A STUDY OF TRANSDUCER BASED END-TO-END ASR WITH ESPNET: ARCHITECTURE, AUXILIARY LOSS AND DECODING STRATEGIES

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ABSTRACT

In this study, we present recent developments of models trained with the RNN-T loss in ESPNet. It involves the use of various architectures such as recently proposed Conformer, multi-task learning with different auxiliary criteria and multiple decoding strategies, including our own proposition. Through experiments and benchmarks, we show that our proposed systems can be competitive against other state-of-art systems on well-known datasets such as LibriSpeech and AISHELL-1. Additionally, we demonstrate that these models are promising against other already implemented systems in ESPNet in regards to both performance and decoding speed, enabling the possibility to have powerful systems for a streaming task. With these additions, we hope to expand the usefulness of the ESPNet toolkit for the research community and also give tools for the ASR industry to deploy our systems in realistic and production environments.

Index Terms: end-to-end speech recognition, RNN-T loss, auxiliary task, decoding strategies

1. INTRODUCTION

In recent years, end-to-end models based on either CTC \cite{1}, attention encoder-decoder \cite{2}, or RNN-Transducer \cite{3} have gained a lot of attention from the speech recognition community, surpassing traditional hybrid ASR systems on various speech recognition tasks. Among them, transducer\cite{3} was found successful in both research and industry environments for its competitive results and its natural ability for streaming \cite{4,5}.

Following this trend, many open-source speech recognition toolkits now support this model and provide various architectures and features for training and decoding, with an emphasis on different aspects. Tencent’s Pika for example improves the training procedure and features for training and decoding, with an emphasis on different aspects. Additional, we hope to expand the usefulness of the ESPNet toolkit for the research community and also give tools for the ASR industry to deploy our systems in realistic and production environments.

In this work, we present an extension of ESPNet \cite{23}, developed to accelerate the research related to this particular model. The extension not only supports composition with architectures such as TDNN, Transformer or Conformer, but also many training and decoding tools. Table \ref{tab:features} summarizes the features in the ESPNet toolkit against the mentioned open-source toolkits. To address the described issues, we focus on introducing and investigating two newly proposed features in the toolkit which are missing from other toolkits: 1 multi-task learning with several auxiliary tasks to improve performance and also reduce the number of expansions at each timestep during training and 2) various beam search strategies, including our own proposition called N-step Constrained Beam Search, to control the expansion behavior during decoding and also enable different optimizations such as vectorization. In addition, we will release all configurations, recipes and pre-trained models to the community through ESPNet so that everyone can reproduce our experiments and accelerate the research related to transducer models.

2. TRANSDUCER

The transducer architecture proposed by Graves \cite{3} consists of an encoder, a decoder and a joint network. The encoder, analogous to RNN such as RNA \cite{7} and makes corresponding training optimizations such as vectorization. In addition, we will release all configurations, recipes and pre-trained models to the community through ESPNet so that everyone can reproduce our experiments and accelerate the research related to transducer models.

The decoder, acting as a language model, produces a high representation \( h_{\text{dec}} \) of length \( U \) given its previous emitted label sequence \( y_{1:t-1} \):

\[
h_{\text{dec}}(y_{1:t-1}) = \text{Decoder}(y_{1:t-1})
\]

The joint network combines each representations \( h_{\text{enc}} \) and \( h_{\text{dec}} \) to compute output logits \( h_{\text{joint}} \) via a network composed of feed-forward layers and a non-linear function:

\[
h_{\text{joint}} = \text{Joint}(h_{\text{enc}}, h_{\text{dec}})
\]

Finally, by applying a Softmax function to the output logits, we can produce the distribution of current target probabilities:

\[
P(y_{t, u} | x_{1:T}, y_{1:t-1}) = \text{Softmax}(h_{\text{joint}})
\]
Given $A$, the set of all possible alignments $a$ between input $x_{1:T}$ and output $y_{1:U}$ with blank labels $(\emptyset)$ included, the loss function of the model can be computed as the following negative log likelihood:

$$
\mathcal{L}_{\text{trans}} = -\log \sum_{a \in A} P(a|x_{1:T})
$$

$\mathcal{L}_{\text{trans}}$ can be minimized using the forward-backward algorithm proposed in [3].

