Investigations on Phoneme-Based End-To-End Speech Recognition

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Abstract
Common end-to-end models like CTC or encoder-decoder-attention models use characters or subword units like BPE as the output labels. We do systematic comparisons between grapheme-based and phoneme-based output labels. These can be single phonemes without context (≈ 40 labels), or multiple phonemes together in one output label, such that we get phoneme-based subwords. For this purpose, we introduce phoneme-based BPE labels. In further experiments, we extend the phoneme set by auxiliary units to be able to discriminate homophones (different words with same pronunciation). This enables a very simple and efficient decoding algorithm. We perform the experiments on Switchboard 300h and we can show that our phoneme-based models are competitive to the grapheme-based models.

Index Terms: end-to-end speech recognition, attention, phonemes

1. Introduction
End-to-end models such as attention-based encoder-decoder models [1–3] have shown competitive performance for speech recognition while being relatively simple [4–9]. Other similar simple models are connectionist temporal classification (CTC) models [10–13] or recurrent neural network (RNN) transducer (RNN-T) [14–19]. In all cases, these models usually operate on

- graphemes (characters),
- subword units (byte-pair encoding (BPE)) [6, 20, 21],
- WordPieces / word piece model (WPM) [7, 22, 23], uni-gram language model (LM) based segmentation [24, 25], or pronunciation-based segmentation [26])
- or whole words [27–32].

Graphemes and subwords have the advantage of allowing out-of-vocabulary words and simplicity because no pronunciation lexicon is needed. End-to-end models usually do not operate on phonemes.

Hybrid hidden Markov model (HMM) - neural network (NN) models [33, 34] usually operate on context-dependent phoneme classes [35, 36], although it has been shown that they can also work on context-dependent grapheme classes [37–40]. As these are too much labels, they are usually clustered via classification and regression trees (CART) [41, 42].

Here we make a tradeoff between a bit of the simplicity towards greater flexibility and controlability of the pronunciation lexicon. Having an explicit pronunciation lexicon allows to easily adapt some pronunciation, or extend by new words with new uncommon pronunciations. This is a common problem for grapheme or subword based models in case of uncommon pronunciations [43].

All the typical end-to-end models like attention models easily allow for phoneme-based labels as well, although in most cases that requires a more complex decoder, and obviously a lexicon. Usually a weighted finite state transducer (WFST) decoder is used [44]. Phoneme-based CTC models (context-independent or clustered context-dependent) [30,45,46] usually perform better than grapheme-based CTC models, just as hybrid HMM-NN models. Phoneme-based encoder-decoder-attention models [44, 47–50] have shown mixed results so far – in most cases the performance was slightly worse than grapheme-based attention models, or only the combination of both helped. More recently also phoneme-based RNN-T-like models [51, 52] were studied, although it’s unclear whether pure phoneme-based RNN-T models perform better than pure grapheme-based models.

Subwords based on phonemes, like phoneme-BPE, was only studied so far by [49], which is a hybrid CTC / attention model [53]. They use multiple LMs in decoding: a phoneme-BPE LM and word LM.

2. A variation of label units
We want to study the difference between phonemes, graphemes and whole words. In this work, we focus on attention-based encoder-decoder models. We note that the results of such label unit study will likely look different depending on the type of model. E.g. maybe the optimal label unit for hybrid HMM-NN or CTC models are phonemes, while the optimal label unit for label-synchronous models are subwords. For hybrid HMM-NN or CTC models, we also know that clustered context-dependendent labels help a lot [40,42]. For models with label feedback, such as RNN-T and encoder-decoder, we don’t need to have the context encoded in the label, as the model already covers the (left) context. We also note that subwords and words can possibly have huge variations in their observed audio lengths, which might be less of a problem for label-synchronous models but more a problem for time-synchronous models. Hybrid HMM-NN models also usually split the context-dependent phonemes into multiple states (usually 3 states – except for silence or some noise tokens, which have a single state). As we perform the experiments with an attention-based encoder-decoder model which is label-synchronous and auto-regressive, we also have the end-of-sentence (EOS) token in our vocabulary. In case of a time-synchronous model, we possibly would add a blank label (like for CTC or RNN-T), or maybe repetition symbols (as in the Auto Segmentation Criterion (ASG) [54]), or silence label (for hybrid HMM-NN models). It also might make sense to add noise or unknown labels (e.g. as in [44]).

