RNN-T Models Fail to Generalize to Out-of-Domain Audio: Causes and Solutions
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Abstract
In recent years, all-neural end-to-end approaches have obtained state-of-the-art results on several challenging automatic speech recognition (ASR) tasks. However, most existing works focus on building ASR models where train and test data are drawn from the same domain. This results in poor generalization characteristics on mismatched-domains: e.g., end-to-end models trained on short segments perform poorly when evaluated on longer utterances. In this work, we analyze the generalization properties of streaming and non-streaming recurrent neural network transducer (RNN-T) based end-to-end models in order to identify model components that negatively affect generalization performance. We propose two solutions: combining multiple regularization techniques during training, and using dynamic overlapping inference. On a long-form YouTube test set, when the non-streaming RNN-T model is trained with shorter segments of data, the proposed combination improves word error rate (WER) from 22.3\% to 14.8\%; when the streaming RNN-T model trained on short Search queries, the proposed techniques improve WER on the YouTube set from 67.0\% to 25.3\%. Finally, when trained on Librispeech, we find that dynamic overlapping inference improves WER on YouTube from 99.8\% to 33.6\%.

Index Terms: Speech recognition, RNN-T, end-to-end, sequence-to-sequence, long-form

1. Introduction
The last decade has seen rapid improvements in automatic speech recognition (ASR) technology through advances in deep learning\(^1\). Recently, there has been growing interest in building so-called end-to-end ASR systems – systems consisting of a single neural network, which directly output character-based or word-based units: e.g., connectionist temporal classification (CTC)\(^2\) with character\(^3\) or word\(^4\) targets; attention-based encoder-decoder models\(^5\)\(^6\)\(^7\)\(^8\)\(^9\); and the recurrent neural network transducer (RNN-T)\(^10\)\(^11\)\(^12\).

Most previous works investigating end-to-end models have evaluated models in the setting where training and test utterances are relatively short (i.e., tens of seconds) and drawn from the same domain\(^11\)\(^12\)\(^13\). In previous work, we identified two problems that affect end-to-end models: first, we observe that end-to-end models are particularly sensitive to a domain-mismatch between training and inference, caused by overfitting to the training domain\(^13\). Since end-to-end models learn all components jointly, the effect is more pronounced than would be expected in conventional models\(^20\). A second problem – a specific kind of domain mismatch – is the observation that end-to-end models trained on short training segments do not perform well when decoding much longer utterances during inference (e.g., longer YouTube videos)\(^19\)\(^21\); this problem is particularly acute for non-streaming attention-based models\(^21\), but, somewhat surprisingly, also affects streaming end-to-end models such as RNN-T\(^1\).

Our previous works proposed a number of solutions to address these problems: training on diverse domains\(^19\); simulating long-form speech by manipulating the encoder/decoder states\(^19\); or by performing inference over short overlapping segments which can be assembled into the complete hypothesis\(^21\). Although our proposed solutions improved performance on out-of-domain and long-form audio, our previous works did not characterize the fundamental reasons for the degradation in performance. In the present work, we perform a detailed analysis of the RNN-T model to determine which models components are primarily responsible for this performance degradation, finding that the encoder network in the model is most susceptible to overfitting. In light of this observation, we reinterpret previously proposed solutions\(^19\)\(^21\) as additional regularization constraints imposed on the model to prevent overfitting, and find that combining multiple regularization techniques results in the best performance. In experimental evaluations, we decode a YouTube test set using three RNN-T models: a model trained using short-segments of YouTube data; a model trained using short-segments of Search data; and a model trained on the Librispeech dataset. We find that combining various regularization techniques improves the models trained on YouTube and Search data by 33.6\% and 62\%, respectively. In combination with our proposed dynamic overlapping inference technique (See Section\(^5\)), our mismatched Librispeech trained models show dramatic word error rate (WER) improvements from 99.8\% to 33.0\% on the YouTube test set.

