Exact Hard Monotonic Attention for Character-Level Transduction

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Abstract

Many common character-level, string-to-string transduction tasks, e.g., grapheme-to-phoneme conversion and morphological inflection, consist almost exclusively of monotonic transductions. However, neural sequence-to-sequence models that use non-monotonic soft attention often outperform popular monotonic models. In this work, we ask the following question: Is monotonicity really a helpful inductive bias for these tasks? We develop a hard attention sequence-to-sequence model that enforces strict monotonicity and learns a latent alignment jointly while learning to transduce. With the help of dynamic programming, we are able to compute the exact marginalization over all monotonic alignments. Our models achieve state-of-the-art performance on morphological inflection. Furthermore, we find strong performance on two other character-level transduction tasks. Code is available at \url{https://github.com/shijie-wu/neural-transducer}.

1 Introduction

Many tasks in natural language processing can be treated as character-level, string-to-string transduction. The current dominant method is the neural sequence-to-sequence model with soft attention (Bahdanau et al., 2015; Luong et al., 2015). This method has achieved state-of-the-art results in a plethora of tasks, for example, grapheme-to-phoneme conversion (Yao and Zweig, 2015), named-entity transliteration (Rosca and Breuel, 2016) and morphological inflection generation (Cotterell et al., 2016). While soft attention is very similar to a traditional alignment between the source characters and target characters in some regards, it does not explicitly model a distribution over alignments. On the other hand, neural sequence-to-sequence models with hard attention are non-monotonic. However, if we look at the data in grapheme-to-phoneme conversion, named-entity transliteration, and morphological inflection (examples are shown in Fig. 1), we see that the tasks require almost exclusively monotonic transduction. Yet, counterintuitively, the state of the art in high-resource morphological inflection is held by non-monotonic models (Cotterell et al., 2017)! Indeed, in a recent controlled experiment, Wu et al. (2018) found non-monotonic models (with either soft or hard attention) outperform popular monotonic models (Aharoni and Goldberg, 2017) in the three above-mentioned tasks. However, the inductive bias of monotonicity, if correct, should help learn a better model or, at least, learn the same model.

In this paper, we hypothesize that the underperformance of monotonic models stems from the lack of joint training of the alignments with the transduction. Generalizing the model of Wu et al. (2018) to enforce monotonic alignments, we show that, for all three tasks considered, monotonicity is a good inductive bias and jointly learning a monotonic alignment improves performance. We provide an exact, cubic-time dynamic-programming inference algorithm to compute the log-likelihood and an approximate greedy decoding scheme. Empirically, our results indicate that, rather than the pipeline systems of Aharoni and Goldberg (2017) and Makarov et al. (2017), we should jointly train monotonic alignments with the transduction model, and, indeed, we set the single-model state of the art on the task of morphological inflection.\footnote{The current state of the art for morphological inflection is held by ensemble systems like parsing and other structured prediction tasks. We present the new best individual system.}

2 Hard Attention

2.1 Preliminary

We assume the source string \(x \in \Sigma^*_x\) and the target string \(y \in \Sigma^*_y\) are drawn from finite vocabularies \(\Sigma_x = \{x_1, \ldots, x|\Sigma_x|\}\) and \(\Sigma_y = \{y_1, \ldots, y|\Sigma_y|\}\), respectively. In tasks where the tag is provided, i.e., labeled transduction (Zhou and Neubig, 2017),
where we denote the tag as an ordered set \( t \in \Sigma_t \) drawn from a finite tag vocabulary \( \Sigma_t = \{ t_1, \ldots, t_{|\Sigma_t|} \} \). We define the set \( \mathcal{A} = \{ 1, \ldots, |x| \}^{|y|} \) to be set of all non-monotonic alignments from \( x \) to \( y \) where an alignment aligns each target character \( y_i \) to exactly one source character in \( x \). In other words, it allows zero-to-one\(^3\) or many-to-one alignments between \( x \) and \( y \). For an \( a \in \mathcal{A} \), \( A_i = a_i \) refers to the event that \( y_i \) is aligned to \( x_{a_i} \), which are the \( i^{\text{th}} \) character of \( y \) and the \( i^{\text{th}} \) character of \( x \), respectively. In general, we will shorten the expression \( A_i = a_i \) to \( a \) for brevity.

