# FAST AND PARALLEL DECODING FOR TRANSDUCER

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# ABSTRACT

The transducer architecture is becoming increasingly popular in the field of speech recognition, because it is naturally streaming as well as high in accuracy. One of the drawbacks of transducer is that it is difficult to decode in a fast and parallel way due to an unconstrained number of symbols that can be emitted per time step.

In this work, we introduce a constrained version of transducer loss to learn strictly monotonic alignments between the sequences; we also improve the standard greedy search and beam search algorithms by limiting the number of symbols that can be emitted per time step in transducer decoding, making it more efficient to decode in parallel with batches. Furthermore, we propose an finite state automaton-based (FSA) parallel beam search algorithm that can run with graphs on GPU efficiently. The experiment results show that we achieve slight word error rate (WER) improvement as well as significant speedup in decoding. Our work is open-sourced and publicly available<sup>1</sup>.

*Index Terms*— speech recognition, transducer, end-toend, beam search, parallel decoding

## 1. INTRODUCTION

The transducer architecture [1] has been growing in popularity in the field of automatic speech recognition (ASR), especially for deployed real-time ASR systems [2, 3] because it support streaming naturally while achieving high accuracy

Unlike decoding with CTC models where at most one symbol can be emitted per time step, the number of symbols emitted per time step is unconstrained in transducer. Therefore, it is difficult to perform parallel decoding with transducer, because the number of sequential operations is hard to bound in advance.

Various efforts have been made to accelerate transducer decoding. In [3], caching techniques are used to avoid redundant computation in the prediction network for identical prediction histories. Pruning is used in [4] to reduce the number of active hypotheses during the search to make computation more efficient. Another way to reduce the number of active hypotheses is proposed in [5] by using a prediction network with limited label context to merge hypotheses with identical prediction histories.

Different from the above-mentioned works that still allow unlimited number of symbols per time step, we limit the number of symbols that can be emitted per time step to 1. The most similar work to ours is [6] and [7], both of which constrain the hypotheses expanded at each decoding step to one. However, there are two differences between our work and [6]. First, we also pose the constraint on model training so that it has the same behavior in training and decoding. Second, [6] uses two transitions in the transducer lattice during decoding, first going upward and then rightward, while there is only one diagonal transition in our work, which can further save computation and is easier to decode in batch mode. In addition, we use a different transducer architecture from [7] to learn monotonic alignments between the sequence, which shows more promising results.

The main contributions of this paper are:

- We accelerate the transducer decoding by limiting the number of symbols emitted per time step to one.
- A constrained transducer is proposed to improve the performance of the one-symbol-per-frame decoding.
- We implement an FSA-based parallel beam search algorithm that can run with graphs on GPU efficiently.

#### 2. TRANSDUCER DECODING ALGORITHMS

We will first analyze the state-space and transitions of transducer decoding algorithms in detail, during which we show how we simplify the decoding process step by step. Then we will describe the implementation details of our proposed FSA-based beam search algorithm.

### 2.1. Traditional Transducer

With the vanilla, fully-recurrent transducer, the **state-space** consists of pairs  $(\mathbf{y}, t)$  where  $\mathbf{y}$  is a sequence of symbols (excluding  $\emptyset$ ) and t is an integer frame index. If there are T frames numbered  $0, 1, \ldots, T-1$ , then ((), 0) is initial (i.e. empty-sequence, 0) and states  $(\mathbf{y}, T)$  are final.

The **transitions** are as follows: for symbols  $a \neq \emptyset$  and for  $0 \leq t < T$ , there are transitions  $(\mathbf{y}, t) \rightarrow (\mathbf{y} + a, t)$  with label *a* and probability  $P(a|\mathbf{y}, t)$ . Also  $(\mathbf{y}, t)$  has a transition to  $(\mathbf{y}, t+1)$  with probability  $P(\emptyset|\mathbf{y}, t)$ . There are no cycles

<sup>&</sup>lt;sup>1</sup>https://github.com/k2-fsa/icefall

in this graph because transitions are always either to larger t or to (same t, longer y).