The label units and types which we are going to study are:

- Phonemes
– Single phonemes (monophones; without context)
– Phoneme-BPE

Variations:
– extra end-of-word (EOW) symbol (for single phonemes)
– extra word-disambiguate symbols
  • Graphemes (characters)
    – Single character (without context)
    – Char-BPE
  • Whole words

Phoneme-BPE is simply the application of BPE on phoneme sequences. We generate the phoneme BPE codes by taking a single pronunciation for each word (the most likely as defined by the lexicon) for all the transcriptions. The same phoneme sequence is also used for training. The end-of-word (EOW) symbol for phonemes is similar as white-space character for grapheme/char. based models, which is standard in that case. Others [44, 47] have observed that the EOW symbol can be helpful for phoneme models.

A phoneme-based model (no matter whether these are single phonemes or subwords) cannot be used as is for recognition. In any case, we need a lexicon for the mapping of phonemes to words. But then there are cases where a phoneme sequences can map to multiple possible words. E.g. the word "T" and "eye" both have the same pronunciation consisting of the phoneme sequence "ay". This is called a homophone. To be able to discriminate between "T" and "eye", usually an external language model on word-level is used. Alternatively, we can also add special word-disambiguate symbols to the labels (the phoneme inventory), in such a way that we can always uniquely discriminate between all words. These symbols are not real phonemes – they are just extra symbols, just like EOW. We go through the pronunciation lexicon and collect all phoneme sequences which can not be uniquely mapped to words. For all these phoneme sequences, we add special symbols #1 to #N. For example:

• ... 
• ay #8 → eye 
• ay #9 → eye-
• ay #10 → 1
• ...
• r eh d #2 → read
• r eh d #3 → red
• r eh d #4 → redd
• ...

These word-disambiguate symbols allow for decoding without an external language model, and also allows us to use our simple decoder implementation. It also might improve the performance as the model now has the power to discriminate between words. Note that this scheme of adding these symbols does not allow for an easy extension of the lexicon for further homophones after we trained the model.

Also in the case of graphemes, we could restrict the search to words in a vocabulary, which might improve the performance in certain cases [13]. In the case of BPE (either phoneme or grapheme), we can also restrict the search to BPE splits seen during training, which might reduce unexpected behavior of the decoder, but which might also decrease the performance.

3. Model

Our model is an attention-based encoder-decoder model [4, 5]. Our encoder consists of 6 layers of bidirectional long short-term memory (LSTM) [55] networks with intermediate time-downsampling via max-pooling by factor 6. Our decoder is a single layer LSTM network with standard global MLP attention. We use SpecAugment [7] for simple on-the-fly data augmentation. For further details, please refer to our earlier work [6, 8], which is exactly the same model, except for the variations of the output label.

3.1. Training

In all cases, we minimize the negative log-likelihood

\[ L := \sum_{(x^1, y^N) \in D} -\log p(y^N | x^1), \]

which is the standard cross entropy loss, for target sequences \( y^N \) and input feature sequences \( x^1 \) from the training dataset \( D \). We always have a single ground-truth target sequence. In the case of phonemes, we reduce the lexicon to contain only a single pronunciation per word, and thus this becomes unique. This is a simplification, which we only do for training, not for decoding. We could also marginalize over all possible pronunciations in training, but that would make it much more complicated, and this is also not possible to do efficiently without approximations such as the maximum approximation. We train with stochastic gradient descent (SGD) and the Adam optimizer [56]. We do pretraining by starting with a two layer encoder and smaller dimensions, and then we grow the encoder in width (dimensions) and depth (number of layers) [57]. Our hyper parameters and training details all follow exactly our earlier work [6, 8].

