grammars largely learned from data.

Originally presented in the context of machine translation (MT), the Transformer [19] relies on attention mechanisms to eliminate recurrence entirely. The architecture consists of an encoder with self-attention and an auto-regressive decoder with self-attention that also attends to the encoder. While [1] reported worse sentence error rates with the full Transformer relative to their model, they sought to showcase the issues of treating text normalization as a pure MT task rather than evaluate the effectiveness of the architecture. Transformers have since been extended far beyond MT tasks, with both the encoder and decoder proving useful independently [20, 21, 22]. One especially salient example is BERT [20] which makes use of bidirectional pre-training for language representations using a masked language modeling objective function. These pre-trained BERT models have often been shown to improve numerous downstream tasks, including, but not limited to, question answering, text classification, and summarization.

We present a survey of several Transformer-based models of text normalization for speech and examine two separate datasets derived from English Wikipedia: Standard [12] data mined in 2016, run through the Google TTS Kestrel text normalization system [7], and released on GitHub [1] and Manual annotated data mined from Wikipedia that was sent to human raters for manual annotation. We describe our models in Section 2 and present training and evaluation results in Section 3.

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2. MODELS

2.1. Single-pass models

In this section, we explore vanilla seq2seq Transformers as proposed by [19] that can be trained with normal cross-entropy loss and used with standard single-pass beam search. Our first baseline maps the character sequence of the full input sentence to its verbalization (a mix of characters and full words for normalized input), i.e. Source to Target (full) in Table 1. To avoid the need for copying unchanged characters, we also experiment with an edit-based representation that uses special pos* tokens to identify spans in the source sequence, shown as Target (edits) in Table 1. In this example, the tokens pos10 and pos13 denote the replacement from the 10th-13th character in the input with one twenty three. This pattern can be repeated in the output sequence to represent non-contiguous replacements. If we assume that the tokenization is known (Table 2), we can use the pos* position tokens in the input to denote token boundaries in the source sequence. The seq2seq model that also outputs pos* markers at token boundaries (Target (full) in Table 2) can use this information to keep track of the alignment between source and target. Edit-based output representations for tokenized inputs are simpler because the character span to replace can be identified by a single token index (e.g. pos3 in the Target (edits) example in Table 2) rather than a pair of

Table 1. Untokenized single-pass representations.

| Source | Target (full) | Target (edits) |
|--------|---------------|---------------|
| I live | I live one twenty three King Avenue | pos10 one twenty three pos13 pos15 Avenue pos22 |

Table 2. Tokenized single-pass representations.

| Source | Target (full) | Target (edits) |
|--------|---------------|---------------|
| I live | I live one twenty three King Avenue | pos3 one twenty three pos5 Avenue |

Fig. 1. Two stage model from [1]
Test SER %

| System                      | Standard | Manual |
|-----------------------------|----------|--------|
| [1]                         | 2.2%     | −      |
| [1]∗                        | 1.80     | −      |
| [23]                        | 1.36     | −      |
| Untokenized single-pass (full) | 2.32    | 7.55   |
| Untokenized single-pass (edits) | 2.12    | 8.00   |
| Tokenized single-pass (full)∗ | 2.00    | 6.16   |
| Tokenized single-pass (edits)∗ | 2.04    | 5.65   |
| RNN (base)                  | 1.99     | 7.18   |
| RNN (large)                 | 2.15     | 8.09   |
| Transformer encoder         | 1.73     | 6.49   |
| Transformer encoder (seq2seq) | 2.15    | 7.40   |
| BERT (fine-tune)            | 1.42     | 5.59   |
| BERT (freeze)               | 2.68     | 7.96   |

Table 3. Test sentence error rates for each dataset. * requires golden tokenized input.

2.2. Stacked tagging and contextual models

The best RNN-based models reported by [1] use a 2-stage neural architecture (Figure 1) specialized for text normalization. The model is trained with a multi-task objective and tokenization levels differ across various stages. In this section, we present a series of modifications to the 2-stage architecture. The first stage, *semiotic class tokenization*, jointly segments and coarsely classifies tokens as trivial (<self>), silent (sil), or non-trivial (NT). In the second stage, a seq2seq model predicts the normalization for non-trivial tokens. Below, we focus on the sentence context encoder because both stages share its hidden states.

- **RNN (base)** 2-stage multi-task model from [1].
- **RNN (large)** increases the size of RNN for a more fair comparison against Transformers by adding layers to the sentence context encoder.

**Transformer encoder** replaces the sentence context encoder (block labeled "BiRNN" for bidirectional RNN in Figure 1) with the base Transformer encoder. This can potentially enhance the semiotic class tokenization by using long-term context which is not handled as well by recurrent models.

**Transformer encoder (seq2seq)** replaces the seq2seq encoder for token verbalization with the base Transformer encoder as a comparison point.