## 3. FRAMEWORK

The transducer architecture in ESPnet follows the same encoder-decoder architecture described in [23] used for joint CTC-Attention. Here, each part of the architecture, excluding the joint network, is separated into two sub-parts. Thus, Eq. 1 is replaced by Eq. 6 for the encoder and Eq. 7 is used instead of Eq. 2 for the decoder.

$$
\begin{align*}
\hat{h}_{\text{pre}}^e &= \text{EncPre}(x_{1:T}) \\
\hat{h}_{1}^e &= \text{EncBody}(\hat{h}_{\text{pre}}^e) \\
\hat{h}_{\text{dec}}^{u-1} &= \text{DecPre}(y_{u-1}) \\
\hat{h}_{\text{dec}}^u &= \text{DecBody}(\hat{h}_{\text{dec}}^{u-1})
\end{align*}
$$

EncPre($\cdot$) can be either a 2-layer CNN [12] or a VGG-like max pooling [24]. DecPre($\cdot$) can be either an embedding layer or a linear layer. Following recent advances in ESPnet, various architectures are made available for EncBody($\cdot$) and DecBody($\cdot$) such as: RNN and variants [23], Transformer [25], Transformer with lightweight and dynamic convolution [26], or Conformer [27].

Additionally, we introduce what we call free-form architecture definition. Here, every components and parameters of the transducer model architecture can be defined and tuned individually. Compared to other models in ESPnet, this also allows us to freely combine previously presented neural networks together or with additional ones (e.g.: Linear, TDNN and Causal-Conv1d) to form a new architecture for EncBody($\cdot$) and DecBody($\cdot$).

## 4. AUGMENTED TRAINING

Alongside the standard training procedure, we propose an augmented procedure based on various auxiliary tasks. This section describes the ones made available in the ESPnet toolkit.

### 4.1. Multi-task learning

The new transducer structure is augmented by four classifier layers used to train auxiliary tasks alongside the standard transducer criterion. The proposed architecture is depicted in Fig. 1 where a single encoder layer is used to compute $\mathcal{L}_{\text{aux-trans}}$ and $\mathcal{L}_{\text{symm-KL}}$ (See explanations in Sec. 4.3 and 4.4). The five losses can be simultaneously trained and jointly optimize the total loss function $\mathcal{L}_{\text{tot}}$ defined as:

$$
\mathcal{L}_{\text{tot}} = \lambda_{\text{trans}} \mathcal{L}_{\text{trans}} + \lambda_{\text{CTC}} \mathcal{L}_{\text{CTC}} + \lambda_{\text{aux-trans}} \mathcal{L}_{\text{aux-trans}} + \lambda_{\text{symm-KL}} \mathcal{L}_{\text{symm-KL}} + \lambda_{\text{LM}} \mathcal{L}_{\text{LM}}
$$

where $\mathcal{L}_{\text{trans}}$ is the main transducer loss, $\mathcal{L}_{\text{CTC}}$ the CTC loss, $\mathcal{L}_{\text{aux-trans}}$ the auxiliary transducer loss, $\mathcal{L}_{\text{symm-KL}}$ the symmetric KL-divergence and $\mathcal{L}_{\text{LM}}$ the LM loss. $\lambda_{\cdot}$ defines their respective contribution to the overall loss. Additionally, each loss can be independently selected or omitted depending on the task.

### 4.2. CTC loss ($\mathcal{L}_{\text{CTC}}$)

Similarly to monotonic RNN-T [17] limiting the number of emitted labels at each timestep to strictly one, we explore the use of another (soft) regularization for transducer model through the auxiliary CTC [28]. In addition to the previously found successful encoder pre-initialization with the CTC model [29], here, we jointly train the transducer loss and the CTC loss in the same manner as joint CTC-Attention [30] in ESPnet.

### 4.3. Auxiliary transducer loss ($\mathcal{L}_{\text{aux-trans}}$)

To address encoder underfitting due to major role given by the decoder in a transducer model, we incorporate the auxiliary transducer loss proposed by Liu et al. [22] to increase the gradients signals. Following their proposed method, one or multiple encoder representations $\hat{h}_{\text{aux}}^l$, from intermediate layers $l \in L$, are passed to
an auxiliary RNN-T criterion, where an additional MLP network is used in place of the linear layer in the joint network:

$$h_{\text{joint- aux}} = \text{JointAux} (\text{MLP}(h_{\text{enc- aux}}; h_{\text{dec}}))$$  \hspace{1cm} (9)

Contrary to the original proposition we choose, based on early experiments, to use an independent joint network we train exclusively for the auxiliary task. However, we do not update the shared decoder parameters and joint parameters if the gradients are back propagated from the auxiliary RNN-T loss.