2. RNN Transducer
The RNN-T model was proposed by Graves\(^22\)\(^13\) as an improvement over CTC\(^2\). As with CTC, the RNN-T model introduces a special blank symbol, (b), which models the alignments between the speech frames, \(x = [x_1, \cdots, x_T]\), and the output label sequence, \(y = [y_1, \cdots, y_J]\). We denote the number of speech frames by \(T\), with each \(x_t \in \mathbb{R}^d\), and \(y\) denotes the set of output labels with \(y_u \in \mathcal{Y}\). The set of all

\(^1\)Work conducted while the authors were at Google
\(^2\)In this context, we use ‘domain’ to refer to utterances which share a common property. E.g., audiobooks (long read speech utterances\(^16\)), or voice search queries (short utterances).
valid frame-level alignments, can be written as: \( B(x, y) = \{ \hat{y} = (\hat{y}_1, \ldots, \hat{y}_{T+U}) \} \), where \( \hat{y}_i \in Y \cup \{ \langle \rangle \} \), such that \( \hat{y} \) is identical to \( y \) after removing all blank symbols. During training, RNN-T uses the forward-backward algorithm to maximize \( P(y|x) \), taking all valid alignments into consideration. The RNN-T model, depicted in Fig. 1, consists of an encoder, a prediction network (an LSTM network), and the joint network (a feed-forward network) which integrates information from the other two. More implementation details can be found in [19].

### 3. The Generalization Problem

This section characterizes the generalization problem for streaming and non-streaming models and presents experimental observations that identify components that contribute to poor generalization.

#### 3.1. Non-streaming ASR Models

Our experimental setup is similar to [21]. The training data is extracted from YouTube videos [24]. The training utterances are generally short: the 50\textsuperscript{th} percentile length is 5.13 seconds and the 90\textsuperscript{th} percentile is 12.67 seconds. During training we filter out utterances that are longer than 15.36 seconds. We evaluate the model on two YouTube test sets, YT-short and YT-long. YT-short is comprised of 119 videos with length ranging from 2 to 10 minutes, with a total duration of 11.37 hours. YT-long is comprised of 87 videos with length ranging from 30.18 seconds to 30 minutes, with a total duration of 24.12 hours. The videos in both test sets are much longer than the training sam-

![Figure 1: Block diagram of an RNN-T model [22][13].](image1)

![Figure 2: WERs for non-streaming model on YT-short (solid line) and YT-long (dotted line) as a function of training steps. Results are also shown when only the encoder, prediction, or the prediction + joint networks are trained after 50k steps of training all components.](image2)

![Figure 3: Probability of blank symbol for steps 1 – 5, as a function of utterance length. Dotted and solid lines correspond to predictions at 50k and 200k steps, respectively. At 200 steps the model exhibited inconsistent prediction as a function of utterance length.](image3)
for blank symbols fails to generalize well on long utterances. Since this model has bidirectional LSTMs, the backward LSTM contributes towards the high variance of blank probability at the first few steps of predictions. This affects the model’s hypotheses in multiple ways: first, a high blank probability would result in partial hypotheses consisting of a sequence of blank tokens to have a higher probability than the correct sequence; eventually this blank sequence would also cause other partial hypotheses that have fewer blanks and are more accurate to be dropped from the beam, causing additional search errors. This results in the WER being dominated by deletions.

3.2. Streaming ASR Models

A typical streaming application is voice search on mobile phones. We, therefore, choose this task for the streaming use-case. Due to latency constraints the model size is more limited than the non-streaming cases, and our experimental setup mimics those in\cite{19}. 128-dimensional log-mel features from 4 contiguous frames are stacked to form a 512 dimensional input, which is then subsampled by a factor of 3 along the time dimension. The RNN-T model has 8 encoder layers made up of unidirectional LSTMs. Each layer has 2048 units and a projection layer with 640 outputs units\cite{27}. The decoder consists of 2 unidirectional LSTMs, also with 2048 units and 640 projections similar to the encoder layers. The joint network has a single layer with 640 units. The target is represented by a sequence of word piece tokens\cite{26}, with a vocabulary size of 4096.