**BERT (fine-tune)** replaces the sentence context encoder with a pre-trained BERT word-piece [24, 25] model. Given the effectiveness of fine-tuning BERT for down-stream tasks [20], it could also improve text normalization.

**BERT (freeze)** matches the previous but freezes the pre-trained model as freezing has been shown to accelerate training and potentially be more stable than fine-tuning [26, 27].

Table 4 provides a more detailed breakdown of the improvements obtained using BERT. We find that mistakes in the first stage semiotic class tokenization (i.e. classifying trivial as non-trivial and vice-versa) account for a majority of the

| System              | Test SER % |
|---------------------|------------|
| RNN (base)          |            |
| base                | 1.99       | 7.18      |
| +golden             | 0.77       | 2.74      |
| BERT (fine-tune)    |            |
| base                | 1.42       | 5.59      |
| +golden             | 0.69       | 2.59      |

Table 4. Test sentence error rates for the 2-stage models with ("+golden") and without ("base") the golden semiotic class tokenization.

3. RESULTS

Table 3 reports sentence error rates (SER) for each model and dataset. Comparing our models and the original 2-stage model from [1], we find that using Transformers in sentence context encoding is most effective, with the BERT (fine-tune) yielding the best performance. This could be because the model is able to leverage the underlying language representations from BERT to focus more on the interesting, non-trivial cases compared to training from scratch, especially when the training data size is as small as it is here. The single-pass models are less robust to the small training data size because not all position tokens pos* are seen often enough in training data to learn reliably. While our models fall slightly short of the performance obtained by the sequence editing approach from [23], our focus is primarily on comparing various Transformer models for text normalization and less on surpassing the state-of-the-art.

Table 4 provides a more detailed breakdown of the improvements obtained using BERT. We find that mistakes in the first stage semiotic class tokenization (i.e. classifying trivial as non-trivial and vice-versa) account for a majority of the
Table 5. Standard dataset side-by-side of RNN (base) and BERT (fine-tune). [ ] marks the target token in context. The top section lists examples corrected by BERT (fine-tune), the middle, uncorrected errors, and the bottom, mistakes in the reference.

| Input               | Reference       | RNN (base)  | BERT (fine-tune) |
|---------------------|-----------------|-------------|-----------------|
| [AAUS]              | a a u s         | aaus        | a a u s         |
| July [93]           | ninety three    | ninety third| ninety three    |
| Final Fantasy [X]   | ten             | x           | ten             |
| [CHARLES]           | charles         | c h a r l e s| charles         |
| chief [ideologue]   | ideologue       | homolog     | homolog         |
| [7/8] inch          | seven eighths   | one dollar  | five eighth     |
| [TIME] Magazine     | t i m e         | time        | time            |
| Cha Seung [pyo’s]   | p y o’s         | pyo’s       | pyo’s           |

errors. Given the golden semiotic class tokenization, the error rate is reduced by 61% for RNN (base). After applying BERT, we see reductions in both the error rates and the gap between them. This observation is further supported when we examine the actual improvements and errors.

Table 5 provides a side-by-side comparing the 2-stage models. Given the input AAUS, RNN (base) incorrectly predicts trivial, resulting in aaus, whereas BERT (fine-tune) correctly predicts non-trivial, resulting in a letter sequence a a u s. On the other hand, both models misclassify ideologue as non-trivial possibly due to normalized British English training examples, such as analogue → analog, resulting in the unrecoverable homolog. While this unrecoverable error is a result of trivial / non-trivial misclassification, it is worth mentioning that these mistakes are possible even with the correct classification: e.g. 7/8 inch → five eighth inch.

While the above examples are genuine errors, the Standard dataset is also known to contain reference errors [12] because it was automatically generated with Google’s Kestrel text normalization system [7]: TIME magazine → t i m e magazine. It may be tempting to view manual annotation as the solution, but even with human raters, mistakes still occur and can be harder to track down due to rater inconsistency: given UEFA Champions League, some raters may provide uefa champions league, while others provide u e f a champions league.

4. CONCLUSION

We presented a survey of Transformer-based models for text normalization for speech and evaluated their performance on different datasets, with our BERT fine-tuning approach yielding the most improvement. While we did achieve good overall accuracy, we also showed that our approaches are still vulnerable to unrecoverable errors. We hope that our work inspires more investigation into text normalization for speech and provides additional evidence that simply switching architectures, using pre-training recipes, or adding labeled data will not completely solve the text normalization problem.

5. REFERENCES

[1] Hao Zhang, Richard Sproat, Axel H. Ng, Felix Stahlberg, Xiaochang Peng, Kyle Gorman, and Brian Roark, “Neural models of text normalization for speech applications,” Computational Linguistics, vol. 45, no. 2, pp. 293–337, June 2019.

[2] Richard Sproat, Alan W. Black, Stanley Chen, Shankar Kumar, Mari Ostendorf, and Christopher Richards, “Normalization of non-standard words,” Computer Speech & Language, vol. 15, no. 3, pp. 287–333, 2001.