4.4. Symmetric KL-divergence ($L_{\text{symm-KL}}$)

We also consider the use an auxiliary symmetric KL-divergence criterion proposed in \cite{saon2018joint} to penalize inconsistent gradients during supervision with auxiliary transducer loss.

$$L_{\text{symm-KL}} = \frac{1}{T} \sum_{t=1}^{T} \sum_{i=1}^{L} \sum_{u=1}^{U} I(l) \cdot \frac{1}{2} \left( D_{\text{KL}}(\text{Softmax}(h_{\text{dec}}^{i, u}), \text{Softmax}(h_{\text{joint- aux}}^{i, u})) + D_{\text{KL}}(\text{Softmax}(h_{\text{joint- aux}}^{i, u}), \text{Softmax}(h_{\text{dec}}^{i, u})) \right)$$  \hspace{1cm} (10)

where $L$ defines the set of encoder layers and $I(l)$ is a binary indicator to denote whether a layer is used for the auxiliary task.

4.5. LM loss ($L_{\text{LM}}$)

Finally, we explore the use of an auxiliary criterion in order to improve and to regularize the decoder network playing a major role in predicting $y_i$. Because the decoder is analogous to a language model, we define auxiliary criterion as a language model criterion, where the final computed loss is based on cross-entropy loss with label smoothing \cite{zoph2016learning}. This addition was also proposed in \cite{wu2016google} and also used to optimize the decoder independently.

5. DECODING

We support four beam search decoding strategies for transducer to allow more flexibility in regards to performance-speed trade-off and the target task. The first one, our default algorithm (Sec. 5.1), expands the label sequence in an unrestricted manner, the second one (Sec. 5.2) acts label-synchronously and the last two strategies (Sec. 5.3 and Sec. 5.4) runs along time axis. For three of them, we enable hypotheses caching and batching to reduce the computation time. Shallow fusion with a RNN-based or Transformer-based LM and multi-level LM \cite{saon2018joint} is also supported.

5.1. Default beam search

The default decoding strategy for transducer in ESPnet is based on the beam search algorithm proposed by Graves in \cite{graves2012sequence}. The procedure runs along both axis $\{1, ..., T\}$ and $\{1, ..., U\}$ and can be expanded in an unrestricted manner. The algorithm is performed using two sets of hypotheses $A$ and $B$, respectively the sets of hypotheses for times $t$ and $t + 1$, where $B$ contains $\emptyset$ hypothesis at $t = 0$. At each timestep $t$, hypotheses from $B$ are first moved to $A$. The best hypothesis from $A$ is extracted and expanded with either a blank transition or non-blank transition. Hypotheses ending with a blank transition are stocked in $B$ whereas the others are moved to $A$, where each hypothesis’ score is updated with the corresponding blank or non-blank transition score. Through a while loop, the procedure is repeated until $B$ contains at least $N_{bs}$ hypotheses more probable than the most probable in $A$. When the condition is met, $B$ is pruned to $N_{bs}$ hypotheses and passed to the next timestep. At the end of the procedure when $t = T$, the N-best hypotheses in $B$ are returned sorted by descending score.

Based on initial experiments, the prefix search part was removed. We found out that it does not necessary insure that the search space won't be redundant without additional duplication check and, in the end, most probable hypotheses are still retained. Thus, removing that part allows us to reduce the computational cost without trading off much of the search accuracy.

5.2. Alignment-length synchronous decoding (ALSD)

**Algorithm 1: Alignment-length synchronous decoding \cite{saon2018joint}**

- **Input:** $h_{\text{enc}}^{n_{bs}}$, $U_{\text{max}}$, $N_{bs}$ and $N_{bs}$
- **Output:** $B = \{\emptyset, 1, \text{state}_{\text{dec}}{}^{0}\}; F = \{\}$

**for** $i = 1 ... T + U_{\text{max}}** do**

- **A** = $\{\}$

- **for** $(y, \delta_{i-1}(y), \text{state}_{\text{dec}}{}^{i-1}) \in B$ **do**

  - $u = |y|$
  - $t = i - u + 1$

  **if** $t > T$ **then**
  
  **continue**

  $h_{\text{dec}}^{i, u}$, state$^{i}{_{\text{dec}}} = \text{Decoder}(y, \text{state}_{\text{dec}}{}^{i-1})$
  