### 2.2 0\(^{\text{th}}\)-order Hard Attention

Hard attention was first introduced to the literature by Xu et al. (2015). We, however, follow Wu et al. (2018) and use a tractable variant of hard attention and model the probability of a target string \( y \) given an input string \( x \) as follows

\[
p(y \mid x) = \sum_{a \in \mathcal{A}} p(y, a \mid x)
\]

\[
= \sum_{a \in \mathcal{A}} \prod_{i=1}^{|y|} p(y_i \mid a_i, y_{<i}, x) p(a_i \mid y_{<i}, x)
\]

\[
= \prod_{i=1}^{|y|} \sum_{a_i=1}^{|x|} p(y_i \mid a_i, y_{<i}, x) p(a_i \mid y_{<i}, x)
\]

where we show how one can rearrange the terms to compute the function in polynomial time.

The model above is exactly an 0\(^{\text{th}}\)-order neuralized hidden Markov model (HMM). Specifically, \( p(y_i \mid a_i, y_{<i}, x) \) can be regarded as an emission distribution and \( p(a_i \mid y_{<i}, x) \) can be regarded as a transition distribution, which does not condition on the previous alignment. Hence, we will refer to this model as 0\(^{\text{th}}\)-order hard attention. The likelihood can be computed in \( O(|x| \cdot |y| \cdot |\Sigma_y|) \) time.

### 2.3 1\(^{\text{st}}\)-order Hard Attention

To enforce monotonicity, hard attention with conditionally independent alignment decisions is not enough: The model needs to know the previous alignment position when determining the current alignment position. Thus, we allow the transition distribution to condition on the previous alignment \( p(a_i \mid a_{i-1}, y_{<i}, x) \) and it becomes a 1\(^{\text{st}}\)-order neuralized HMM. We display this model as a graphical model in Fig. 2. We will refer to it as 1\(^{\text{st}}\)-order hard attention. Generalizing the 0\(^{\text{th}}\)-order model, we define the 1\(^{\text{st}}\)-order extension as follows

\[
p(y \mid x) = \sum_{a \in \mathcal{A}} p(y, a \mid x)
\]

\[
= \sum_{a \in \mathcal{A}} \prod_{i=1}^{|y|} p(y_i \mid a_i, a_{i-1}, y_{<i}, x) p(a_i \mid a_{i-1}, y_{<i}, x)
\]

### Figure 1: Example of source and target string for each task. Tag guides transduction in morphological inflection.
The goal of this section is to take the vectors, which are fed into an encoder bidirectional encodings produce hidden state representations of Wu et al. (2018). The source string is a neural parameterization to perform efficient inference with dynamic programming. We follow the neural parameterization to achieve this by adding structural forwardly enforce the monotonicity of the alignment. We will show how we can straight-forwardly enforce the hard constraint with eq. (2).

\[ h_i^d = \text{LSTM}([e^d(y_{i-1}); h_i^d], h_{i-1}^d) \] (4)

where \( e^d \) encodes target characters into character embeddings. The tag embedding \( h^t \) is produced by

\[ h^t = \text{ReLU}(Y | e^t(t_1); \ldots; e^t(t_{|\Sigma_t|})) \] (5)

where \( e^t \) maps the tag \( t_k \) into tag embedding \( h^t_k \in \mathbb{R}^{d_t} \) or zero vector \( 0 \in \mathbb{R}^{d_t} \), depends on whether the tag \( t_k \) is presented. Note that \( Y \in \mathbb{R}^{d_t \times |\Sigma_t| d_t} \) is a learned parameter matrix. Also, \( h^t_{a_i} \in \mathbb{R}^{d_t} \), \( h^d_{a_i} \in \mathbb{R}^{d_t} \) and \( h^t \in \mathbb{R}^{d_t} \) are hidden states.