3.2. Decoding

Our simple decoder performs the standard beam search over the labels with a fixed beam size (e.g. 12 hypotheses) without any restrictions (i.e. it allows any possible label sequence). The simple decoder would allow for log-linear combination with a language model on the same label-level (e.g. phone-BPE) but not with word-level LM when we use phone-BPE labels. After we found a label sequence with this simple beam search, we map it to words. In case of BPE, we first do BPE merging. In case of phonemes with word-disambiguate symbols, we try to lookup the corresponding word (which should be unique because of the word-disambiguate symbols), or replace by some UNK symbol if not found. That way, we eventually end up with a sequence of words.

Our advanced decoder performs prefix-tree search based on a lexicon. This lexicon defines the mapping between words and corresponding phoneme or grapheme label sequences. The resulting lexical tree restricts the search to possible label sequences from the lexicon. It also allows log-linear combination with a word-level LM. The LM score is applied to a hypothesized path whenever it reaches a word-end. Optionally, LM lookahead can also be applied to incorporate the LM score into the tree for a more robust search. The standard beam pruning using a fixed beam size is applied at each search step. Finally, the decoded best path directly gives the recognized word sequence.
Table 1: On Switchboard 300h, comparing phoneme and grapheme and whole word models. Using simple decoding, using beam size 12. All phoneme models here have word-disambiguate symbols. Phoneme single is with end-of-word (EOW) symbol. Grapheme single is with whitespaces, which is like a EOW symbol. All results are without language model.

Table 2: On Switchboard 300h, comparing decoding. All phoneme models here have word-disambiguate symbols. Phoneme single is with end-of-word (EOW) symbol. Grapheme single is with whitespaces, which is like a EOW symbol. The optional LSTM LM is on word-level. The advanced decoder is also restricted on the lexicon, and more specifically the unique greedy BPE-split.

4. Experiments

We use RETURNN [58] as the training framework, which builds upon TensorFlow [59]. The advanced decoder is implemented as part of RASR [60], while the simple decoder is implemented in pure TensorFlow within RETURNN. All our config files and code to reproduce these experiments can be found online\(^1\). All our experiments are performed on the Switchboard 300h English telephone speech corpus [61]. We collect our experiments with our simple decoder in Table 1. The simple decoder can only produce reasonable results if the label units allow for word disambiguations, such as in the case of graphemes, but also for phonemes with added word-disambiguate symbols. We find that BPE subwords perform much better than single units, both for phonemes and graphemes, and also better than whole words. We also find that a BPE-500 seems to perform best. Note that BPE-500 results in 592 phoneme classes, or 534 grapheme classes.

For all further experiments, we need to use our advanced decoder, which allows for a word-level LM. It also restricts the search to only label sequences which occur in the lexicon, including only the BPE-splits seen during training, in contrast to the simple decoder, which does not have this restriction. We studied the effect of the different decoder in Table 2. We see that in the case of single phone or grapheme labels, i.e. where we have a weaker model, the restriction on the lexicon by the advanced decoder is helpful, while it is hurtful for the BPE variants, esp. in the case of phoneme-BPE. We also see the effect of the external LM combination, which is helpful (as expected).

We study the effect of the word-disambiguate symbols for phoneme-based models in Table 3. We find that the word-disambiguate symbols seems to be hurtful. We are still careful in drawing conclusions from this, as this might be due to the specific variant of how we added the word-disambiguate symbols.

We also study the effect of the end-of-word (EOW) symbol for single phoneme labels and collect the results in Table 4. We see that without EOW symbol, the model cannot disambiguate words and the decoding does not work at all without LM. However, together with a LM, the EOW symbol seems to hurt slightly. This is inconsistent to what was reported earlier [44,47], so this might just be an artifact (but this might not be so important after all).