## 2.2. Stateless Transducer

In the stateless transducer as in [8] the decoder network requires only a finite context, for instance two symbols. Therefore, the state-space can be reduced to only the most recent symbols, e.g. two symbols of y; the initial state can be taken to be  $((\emptyset, \emptyset), 0)$ , and when a transition  $c \neq \emptyset$  is made from state  $((a, b), t), ((b, c), t)^2$  is reached.

## 2.3. Max-symbols decoding

Here, we describe decoding methods where we limit the maximum number of symbols S that can be emitted per frame, to 1, 2 or 3. The state-space is extended by a number  $0 \le n < S$  saying how many symbols we have already emitted on this frame, so a state would be of the form  $(\mathbf{y}, t, n)$ . Transitions with a blank label  $(\emptyset)$  are:  $(\mathbf{y}, t, n) \rightarrow (\mathbf{y}, t+1, 0)$ . For  $n \le S-1$ , transitions with label  $a \ne \emptyset$  are:  $(\mathbf{y}, t, n+1)$ . For n = S-1, transitions with labels  $a \ne \emptyset$  are:  $(\mathbf{y}, t, S-1) \rightarrow (\mathbf{y}+a, t+1, 0)$ . This is equivalent to assuming the probability of blank is always 1 after emitting S symbols on a given frame.

The expansion of the state space in max-symbols decoding does not in itself affect the decoding result: for sufficiently large n, the sequence y of the best path will still be the same, and the y with the greatest total probability will also be the same, as it is in conventional transducer decoding. This is because there is a one-to-one mapping between paths in the conventional and max-symbols decoding algorithm (for large n).

#### 2.4. FSA-based decoding

For simplicity, our FSA decoding algorithm assumes:

- We are using stateless transducer where the decoder consumes a fairly small number of input symbols<sup>3</sup>.
- We are doing *max-symbols* decoding with S = 1. This is quite similar to hybrid or CTC decoding, since all transitions are to the next frame.

We further extend the state-space to enable decoding with graphs (like conventional hybrid decoding, except with no hidden Markov model topology). Taking the history-length of stateless transducer to be 2, the states are of the form ((a, b), t, s) where a and b are symbols (possibly  $\emptyset$  if we are near the start of the utterance),  $t \ge 0$  is the frame-index, and s is the decoding-graph state. Thus, our decoding algorithm implements graph composition. For each arc  $s \rightarrow r$  in the decoding graph with label  $c \neq \emptyset$ , and probability q, there exists a transition in the lattice  $((a, b), t, s) \rightarrow ((b, c), t+1, r)$  with label c and probability qP(c|(a, b), t). In addition, we

have blank transitions  $((a, b), t, s) \rightarrow ((a, b), t+1, s)$  with probability  $P(\emptyset|(a, b), t)$  and label  $\emptyset = 0$ . The graph is assumed to be epsilon-free.

Our decoding algorithm is implemented in k2<sup>4</sup> using ragged tensor data structures, which enables rapid processing of irregular-sized objects in parallel on the GPU.

## 2.5. Beam search

It is hard to compactly describe the search strategy of the algorithm in [1], but the goal generally seems to be to keep no more than the N best paths active; and the frames are processed one by one. The order of processing within a frame is "best-first". This is not consistent with the goal of summing probabilities, because we may have already processed a sequence before its prefix; also, the algorithm generates duplicates and is not very explicit about how to deal with this. People have implemented slightly different versions of this algorithm, e.g. ESPNet [9] dispenses with the "prefix search" part of the algorithm and instead implements de-duplication of hypotheses.

For our proposed **FSA-based decoding**, all transitions are from frame t to t+1 because we use max-symbols = 1. There are 3 constraints: a log-probability beam, a max-states constraint (that limits the number of tuples ((a, b), t, s) for a given t), and a max-contexts constraint that limits the number of symbol contexts like (a, b) that are active on a given t. On each frame we first do propagation to the next frame without pruning. We then apply the max-states and beam constraints in one pruning operation; and then apply the max-contexts constraint in a second pruning operation.