**The Emission Distribution.** All of our hard-attention models employ the same emission distribution parameterization, which we define below

\[ p(y_i | a_i, y_{<i}, x) = \text{softmax} (W f(h_i^d, h_i^c)) \]

\[ f(h_i^d, h_i^c) = \text{tanh} (V [h_i^d; h_i^c]) \] (6)

where \( V \in \mathbb{R}^{d_h \times d_h} \) and \( W \in \mathbb{R}^{d_t \times |\Sigma_t| \times d_t} \) are learned parameters.

**0th-order Hard Attention.** In the case of the 0th-order model, the distribution is computed by a bilinear attention function with Eq. (1)

\[ p(a_i | y_{<i}, x) = \frac{\exp(h_i^d^T T h_i^c)}{\sum_{j=1}^{|\Sigma_t|} \exp(h_j^d^T T h_j^c)} \] (7)

where \( T \in \mathbb{R}^{d_h \times d_t} \) is a learned parameter and \( A_i \) is a random variable range over the values of the \( i \)-th alignment.

**0th-order Hard Monotonic Attention.** We may enforce string monotonicity by zeroing out any non-monotonic alignment without adding any additional parameters, which can be done by adding structural zeros to the distribution as follows

\[ p(a_i | a_{i-1}, y_{<i}, x) = \frac{\mathbb{1} \{ a_i \geq a_{i-1} \} \exp(h_i^d^T T h_i^c)}{\sum_{j=1}^{|\Sigma_t|} \mathbb{1} \{ j \geq a_{i-1} \} \exp(h_j^d^T T h_j^c)} \] (8)

These structural zeros prevent the alignments from jumping backwards during transduction and, thus, enforce monotonicity. The parameterization is identical to the 0th-order model up to the enforcement of the hard constraint with eq. (2).
Algorithm 1 Greedy decoding. \((N)\) is the maximum length of the target string.)

1: \(\textbf{for } i = 1, \ldots, N \textbf{ do} \)
2: \(\) if \(i = 1\) then
3: \(y_i^* = \text{arg}\max_{y_i} \sum_{a_i=1}^{\vert x \vert} p(y_i \mid a_i) p(a_i \mid a_{i-1}) \alpha(a_0)\) \(\triangleright \) Greedy decoding
4: \(\alpha(a_1) = p(y_1^* \mid a_1) p(a_1 \mid a_0) \alpha(a_0)\) \(\triangleright \) Forward probability
5: \(\) else
6: \(y_i^* = \text{arg}\max_{y_i} \sum_{a_i=1}^{\vert x \vert} p(y_i \mid a_i) \sum_{a_{i-1}=1}^{\vert x \vert} p(a_{i-1} \mid a_i) \alpha(a_{i-1})\) \(\triangleright \) Greedy decoding
7: \(\alpha(a_i) = p(y_i^* \mid a_i) \sum_{a_{i-1}=1}^{\vert x \vert} p(a_{i-1} \mid a_i) \alpha(a_{i-1})\) \(\triangleright \) Forward probability
8: \(\) if \(y_i^* = \text{EOS}\) then
9: \(\text{return } y^*\)

1st-order Hard Monotonic Attention. We may also generalize the 0th-order case by adding more parameters. This will equip the model with a more expressive transition function. In this case, we take the 1st-order hard attention to be an offset-based transition distribution similar to Wang et al. (2018):

\[
p(a_i \mid a_{i-1}, y_{<i}, x) = \begin{cases} 
\text{softmax}(U[h_i^d; T h_{i-1}^e])a_i & 0 \leq \Delta \leq w \\
0 & \text{otherwise}
\end{cases}
\]

where \(\Delta = a_i - a_{i-1}\) is relative distance to previous attention position, \(U \in \mathbb{R}^{(w+1) \times 2dh}\) is a learned parameter, and \(w \in \mathbb{N}\) is an integer hyperparameter. Note that, as before, we also enforce monotonicity as a hard constraint in this parameterization.