Finally, we compare our results to other results from the literature in Table 5. We observe that many other works train for much longer, and that seems to lead to yet better results. Our final phoneme-based models perform slightly better than our final grapheme-based models, although they are very close.

5. Conclusions

We compared phoneme-based labels vs. grapheme-based labels for attention-based encoder-decoder models and found their performance to be very similar – the phoneme-based models are maybe slightly better. We also compared single units vs. subword (BPE) units vs. whole words, and found that subword units are best, both for phonemes and graphemes. While this was already well-known for grapheme-based models, this is a new observation for phoneme-based models.

As mentioned, this result is probably dependent on the type of model, which is an attention-based encoder-decoder model

\(^1\)https://github.com/rech-ls/returnx-experiments/tree/master/2020-phone-bpe-attn
Table 3: On Switchboard 300h, studying word-disambiguate symbols, comparing different phone variants. All with beam size 32, word-level LSTM LM, and the advanced decoder.

| Phoneme Type | #Num | Labels | Disamb. | SWB | Hub5’00 |
|--------------|------|--------|---------|-----|---------|
| Single       | 62   | Yes    | 23.7    | 31.5 | 27.7    |
| BPE          | 592  | Yes    | 9.5     | 21.3 | 15.4    |

Table 4: On Switchboard 300h, WER on Hub 5’00. Comparing end-of-word (EOW) for single phonemes, without word-disambiguate symbols, with and without LM. All with beam size 32. In case of no LM, when there are multiple words corresponding to the same phone sequence, the decoder will just pick the first (alphabetically).

| Work | Unit | Type | #Ep | LM | WER [%] | Hub500 | Hub500RT |
|------|------|------|-----|----|---------|--------|---------|
| [56] Phon. | CART | 4Sk | 13 | yes | 9.6  | 18.5 | 14.0 |
| [8] Graph. | BPE  | 1k  | 33 | no  | 10.1 | 20.6 | 15.4 |
| [62] Phon. | 4K  | 5k  | no | 8.8 | 17.2 | 13.0 |
| [63] Phon. | 2K  | 10k | yes | 9.0 | 18.1 | 13.6 |
| [49] Phon. | 500 | 150 | yes | 7.9 | 16.1 | 14.0 |
| [9] Graph. | 600 | 250 | no  | 7.6 | 14.6 |       |
| [7] Phon. | 1K  | 760 | no  | 7.2 | 14.0 |       |

Table 5: On Switchboard 300h, comparing results from the literature. One big difference in varying results is the different amount of training time, which we state as number of epochs. *with word-disambiguate symbols.

| Work | Label | Unit | Type | #Ep | LM | WER [%] | Hub500 | Hub500RT |
|------|-------|------|------|-----|----|---------|--------|---------|
| [56] | Phon. | CART | 4Sk | 13 | yes | 9.6  | 18.5 | 14.0 |
| [8]  | Graph. | BPE  | 1k  | 33 | no  | 10.1 | 20.6 | 15.4 |
| [62] | Phon. | 4K  | 5k  | no | 8.8 | 17.2 | 13.0 |
| [63] | Phon. | 2K  | 10k | yes | 9.0 | 18.1 | 13.6 |
| [49] | Phon. | 500 | 150 | yes | 7.9 | 16.1 | 14.0 |
| [9]  | Graph. | 600 | 250 | no | 7.6 | 14.6 |       |
| [7]  | Phon. | 1K  | 760 | no | 7.2 | 14.0 |       |