The training data consists of anonymized and hand-transcribed utterances representative of the Google search traffic\cite{19}. We use multi-condition training (MTR) to simulate noisy conditions, and randomly downsample the data from 16 kHz to 8 kHz to improve generalization to varying input sample rates. The training utterances are short, with mean and median duration of 6.3 and 4.8 seconds, respectively. The 90th percentile is 10.9 seconds. The 50th and 90th percentiles for the target sequences of word-pieces, are respectively, 5 and 17 tokens. As test sets, we use a mix of in-domain and out-domain data. A test set similar to the training domain and composed of 60 hours of anonymized and hand transcribed search queries forms the in-domain test set (Search; median length is 6 seconds). Our out-of-domain test set consists of 7 hours of speech generated using a text-to-speech system\cite{29}, which is acoustically simple but much longer than the training utterances (TTS-Audiobook; median length is 62 seconds).

**Observations**: Similar to the non-streaming models, we observe that the streaming model also overfits to the training domain after approximately 50k steps as shown in Fig.\ref{fig:streaming_asr_models}. Unlike non-streaming models, however, performance keeps improving on the in-domain Search set with more training. Performance on the TTS-Audiobook set, in contrast, gets worse as training progresses. Next, we freeze parts of the model after 50k steps, as before, and continue training just the encoder; the prediction network; or both the prediction and joint networks. Confirming the observations made for the non-streaming models, freezing the encoder layers and only updating the prediction, or the prediction and the joint layers prevents this overfitting behavior. After 300k steps, both the baseline, which updates all model parameters, and the model that only updates encoder layers obtain WERs of 45.1 and 48.7, respectively, on TTS-Audiobook; the model that only updates the prediction network obtains a WER of 14.0%. Thus, the degradation in performance is significantly less severe when the model does not update the encoder after 50k steps.

The results presented in the streaming and the non-streaming case indicate that the encoder is most responsible for the overfitting behavior of RNN-T. In the next section, we explore various regularization strategies to reduce overfitting.

4. Regularization Cocktail

As the generalization issue is caused by encoder overfitting, it can be remedied effectively through regularization. Different domains and architectures can benefit from different regularization techniques, and thus we combine them during training to create a regularization cocktail:

- **Variational Weight Noise**: Variational weight noise adds Gaussian noise to the weight matrix during training\cite{29}, and has been shown to be effective in improving generalization\cite{19}. In our approach we start the training process without noise, and start adding it after a predefined number of steps. The weight noise is re-sampled at every training step.

- **SpecAugment**: SpecAugment\cite{17, 30} is a data augmentation algorithm that alters the spectrogram of the input utterances. The approach applies time warping, time masking, and frequency masking on the spectrogram, and trains the model to be robust to such data augmentation.

- **Random state sampling and random state passing**: Random state sampling (RSS) and random state passing (RSP) were proposed in\cite{19} as a way to address generalization of streaming RNNT models to long-form speech. RSS assumes that LSTM states follow a normal distribution and samples initial LSTM states from it during training. RSP is readily applicable for bidirectional models as well. RSP, on the other hand, saves LSTM states from each mini-batch during training, and uses them as initial states for examples in the subsequent batch. When used with unidirectional models, this mimics random concatenation of examples during training.

5. Dynamic Overlapping Inference

In addition to improving generalization during training, we attempt to improve generalization during decoding with overlapping inference\cite{21}. This method segments a long utterance into multiple fixed-length segments which are decoded independently. Since each segment lacks context from neighboring segments, we allow some overlap between successive segments, and merge the decoded hypotheses in the overlapped region. The original method\cite{21} was proposed in the context of models.
which do not have any alignment information for the hypothesis which required a 50% overlap between segments, and thus 2× the computational cost compared to regular inference.

Here, we extend overlapping inference to relax the 50% overlap requirement. Our proposed algorithm – dynamic overlapping inference (DOI) – infers frame-level alignment obtained from each RNN-T hypothesis, $\hat{x}$, (i.e., we use the frame associated with each non-blank label) to match and merge hypotheses between segments. This allows us to significantly relax the 50% overlap requirement, thus greatly increasing computational efficiency. The process is illustrated in Fig 5.

6. Experiments

We evaluate generalization performance of the proposed techniques for the models described in Sec. 3. All models are implemented with Lingvo [31].