4 Related Work

There have been previous attempts to look at monotonicity in neural transduction. Graves (2012) first introduced the monotonic neural transducer for speech recognition. Building on this, Yu et al. (2016) proposes using a separated shift/emit transition distribution to allow a more expressive model. Like us, they also consider morphological inflection and outperform a (weaker) soft attention baseline. Rastogi et al. (2016) offer a neural parameterization of a finite-state transducer, which implicitly encodes monotonic alignments. Instead of learning the alignments directly, Aharoni and Goldberg (2017) take the monotonic alignments from an external model (Sudoh et al., 2013) and train the neural model with these alignments. In follow-up work, Makarov et al. (2017) show this two-stage approach to be effective, winning the CoNLL-SIGMORPHON 2017 shared task on morphological inflection (Cotterell et al., 2017). Raffel et al. (2017) propose a stochastic monotonic transition process to allow sample-based online decoding.

5 Experiments

5.1 Experiments Design

Tasks. We consider three character-level transduction tasks: grapheme-to-phoneme conversion (Weide, 1998; Sejnowski and Rosenberg, 1987), named-entity transliteration (Zhang et al., 2015) and morphological inflection in high-resource setting (Cotterell et al., 2017).

Empirical Comparison. We compare (i) soft attention without input-feeding (SOFT) (Luong et al., 2015), (ii) 0th-order hard attention (0-HARD) (Wu et al., 2018), (iii) 0th-order monotonic hard attention (0-MONO) and (iv) 1st-order monotonic hard attention (1-MONO). The SOFT, 0-HARD and 0-MONO models have an identical number of parameters, but the 1-MONO has more. All of them have approximately 8.6M parameters. Experimental details and hyperparameters may be found in App. A.

5.2 Experimental Findings

Finding #1: Morphological Inflection. The first empirical finding in our study is that we achieve single-model, state-of-the-art performance on the CoNLL-SIGMORPHON 2017 shared task dataset. The results are shown in Tab. 2. We find that the 1-MONO ties with the 0-MONO system, indicating the additional parameters do not add much. Both of these monotonic systems surpass the non-monotonic system 0-HARD and SOFT. We also compare to other top systems at the task in Tab. 1. The previous state-of-the-art model, Bergmanis et al. (2017), is a non-monotonic system that outperformed the monotonic system of Makarov et al. (2017). However, Makarov et al. (2017) is a pipeline system that took alignments from an existing aligner; such a system has no manner, by which it can recover from poor initial alignment. We show
Morphological Inflection | ACC
---|---
Silfverberg et al. (2017) | 93.0
SOFT | 93.4
Makarov et al. (2017) | 93.9
0-HARD | 94.5
Bergmanis et al. (2017) | 94.6
Makarov and Clematide (2018) | 94.6
0-MONO | 94.8
1-MONO | 94.8

Table 1: Average dev performance on morphological inflection of our models against single models from the 2017 shared task. All systems are single model, i.e., without ensembling. Why dev? No participants submitted single-model systems for evaluation on test and the best systems were not open-sourced, constraining our comparison. Note we report numbers from their paper.

Finding #2: Effect of Strict Monotonicity. The second finding is that by comparing SOFT, 0-HARD, 0-MONO in Tab. 2, we observe 0-MONO outperforms 0-HARD in turns outperforms SOFT in all three tasks. This shows that monotonicity should be enforced strictly since strict monotonicity does not hurt the model. We contrast this to the findings of Wu et al. (2018), who found the non-monotonic models outperform the monotonic ones; this suggests strict monotonicity is more helpful when the model is allowed to learn the alignment distribution jointly.