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7. References

[1] I. Sutskever, O. Vinyals, and Q. V. Le, “Sequence to sequence learning with neural networks,” in Advances in neural information processing systems, 2014, pp. 3104–3112.
[2] D. Bahdanau, K. Cho, and Y. Bengio, “Neural machine translation by jointly learning to align and translate,” in 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings, 2015. [Online]. Available: http://arxiv.org/abs/1409.0473
[3] M.-T. Luong, H. Pham, and C. D. Manning, “Effective approaches to attention-based neural machine translation,” Preprint arXiv:1508.04025, 2015.
[4] J. K. Chorowski, D. Bahdanau, D. Serdyuk, K. Cho, and Y. Bengio, “Attention-based models for speech recognition,” in Advances in neural information processing systems, 2015, pp. 577–585.
[5] W. Chan, N. Jaitly, Q. V. Le, and O. Vinyals, “Listen, attend and spell: A neural network for large vocabulary conversational speech recognition,” in ICASSP, 2016. [Online]. Available: http://williamchan.ca/papers/wchan-icassp-2016.pdf
[6] A. Zeyer, K. Irie, R. Schlüter, and H. Ney, “Improved training of end-of-end attention models for speech recognition,” in InterSpeech, Hyderabad, India, Sep. 2018.
[7] D. S. Park, W. Chan, Y. Zhang, C.-C. Chiu, B. Zoph, E. D. Cubuk, and Q. V. Le, “SpecAugment: A simple data augmentation method for automatic speech recognition,” in Proc. Interspeech 2019, 2019, pp. 2613–2617.
[8] A. Zeyer, P. Bahar, K. Irie, R. Schlüter, and H. Ney, “A comparison of Transformer and LSTM encoder decoder models for ASR,” in IEEE Automatic Speech Recognition and Understanding Workshop, Sentosa, Singapore, Dec. 2019, pp. 8–15.
[9] Z. Tüße, G. Saon, K. Audhkhasi, and B. Kingsbury, “Single headed attention based sequence-to-sequence model for state-of-the-art results on switchboard-300,” Preprint arXiv:2001.07263, 2020.
[10] A. Graves, S. Fernández, F. Gomez, and J. Schmidhuber, “Connectionist temporal classification: labelling unsegmented sequence data with recurrent neural networks,” in Proceedings of the 23rd international conference on Machine learning. ACM, 2006, pp. 369–376.
[11] Y. Miao, M. Gowayyed, and F. Metze, “EESEN: End-to-end speech recognition using deep RNN models and WFST-based decoding,” in 2015 IEEE Workshop on Automatic Speech Recognition and Understanding (ASRU). IEEE, 2015, pp. 167–174.
[12] D. Amodei, R. Anubhai, E. Battenberg, C. Case, B. Catanazzo, J. Chen, M. Chrzanowski, A. Coates, G. Diamos et al., “Deep speech 2: End-to-end speech recognition in english and mandarin,” arXiv preprint arXiv:1512.02595, 2015.
[13] G. Zweig, C. Yu, J. Droppo, and A. Stolcke, “Advances in all-neural speech recognition,” in ICASSP. IEEE, 2017, pp. 4805–4809.
[14] A. Graves, “Sequence transduction with recurrent neural networks,” Preprint arXiv:1211.3711, 2012.
[15] R. Prabhavalkar, K. Rao, T. N. Sainath, B. Li, L. Johnson, and N. Jaitly, “A comparison of sequence-to-sequence models for speech recognition,” in Interspeech, 2017, pp. 939–943.
[16] K. Rao, H. Sak, and R. Prabhavalkar, “Exploring architectures, data and units for streaming end-to-end speech recognition with RNN-transducer,” in ASRU. IEEE, 2017, pp. 193–199.
[17] M. Jain, K. Schubert, J. Mahadeokar, C.-F. Yeh, K. Kalgaonkar, A. Sriram, C. Fuegen, and M. L. Seltzer, “RNN-T for large vocabulary connected speech recognition with improved beam search,” Preprint arXiv:1911.01629, 2019.
[18] J. Li, R. Zhao, H. Hu, and Y. Gong, “Improving RNN transducer modeling for end-to-end speech recognition,” Preprint arXiv:1909.12415, 2019.
[19] W. Han, Z. Zhang, Y. Zhang, J. Yu, C.-C. Chiu, J. Qin, A. Gulati, R. Pang, and Y. Wu, “ContextNet: Improving convolutional neural networks for automatic speech recognition with global context,” Preprint arXiv:2005.03191, 2020.