  $p^f = \text{Softmax}(\text{Joint}(h_{\text{dec}}^{i, u}, h_{\text{enc}}^{i, u}))$
  
  $\delta_i(y) = \delta_{i-1}(y) + \text{state}_{\text{dec}}{}^{i}$

  $A = A \cup \{(y, \delta_i(y), \text{state}_{\text{dec}}{}^{i-1})\}$

  **if** $t == T$ **then**

  $F = F \cup \{(y, \delta_i(y))\}$

  **for** $k \in Y$ **do**

  $\delta_i(y + k) = \delta_i(y) + p^f(k)$

  $A = A \cup \{(y + k, \delta_i(y + k), \text{state}_{\text{dec}}{}^{i})\}$

- $B = \text{PruneAndRecombineHyps}(A); \text{N}_{bs}$

**Return:** SortedByScore($F$); $N_{bs}$

Alignment-length synchronous decoding is the procedure proposed by Saon et al. \cite{saon2018joint} which runs along axis $\{1, ..., U\}$ and uses $U_{\text{max}}$ parameter, an estimate of the maximum output sequence length, where $U_{\text{max}} < T$. The procedure keeps track of 2 set of hypotheses $A$ and $B$ at alignment step $i$ and $i - 1$. At step $i$, for each hypothesis of $B$, the number of frames covered by the output sequence $y$ is computed by subtracting its length from $i + 1$, then the hypothesis is added to $A$ with its score ($\delta_y$) updated by adding the blank transition score. If the last frame is reached, the hypothesis is also put into the set of final hypotheses $F$. After that, each $y$ of $A$ are expanded with every output label minus blank, and each new hypothesis is added to $A$ with its corresponding score and decoder network state updated. Finally, a pruning is applied for the set $A$ and duplicate hypotheses are merged altogether with their respective score added. The set of unique hypotheses, reduced to the beam size ($N_{bs}$), become the set $B$ for the next alignment step. At the end of the procedure, the N-best ($N_{bs}$) hypotheses in $F$ are returned sorted by descending score. The complete procedure is given in Algol. 1.

5.3. Time-synchronous decoding (TSD)

Time-synchronous decoding is a procedure also proposed by Saon et al. \cite{saon2018joint}. It runs along axis $\{1, ..., T\}$ and uses a parameter $\text{max}_{\text{sym- exp}}$ to control the number of hypotheses expansion at each timestep. Algorithm 2 shows the complete procedure and can
be described as follow. Here, the procedure keep track of 4 set of hypotheses, where $A$ and $B$ store hypotheses for times $t$ and $t-1$ and $C$ and $D$ store hypotheses for expansion steps $v-1$ and $v$. At each timestep, in case of a blank transition, hypotheses from $C$ are added to $A$ with blank score added to their score if $y \notin A$, otherwise scores ($\delta_y$) are summed. For a non-blank transition, hypotheses from $C$ are expanded with every output label minus blank and added to set $D$ with their score updated. After that, hypotheses from $D$ are pruned to define a new set $C$ limited to $N_{\text{h}}$ hypotheses. The procedure is then repeated max sym_exp times. When $v$ reaches max sym_exp, hypotheses from $A$ are stored in $B$ and the procedure is repeated for each timestep. At the end of the procedure, the N-best ($N_{\text{best}}$) hypotheses in $B$ are returned sorted by a descending score.

5.4. N-step constrained beam search (NSC)

We also include an improved version of the One-Step Constrained (OSC) beam search proposed by Kim et al. [33], which originally constrains the default beam search to a single label emission plus blank label at each timestep. Although the authors demonstrate the efficiency of the algorithm for different speech recognition tasks and investigate the number of emitted labels at each timestep during the expansion search for the presented tasks, we found the initial constraint too strong, resulting in two weakness:

1. For low-resources tasks, the number of needed label emissions at each timestep should be higher than 1 as shown Table 2. Here, the investigation on expansion search was conducted on two smaller corpora, VIVOS (15 hours) and Voxforge (20 hours), and a significant number of more than one expansions was observed in comparison to the initial investigation (+4.24% for Voxforge and +7.28% for VIVOS).