The pseudocode of our **FSA-based decoding** is given in Algorithm 1<sup>5</sup>, it can decode many streams in parallel. The output of our algorithm is a lattice (i.e. an FSA), we can find either the best path or the  $\emptyset$ -free label sequence y with the highest probability, using standard FSA operations, after generating the lattice. The label sequence with the highest probability is found by

- Generating *n*-best paths from the lattice using an easyto-parallelize randomized algorithm.
- Finding the unique paths y from the *n*-best paths by removing Ø from the label sequences.
- Generating FSAs from the unique paths, composing these with the lattice, and computing the total probability of the results.

#### 3. CONSTRAINED TRANSDUCER TRAINING

Since we find that decoding with *max-symbols*=1 works well, so that in the decoding algorithm, consuming a non- $\emptyset$  symbol takes us from frame t to t + 1, it is natural to try incorporating this rule in training as well.

<sup>&</sup>lt;sup>2</sup>Our FSA-based decoding uses this reduced search-space, but our non-FSA-based beam search algorithm still uses the full sequence  $(\mathbf{y}, t)$  as the state space (so we can re-use the previous beam-search code).

<sup>&</sup>lt;sup>3</sup>This makes it possible to encode the history sequence into a single integer.

<sup>&</sup>lt;sup>4</sup>https://github.com/k2-fsa/k2

<sup>&</sup>lt;sup>5</sup>We call it fast\_beam\_search in icefall (https://github.com/k2-fsa/icefall).

<sup>&</sup>lt;sup>6</sup>This is a RaggedShape in k2 (https://github.com/k2-fsa/k2)

## Algorithm 1 FSA-based Parallel Beam Search

Inp	<b>ut:</b> The decoding graphs for each sequence $f sas$ ;
_	The pruning parameters beam, max_contexts, max_states;
	The instance of transducer model $M$ ;
	The input acoustic features <i>feats</i> ;
1:	$Streams \leftarrow []$
2:	for $i \leftarrow 0$ to num_sequences do;
3:	$Streams[i] \leftarrow Init(fsas[i], beam, max\_contexts, max\_states);$
4:	end for
5:	for $t \leftarrow 0$ to T do;
6:	$Enc_t \leftarrow M.encoder(feats[t])$
7:	$shape^{6}, contexts \leftarrow GetContexts(Streams)$
8:	$Dec_{out} \leftarrow M.decoder(contexts)$
9:	$Enc_{out} \leftarrow IndexSelect(Enc_t, shape.RowIds(1))$
10:	$log\_probs \leftarrow M.joiner(Enc_{out}, Dec_{out})$
11:	$Streams. ExpandArcs(log\_probs)$
12:	Streams.Prune()
13:	end for
14:	Streams.TerminateAndFlushToStreams()
15:	$lattice \leftarrow Streams.FormatOutput()$
16:	return lattice
-	

## 3.1. Modified Transducer

We first try training the transducer by introducing a diagonal transition in the transducer lattice, just like the way that [7] did, where emitting a non-blank symbol takes you to the next frame. We call this "modified transducer". If the regular core transducer recursion is:

$$\alpha(t, u) = \log_{-add} \left( \alpha(t-1, u) + \varnothing(t-1, u) \right),$$
  
$$\alpha(t, u-1) + y(t, u-1) \right)$$
(1)

with the final data-likelihood being  $\alpha(T-1, U) + \varnothing(T-1, U)$ , the modified transducer is:

$$\begin{split} \alpha(t,u) &= \log\_\mathrm{add}\left(\alpha(t-1,u) + \mathcal{O}(t-1,u) \right., \\ \alpha(t-1,u-1) + y(t-1,u-1))) \end{split} \tag{2}$$

with the final data-likelihood being  $\alpha(T, U)$ .

#### **3.2.** Constrained transducer

We also propose a new architecture called constrained transducer, which is like modified transducer in that you have to go to next frame when you emit a non-blank system, but this is done by "forcing" you to take the blank transition from the **next** context on the **current** frame, e.g. if we emit c given "a b" context, we are forced to emit "blank" given "b c" context on the current frame. The core recursion is:

$$\alpha(t, u) = \log_{-} \operatorname{add} \left( \alpha(t-1, u) + \varnothing(t-1, u) , \\ \alpha(t-1, u-1) + y(t-1, u-1) + \varnothing(t-1, u)) \right)$$
(3)

with the final data-likelihood being  $\alpha(T, U)$ .