[3] Paul Taylor, Text-to-Speech Synthesis, Cambridge University Press, 2009.

[4] Jonathan Allen, Sharon M. Hunnicutt, and Dennis Klatt, From Text to Speech: The MITalk system, Cambridge Studies in Speech Science and Communication. Cambridge University Press, 1987.

[5] Richard Sproat, “Multilingual text analysis for text-to-speech synthesis,” Natural Language Engineering, vol. 2, no. 4, pp. 369–380, 1996.

[6] Richard Sproat, Multilingual Text-to-Speech Synthesis: The Bell Labs Approach, Springer US, 1997.

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

[8] Richard Sproat and Keith B. Hall, “Applications of maximum entropy rankers to problems in spoken language processing,” in INTERSPEECH, 2014.

[9] Brian Roark and Richard Sproat, “Hippocratic abbreviation expansion,” in ACL, Baltimore, Maryland, June 2014, pp. 364–369, ACL.
[10] Kyle Gorman and Richard Sproat, “Minimally supervised number normalization,” *Transactions of the Association for Computational Linguistics*, vol. 4, pp. 507–519, 2016.

[11] Hao Zhang, Jae Ro, and Richard Sproat, “Semi-supervised URL segmentation with recurrent neural networks pre-trained on knowledge graph entities,” in *COLING*, Barcelona, Spain (Online), 2020, pp. 4667–4675, International Committee on Computational Linguistics.

[12] Richard Sproat and Navdeep Jaitly, “RNN approaches to text normalization: A challenge,” 2016.

[13] Richard Sproat and Navdeep Jaitly, “An RNN model of text normalization,” in *INTERSPEECH*, 2017.

[14] Sevinj Yolchuyeva, Géza Németh, and Bálint Gyires-Tóth, “Text normalization with convolutional neural networks,” *Int. J. Speech Technol.*, vol. 21, no. 3, pp. 589–600, 2018.

[15] Courtney Mansfield, Ming Sun, Yuzong Liu, Ankur Gandhe, and Björn Hoffmeister, “Neural text normalization with subword units,” in *NAACL*, Minneapolis, Minnesota, 2019, pp. 190–196, ACL.

[16] Alistair Conkie and Andrew M. Finch, “Scalable multilingual frontend for TTS,” in *ICASSP*. 2020, pp. 6684–6688, IEEE.

[17] Shubhi Tyagi, Antonio Bonafonte, Jaime Lorenzo-Trueba, and Javier Latorre, “Proteno: Text normalization with limited data for fast deployment in text to speech systems,” in *NAACL*, Online, June 2021, pp. 72–79, Association for Computational Linguistics.

[18] William Chan, Navdeep Jaitly, Quoc Le, and Oriol Vinyals, “Listen, attend and spell: A neural network for large vocabulary conversational speech recognition,” in *ICASSP*, 2016, pp. 4960–4964.

[19] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin, “Attention is all you need,” in *Advances in Neural Information Processing Systems*, I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, Eds. 2017, vol. 30, Curran Associates, Inc.

[20] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova, “BERT: Pre-training of deep bidirectional transformers for language understanding,” in *NAACL*, Minneapolis, Minnesota, June 2019, pp. 4171–4186, ACL.

[21] Alec Radford and Karthik Narasimhan, “Improving language understanding by generative pre-training,” 2018, Technical report, OpenAI.

[22] Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei, “Language models are few-shot learners,” *CoRR*, vol. abs/2005.14165, 2020.

[23] Felix Stahlberg and Shankar Kumar, “Seq2Edits: Sequence transduction using span-level edit operations,” in *EMNLP*, Online, Nov. 2020, pp. 5147–5159, ACL.

[24] Rico Sennrich, Barry Haddow, and Alexandra Birch, “Neural machine translation of rare words with subword units,” in *ACL*, Berlin, Germany, Aug. 2016, pp. 1715–1725, ACL.

[25] Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V. Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, Jeff Klingner, Apurva Shah, Melvin Johnson, Xiaobing Liu, Łukasz Kaiser, Stephan Gouws, Yoshikiyo Kato, Taku Kudo, Hideto Kazawa, Keith Stevens, George Kurian, Nishant Patil, Wei Wang, Cliff Young, Jason Smith, Jason Riesa, Alex Rudnick, Oriol Vinyals, Greg Corrado, Macduff Hughes, and Jeffrey Dean, “Google’s neural machine translation system: Bridging the gap between human and machine translation,” *CoRR*, vol. abs/1609.08144, 2016.

[26] Marius Mosbach, Maksym Andriushchenko, and Dietrich Klakow, “On the stability of fine-tuning BERT: Misconceptions, explanations, and strong baselines,” in *ICLR*, 2021.

[27] Jaejun Lee, Raphael Tang, and Jimmy Lin, “What would else do? freezing layers during transformer fine-tuning,” 2019.