2. If no equivalent constraint is applied during training (e.g.: [17]), adding a blank transition score after each expansion may result in the deletion of reasonable hypotheses during the pruning process and sorting phase.

In order to address these issues, we propose a novel N-Step Constrained beam search (NSC) algorithm. The algorithm is similar to the TSD (Sec. 5.3) and extends the original OSC algorithm to $N$ expansion steps (plus blank) through an additional loop controlled by a parameter $N_{\text{step}}$. To overcome the second issue, we add a new condition for the final expansion step in NSC. If $N_{\text{step}} = 1$ and auto-$N_{\text{step}} = 1$, then we allow incomplete hypotheses to be passed to the next time step without adding the blank score transition. The parameter auto-$N_{\text{step}}$ is obtained by a counting method, built upon default beam search (See Sec. 5.1), which computes the expected number of needed expansions. The complete procedure is given by Algorithm 3 where lines highlighted in red refer to our addition to the original OSC algorithm, and the parameters $N_{\text{ns}}$ and $N_{\text{best}}$ define respectively the beam size and the $N$ best hypotheses.

With the exception of default beam search, all strategies propose to resolve the unrestricted expansion in transducer model by

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**Algorithm 2:** Time synchronous decoding [19]

**Input:** $h_t, \text{max sym exp, } N_0$ and $N_{\text{best}}$

**B = \{ \emptyset, 1, \text{state}_{\text{enc}} \}**

**for** $t = 1 ... T$ **do**

$A = \{ \}; C = B$

**for** $v = 1 ... \text{max sym exp}$ **do**

$D = \{ \}$

**for** $(y, \delta_{t-1, u-1}(y), \text{state}_{\text{enc}}_{u-1}) \in C$ **do**

$h_{\text{enc}}^t, \text{state}_{\text{dec}}_{u-1} = \text{Decoder}(y, \text{state}_{\text{enc}}_{u-1})$

$p^t = \text{Softmax}(\text{Joint}(h_{\text{enc}}^t, h_{\text{enc}}^{t-1}))$

if $y \notin A$ **then**

$\delta_{t, u-1}(y) = \delta_{t-1, u-1}(y) * p^t(\emptyset)$

$A = A \cup \{(y, \delta_{t, u-1}(y), \text{state}_{\text{dec}}_{u-1})\}$

else

$\delta_{t, u-1}(y) = \delta_{t-1, u-1}(y) * p^t(k)$

**if** $v < \text{max sym exp}$ **then**

**for** $k = 1 ... \text{max sym exp}$ **do**

$\delta_{t, u-1}(y+k) = \delta_{t-1, u-1}(y+k) * p^t(k)$

$D = D \cup \{(y+k, \delta_{t, u-1}(y+k), \text{state}_{\text{dec}}_{u-1})\}$

$C = \text{PruneHypo}(D, N_0)$

$B = A$

**Return:** SortedByScore($B$)[:$N_{\text{best}}$]

---

**Algorithm 3:** N-step constrained beam search.

**Input:** $h_{\text{enc}}^t$, $N_{\text{step}}$, auto-$N_{\text{step}}$, $\alpha$, $N_{\text{ns}}$ and $N_{\text{best}}$

$h_{\text{batch}_{\text{enc}}}$, state$_{\text{batch}_{\text{dec}}}$ = BatchDecoder($\emptyset$, Duplicate(state$_{\text{dec}}$, state$_{\text{enc}}$))

$B = \{ \emptyset, 1, \text{state}_{\text{batch}_{\text{enc}}}, \text{state}_{\text{batch}_{\text{dec}}} \}$

**for** $t = 1 ... T$ **do**

$A = \text{SortedByLength}(B); B = \{ \}$

**for** $(y_i, \delta(y_i)) \in A$ **do**

$p^t = \text{Softmax}(\text{Joint}(h_{\text{enc}}^t, h_{\text{enc}}^{t-1}))$

**if** $y_i \notin A$ **then**

$\delta(y_i) = \delta(y_i) * p^t(\emptyset)$

$S = S \cup \{(y_i, \delta(y_i), \text{state}_{\text{enc}}_{y_i})\}$

**for** $k = 1 ... \text{N}_{\text{step}}$ **do**

$\delta(y_i + k) = \delta(y_i) * p^t(k)$

$V = V \cup \{(y_i + k, \delta(y_i + k), h_{\text{enc}}^{t-1}, \text{state}_{\text{enc}}_{y_i})\}$