## 4. PRUNED RNN-T TRAINING AND LM-SCALE

We proposed the pruned RNN-T training in our previous work [10]. This is a more efficient way of evaluating the RNN-T recursion, by using a "trivial" joiner network to quickly evaluate the recursion and figure out which (t, u)pairs are important, then only evaluating the full joiner on a subset of symbols. For the purpose of this work, the details on pruning are emitted. What is important to know is that as part of the pruned RNN-T training, we regularize the loss function with a *trivial joiner*, which simply adds logprobs derived from the encoder with logprobs from the decoder; and we interpolate the trivial-joiner logprobs with  $\alpha^{\rm lm}$ , or *lm*scale, times logprobs derived from the decoder alone. This essentially means that we are including a language-model probability (predicting the tokens or blanks) in the log-probs used in the simple-joiner recursion. This *lm-scale* term forces the decoder log-probs used in the trivial joiner to be close to the probabilities of a "real" language model (on the vocabulary including  $\emptyset$ ). For reasons that are currently unclear to us, this appears to affect the model in some way that makes decoding with *max-symbols*= 1 work better, and also slightly improves WERs. The trivial joiner that is being affected by this regularization is not used in decoding, so it must be an indirect effect that acts by changing the encoder output in some way.

#### 5. EXPERIMENTS

#### 5.1. Dataset and Setup

We conduct all our experiments on the popularly used Librispeech corpus [11]. Lhotse [12] is used for data preparation. The acoustic feature is 80-channel Fbank extracted from a 25ms window with a stride of 10ms. We also use spec-augmentation [13] and noise augmentation (by mixing MUSAN [14]) to improve generalization. Furthermore, speed perturbation [15] with factors 0.9 and 1.1 is used to triple the training set.

Our encoder model is a re-worked version of Conformer [16]. It has 12 encoder layers, each of which contains 8 self-attention [17] heads with attention-dim 512. The subsampling factor in the convolution module is 4 and the feed forward dimension is 2048. The decoder model is a stateless network [8], consisting of an embedding layer with embedding dimension 512 followed by a 1-D convolution layer with kernel size 2. The outputs of the model are 500 sentence pieces [18] with byte pair encoding (BPE). All of the models are trained with pruned RNN-T loss [10].

#### 5.2. ASR accuracy

Table 1 shows the max-symbols decoding results of three types of transducers. For regular transducer, the WERs increase when the number of symbols per frame is constrained during decoding, while there are no degradations in WERs for constrained transducer. We also find that the modified transducer produces much worse results than the other two, and there will be a lot of insertion errors when we increase the number of symbols that can be emitted per frame. It seems that during the training, blank probability is important when transiting to the next frame given a non-blank symbol.

 Table 1. The max-symbols decoding results (WER) of different architecture of transducers (without lm\_scale).

Setup	Max	Greedy		Beam		FSA based		
	Symb	ol Sea	ol Search		Search		Beam Search	
		clean	other	clean	other	clean	other	
	1	2.72	6.33	2.67	6.21	2.70	6.21	
Regular	2	2.68	6.28	/	/	/	/	
	$\infty$	2.68	6.28	2.65	6.18	/	/	
	1	2.76	6.46	2.74	6.35	2.74	6.33	
Constrained	2	2.76	6.46	/	/	/	/	
	$\infty$	2.76	6.46	2.74	6.32	/	/	
	1	3.68	9.43	3.54	9.07	3.57	9.03	
Modified	2	70.9	70.7	/	/	/	/	
	$\infty$	1179	1089	-	-	/	/	

Table 2. The max-symbols decoding results (WER) of different architecture of transducers (with Im\_scale=0.25).

Setup	Max	Max Greedy		Beam		FSA based		
	Symb	ol Sea	ol Search		Search		Beam Search	
		clean	other	clean	other	clean	other	
	1	2.66	6.25	2.62	6.08	2.67	6.20	
Regular	2	2.66	6.25	/	/	/	/	
	$\infty$	2.66	6.25	2.62	6.10	/	/	
	1	2.61	6.45	2.6	6.39	2.64	6.39	
Constrained	2	2.61	6.45	/	/	/	/	
	$\infty$	2.61	6.45	2.6	6.39	/	/	
	1	2.62	6.41	2.59	6.33	2.64	6.32	
Modified	2	6.35	10.6	/	/	/	/	
	$\infty$	108	114	-	-	/	/	

By comparing Table 2 with Table 1, it shows that the  $lm\_scale$  in the pruned RNN-T loss not only makes decoding with *max-symbols*= 1 work better, but also helps to improve the performance.