Finding #3: Do Additional Parameters Help? The third finding is that 1-MONO has a more expressive transition distribution and, thus, outperforms 0-MONO and 0-HARD in G2P. However, it performs as well as or worse on the other tasks. This tells us that the additional parameters are not always necessary for improved performance. Rather, it is the hard constraint that matters—not the more expressive distribution. However, we remark that enforcing the monotonic constraint does come at an additional computational cost.

6 Conclusion

We expand the hard-attention neural sequence-to-sequence model of Wu et al. (2018) to enforce monotonicity. We show, empirically, that enforcing monotonicity in the alignments found by hard attention models helps significantly, and we achieve state-of-the-art performance on the morphological inflection using data from the CoNLL-SIGMORPHON 2017 shared task. We isolate the effect of monotonicity in a controlled experiment and show monotonicity is a useful hard constraint for three tasks, and speculate previous underperformance is due to a lack of joint training.

Acknowledgments

RC acknowledges a Facebook Fellowship.

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A Experimental Details

A.1 Tasks
We use Wu et al.’s (2018) data splits of grapheme-to-phoneme conversion (CMUDict; Weide, 1998) and NetTalk (Sejnowski and Rosenberg, 1987) and NEWS 2015 shared task on named-entity transliteration. In named-entity transliteration, we only run experiments on 11 language pairs.\(^5\) Grapheme-to-phoneme conversion is evaluated by word error rate (WER) and phoneme error rate (PER; Yao and Zweig, 2015), where PER is the edit distance divided by the number of the phonemes. Named-entity transliteration is evaluated by word accuracy (ACC) and mean F-score (MFS; Zhang et al., 2015). F-score is computed by

\[
\text{LCS}(c_i, r_i) = \frac{1}{2}(|c_i| + |r_i| - \text{ED}(c_i, r_i))
\]

(10a)

\[R_i = \frac{\text{LCS}(c_i, r_i)}{|r_i|}
\]

(10b)

\[P_i = \frac{\text{LCS}(c_i, r_i)}{|c_i|}
\]

(10c)

\[\text{FS}_i = \frac{2R_i \times P_i}{R_i + P_i}
\]

(10d)

where \(r_i\) and \(c_i\) is the \(i\)th reference and prediction and \(\text{ED}(c_i, r_i)\) is the edit distance between \(c_i\) and \(r_i\). Morphological inflection is evaluated by word accuracy (ACC) and average edit distance (MLD) (Cotterell et al., 2017).

A.2 Parameterization
For completeness, we also include the parameterization of transducer with soft attention:

\[p(y_i \mid y_{<i}, x) = \text{softmax} \left( \mathbf{W} f(h_i^d, c_i) \right)_{y_i}
\]

(11a)

\[c_i = \sum_{j=1}^{\text{|x|}} \alpha_{ij} h_j^c
\]

(11b)

\[e_{ij} = h_i^d^T T h_j^c
\]

(11c)

\[\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_j \exp(e_{ij})}
\]

(11d)

The dimensions of the character and tag embedding are 200 and 40, respectively. The encoder and decoder LSTM both have 400 hidden dimensions (\(d_h\)). We also have a 2 layer encoder LSTM. We have 0.4 dropout in embedding and encoder LSTM. The \(w\) in 1st-order hard monotonic attention model is 4.

A.3 Optimization
The model is trained with Adam (Kingma and Ba, 2015) and the learning rate is 0.001. We halve the learning rate whenever the development log-likelihood increase and we stop early when the learning rate reaches 0.00001. We apply gradient clipping with maximum gradient norm 5. The models are selected by development evaluation metric and decoded greedily since no improvements are observed when using beam search (Wu et al., 2018).

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\(^5\)Ar–En, En–Ba, En–Hi, En–Ja, En–Ka, En–Ko, En–Pe, En–Ta, En–Th, Jn–Jk and Th–En.