$V = \text{SubtractSet}(\text{SortedByScore}(V), B)[:N_{\text{ns}}]$

$V_{\text{batch}} = \{y_i, \delta(y_i), h_{\text{enc}}^{t-1}, \text{state}_{\text{enc}}_{y_i}\}$

if $n < N_{\text{step}} - 1$ **then**

**for** $(y_i, h_{\text{enc}}^{t-1}, \text{state}_{\text{enc}}_{y_i}) \in V$ **do**

$h_{\text{enc}}^{t-1} = h_{\text{batch}_{\text{enc}}}$

state$_{\text{enc}}^{t-1} = \text{state}_{\text{batch}_{\text{enc}}}$

$A = V$

else

$p^t = \text{Softmax}(\text{Joint}(h_{\text{enc}}^t, h_{\text{enc}}^{t-1}))$

**for** $(y_i, \delta(y_i), h_{\text{enc}}^{t-1}, \text{state}_{\text{enc}}_{y_i}) \in V$ **do**

if $N_{\text{step}} = 1$ and auto-$N_{\text{step}} = 1$ **then**

$\delta(y_i) = \delta(y_i) * p^t(\emptyset)$

state$_{\text{enc}}^{t-1} = \text{state}_{\text{batch}_{\text{enc}}}$

$B = \text{SortedByScore}(S + V)[:N_{\text{best}}]$**

**return:** SortedByScore($B$)[:$N_{\text{best}}$]
controlling the search space either time-synchronously (TSD, OSC NSC) or label-synchronously (ALSD). While the latter was found promising in regards to its decoding speed, it cannot be used for streaming [19]. For the strategies running along time axis, OSC and TSD shown some drawbacks compared to our proposed algorithm, which can be summarized as follow: 1) OSC rely on a too strong constraint resulting in performance degradation for some tasks such as low resources and 2) TSD, while adding more control to alleviate previous issue, fell short against our own due to the blank transition score addition on some edge cases (see Sec. 6.2).

6. EXPERIMENTS

Our experiments are formulated as follow. First, we investigate the proposed training augmentation through several experiments. Second, we compare the decoding strategies in regards to both error rate and real-time factor. Finally, we present a comparison against other models in ESPnet and state-of-art systems on different datasets. For the first two sections, we use the Voxforge italian dataset [34] (~20 hours), which has the advantages of being free and experiments are easily reproducible without a consequent need in terms of resources. For the last section, we use LibriSpeech [35] and AISHELL-1 [36]. For the different configurations and the pre-trained models used in our experiments, we refer the reader to the ESPnet toolkit where all needed resources will be made available.

6.1. Architecture and training augmentation

To assess the effectiveness of the auxiliary tasks, we conduct several experiments with a RNN-T model on the Voxforge dataset. In order to perform our primary experiments, we first need to rank our auxiliary tasks, based on the observed average CER/WER gain, and select an optimal weight for each task. From here, our final ranking is as follows: 1) with the same weight. While we observed an average gain in terms of the model makes the model starts with more emphasis on the context level by enforcing monotonicity, adding LM criterion further improves decoder prediction resulting in a significative gain in terms of the WER.

Next, we compare our two best performing auxiliary tasks, \( L_{CTC} \) and \( L_{\text{LM}} \), against other techniques incorporating CTC and LM tasks: 1) transfer learning with a pre-trained CTC model for the encoder part [29] and a pre-trained language model [37] for the decoder part, and 2) decoding with an external language model. The table 4 summarizes our experiments, where "ext. LM" refers to the external LM and "p.t. \( X \)" to the transfer of pre-trained weights from a model \( X \). Relying on a pre-trained CTC model for encoder initialization results in a lower CER and an higher WER compared to training a transducer model with \( L_{CTC} \). For the LM task, training a vanilla RNN-T and using an external LM for decoding brings the most improvement (avg. -0.15% CER and -0.9% WER) at the cost of a significant increase in terms of decoding time (almost doubled). Using transfer learning or \( L_{\text{LM}} \) to regularize the decoder part during training brings almost the same performance, with a slightly better performance in terms of CER (-0.2%) for the first and a WER improvement (-0.25%) for the latter. From our observation, transfer learning for either part of the model makes the model starts with more emphasis on the conditional independence between predictions in comparison to training the model with an auxiliary task.