Non-Streaming Models: The results using the regularization cocktail and dynamic overlapping inference (DOI) are shown in Tab. 1. All regularization techniques and their combinations help improve performance. In particular, SpecAugment + RSP + VN obtains a 14.2% improvement on YT-short and a 33.6% improvement on YT-long, and DOI obtains 8.5% and 23.8% improvement on YT-short and YT-long, respectively. We further evaluate the model on a long-form call-center test set described in [27] to assess its robustness on unseen domain. The proposed regularization cocktail improves WER by 30.1% and 18.8% when using regular inference and DOI, respectively. In general, DOI provides significant improvement when models have generalization issue on the target domain, and provide similar quality as regular inference for models that do not have this issue.

Streaming Models: Results are shown in Tab. 2. As with the non-streaming models, the model with multiple regularizations gave the best improvements. SpecAugment + VN + RSP obtains a 76% improvement on TTS-Audiobook and a 62% improvement on YT-short. Other combinations also help, but are slightly worse than SpecAugment + VN + RSP. It should be noted that some of these models still perform better at 50k checkpoint. For example, SpecAug + VN obtains 14.5% and 22.5% on TTS-Audiobook and YT-short, respectively, at 50k steps. Although the combination doesn’t completely prevent overfitting, the degradation, as the model converges on the training data, is much lower than the baseline. We note that DOI does not help with streaming models, likely because it relies on alignment and end-to-end streaming models are know to produce poor alignments unless they are constrained during training.

Librispeech: The final set of results are when the RNN-T model is trained on Librispeech [33]. We follow the architecture of LAS-6-1280 described in [17]. The prediction network has the same LSTM setup as the LAS decoder. The joint network has 640 hidden units, and uses the same word piece model. The results are shown in Tab. 3. Despite achieving low WERs on the Librispeech test sets, the model exhibits high deletion errors on YT-short. DOI reduces the deletion error from 99.5% to 3.6%. The model still has a WER of 33.0% after using DOI, mainly due to substitutions (22.2%) caused by phonetically similar words. This is likely caused by the limited vocabulary the Librispeech model is exposed to during training.

7. Conclusions

This work presents an analysis of the generalization problem observed in RNN-T based end-to-end ASR models. Our results demonstrate that the model’s affinity to predict blank sequences when there is a mismatch between training and test distributions causes this problem, which results in high deletion rates. Our analysis identified the root cause of this problem to be encoder overfitting. We proposed a regularization cocktail that significantly improves the performance of streaming and non-streaming RNN-T models trained with large-scale data. For models trained on a smaller dataset, where regularization alone doesn’t improve performance, we proposed a dynamic overlapping inference strategy that significantly improves generalization. Future work will explore alternative model architectures and regularization techniques that address the generalization of models trained on smaller datasets.

![Dynamic overlapping inference with 16 second segments and 2 second overlap. Reducing the overlapped regions from 8 seconds as in [27] greatly improves inference efficiency.](image)

Table 1: Non-streaming model WERs with regular inference (Reg.) and DOI on YT-short, YT-long and Call-center test sets. VN uses encoder variational noise (std= 0.05) and SpecAugment uses 10 time masks up to 4% of audio length, 2 frequency masks up to 27 dims.

| Models            | YT-short Reg | YT-long Reg | Call-center Reg | DOI |
|-------------------|--------------|-------------|-----------------|-----|
| Base              | 10.6/6.9     | 17.0/7.4    | 19.3/7.5        |     |
| SpecAugment       | 9.4/7.0      | 15.3/10.0   | 19.3/7.5        |     |
| + RSP             | 9.3/7.0      | 15.6/10.0   | 19.3/7.5        |     |
| + RSP + VN        | 9.1/7.0      | 14.8/10.0   | 19.3/7.5        |     |

Table 2: WERs using streaming RNN-T models trained on Search data with variational noise on all layers (std=0.03) and SpecAugment uses 2 time masks and 2 frequency masks with widths up to 1.5 seconds and 27 dimensions, respectively.

| Models            | Search | TTS-Audiobook | YT-short |
|-------------------|--------|---------------|----------|
| Baseline          | 4.9    | 48.6          | 67.0     |
| VN                | 4.7    | 31.3          | 59.8     |
| SpecAugment       | 4.6    | 16.5          | 52.9     |
| + RSP             | 5.1    | 11.9          | 27.3     |
| + RSP + VN        | 5.1    | 11.9          | 25.3     |

Table 3: WERs / deletions for Librispeech with regular inference (Reg.) and DOI using 16s window with 2s overlap.
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