 Table 3. The effects of how duplicated alignments of the same hypotheses are handled.

Decoding	Max		Merg	e OP		
Method	Symbol	Max		LogAdd		
		clean	other	clean	other	
Beam	1	2.63	6.37	2.60	6.39	
Search	$\infty$	2.64	6.37	2.60	6.39	
FSA based	1	2.64	6.39	2.66	6.42	

The stated goal of the beam search algorithm presented in [1] seems to be to find the y with the largest lengthnormalized probability  $\operatorname{argmax}_{\mathbf{y}} p(\mathbf{y})$ . So we also investigated the effects of length normalization and the way how we handle duplicate alignments of the same hypotheses. Table 3 and 4 show that both of them have little impact on the WER.

#### 5.3. Decoding speed

Table 5 illustrates the real-time factor (RTF) for the test-clean and test-other datasets using different decoding methods. We conduct the benchmark on an NVIDIA V100 GPU with 32 GB RAM, when running in batches, dynamic batch size is used to make full use of the memory. For greedy search and beam search that are hard to support parallel decoding with max-symbol=  $\infty$ , only the encoder network runs in batches when batched equals "Yes". The results show that there is a clear speed advantage in decoding by limiting the number

<b>Table 4</b> . The effects of length normalization to WERs.								
Decoding	Max		Norm	Norm				
Method	Symbol	(	Yes)	1)	No)			
		clean	other	clean	other			
Beam	1	2.60	6.39	2.60	6.40			
Search	$\infty$	2.60	6.39	2.60	6.38			
Table 5. The RTF of different decoding methods.								
Decoding	Ma	ıx		RTF				
Method	Sym	bol	batched(No	o) ba	tched(Yes)			
Cready Saarah	1		0.011		0.0009			
Gleedy Search	$\propto$	C	0.011		0.0078			
baam aaarab	1		0.03		0.0068			
beam search	$\propto$	C	0.126		0.125			
FSA based beam search	1		0.05		0.002			

of symbols to 1, especially when running in parallel. It also shows that our proposed FSA-based beam search is 3.4 times faster than the standard beam search in [1].

#### 5.4. Decoding with FSA

**Table 6**. The WERs and RTF of FSA based Beam Search with trivial graph and LG graph.

	Decoding	Merge OP	WERs		RTF
	Graph		clean	other	
	Trivial Graph	Max	2.64	6.39	0.0024
		LogAdd	2.66	6.42	0.0112
	LG Graph	Max	2.84	6.37	0.0025
		LogAdd	2.86	6.36	0.004

The FSA-based beam search results in table 1 2 3 5 are all decoded with a "trivial graph" that has only one state. Table 6 gives the WERs and RTF for FSA-based beam search with a general graph. The G in LG graph is a 3-gram LM trained on Librispeech text corpus, which has around 180MB in arpa text format. From the table, we can see that using a larger FSA graph won't affect the RTF too much, which shows that our FSA-based beam search algorithm also works efficiently on general FSA graphs. As for the performance degradation on LG graph, we find that there are some words not present in the released lexicon, making the results on LG graph worse than the trivial graph. As for the larger RTF on trivial graph using log\_add comparing with LG graph, it is because the decoding lattice generated with trivial graph is larger than that generated with LG graph, which makes it take more time to find the label sequence with the highest probability.

## 6. CONCLUSIONS

In this paper, we improve the transducer decoding algorithms by limiting the number of symbols that can be emitted per time step to one, making it possible to decode in parallel using batches. We also propose a constrained transducer architecture and  $lm\_scale$  training in our pruned RNN-T loss that make the decoding with max-symbol= 1 work better. What's more, we have implemented a fast and highly-parallel FSA-based decoding algorithm for transducer that generates lattices; it gives slightly better accuracy and up to 3.4 times faster performance than conventional transducer decoding.

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