From here, we extend our investigation with a comparison between different pairs of techniques. Most pairs seems to work well together and further decrease both CER and WER compared to training with a single technique. Notably, we found out that pre-initializing the encoder with a CTC model and adding an auxiliary...
LM task during training to focus on the decoder part decrease significantly the number of errors at character level compared to training with $L_{CTC}$ and $L_{LM}$. That setup also outperforms our model trained with all auxiliary tasks in terms of CER vs RTF, averaged on 5 runs. We use the vanilla RNN-T and the RNN-T trained with all auxiliary tasks, and a beam of size 5 under all conditions. Three different values are evaluated for each algorithm: [25, 50, 100] for $U_{\text{max}}$ in ALSD, [2, 3, 4] for max_sym_exp in TSD and [1, 2, 3] for $N_{\text{step}}$ in NSC. All experiments were performed using a CPU Intel i7-6950X limited to one thread (the default setting in ESPnet).

With the baseline model, ALSD outperforms all other algorithms in terms of the decoding speed, with a maximum RTF of 0.1, comparable to the best RTF observed for frame-synchronous strategies. For the latter, TSD and NSC, reducing each time by one the value for the parameter controlling number of emitted labels, respectively max_sym_exp and $N_{\text{step}}$, results in an average 25% RTF reduction but increase the CER. Because TSD suffers from the same issue as OSC (See [54]), its performance is significantly impacted when max_sym_exp = 2, resulting in an CER increase of 80% while NSC with $N_{\text{step}} = 1$ is increased by 36%. Reducing $U_{\text{max}}$ for ALSD also significantly impacts the CER (+29% with $U_{\text{max}} = 25$). Using auxiliary tasks reduces the number of emitted labels by timestep, mainly due to the auxiliary CTC. Compared to the report in Table 2, we denote the following: 96.32% of 1-labels by timestep, mainly due to the auxiliary CTC.

### 6.2. Investigation on decoding strategies

Figure 2 compares the decoding strategies, introduced in section 5 with different parameter values in terms of CER vs RTF, averaged on 5 runs. We use the vanilla RNN-T and the RNN-T trained with all auxiliary tasks, and a beam of size 5 under all conditions. Three different values are evaluated for each algorithm: [25, 50, 100] for $U_{\text{max}}$ in ALSD, [2, 3, 4] for max_sym_exp in TSD and [1, 2, 3] for $N_{\text{step}}$ in NSC. All experiments were performed using a CPU Intel i7-6950X limited to one thread (the default setting in ESPnet).

We evaluate ESPnet’s transducer models on AISHELL-1 [36] and LibriSpeech [35] to compare their performance with other models in the literature. Specifically, RNN-T and Conformer-T models without and with auxiliary tasks are evaluated, where $L_{CTC}$ is used for AISHELL-1, and $L_{CTC}$ and $L_{LM}$ are used for LibriSpeech. The default beam search is used with a beam size of 10 for both datasets. Table 5 presents the results on AISHELL-1. Our RNN-T and Conformer-T models achieved CERs of 7.2% and 5.0% respectively on the test set, which are both significantly better than the performance of RNN-T/Conformer-T models in the literature [38][39]. With the help of the auxiliary task, the RNN-T and Conformer-T models reached CERs of 6.9% and 4.7%, respectively. The latter is on par with the state-of-the-art performance achieved by the attention-based Conformer model [27]. Table 6 summarizes the results on LibriSpeech. The use of the auxiliary tasks again helped to reduce the WERs of our RNN-T model on the test sets. An even better performance of 2.9%/6.8% was obtained by switching from RNN-T to Conformer-T. Finally by using shallow-fusion and an external LM trained on the default training material for LibriSpeech’s LM, the Conformer-T achieved 2.6%/6.1%, which is comparable to the performance of other open-source toolkits.

### 7. CONCLUSION

This paper introduced an extension of the ESPnet speech recognition toolkit dedicated to the transducer models. Through an experimental evaluation of the models and some main proposed features, we demonstrated that our models can achieve state-of-art results on AISHELL-1 dataset and also exhibit promising performance in regards to real-time decoding and others models in ESPnet. Future work will focus on improving the model trained on Librispeech and adding features currently in development, namely: training with MBR and streaming. Further analysis of our proposed Transducer against non-autoregressive models [41][42] is also considered.
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