# Fast Text-Only Domain Adaptation of RNN-Transducer Prediction Network

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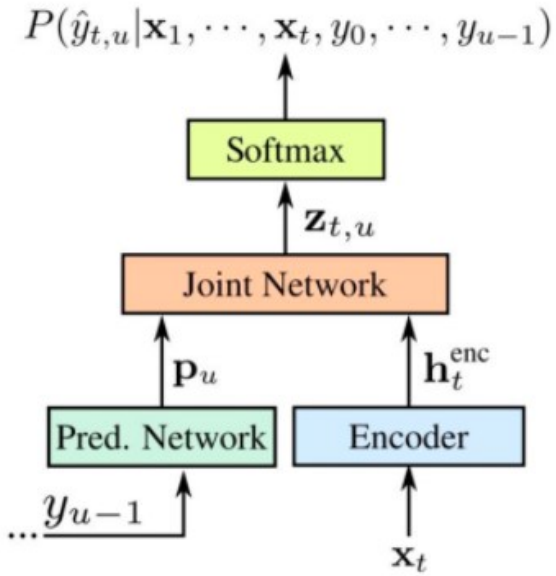
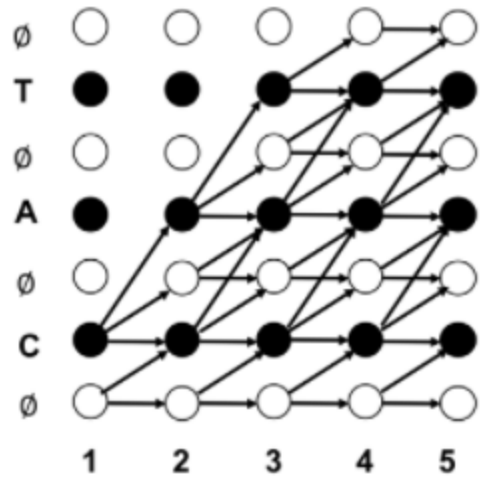
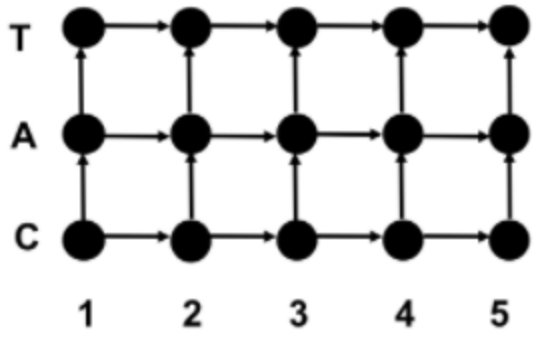
# Preliminary

- RNN-Transducer
  - Architecture (left), alignment (right)




(a) CTC




(b) RNN-Transducer

# Problem

- To customize E2E models for a particular domain ..
  - Shallow fusion with external LMs
  - TTS-adaptation (fine-tune using TTS-generated data)

- However ..
  - Require changes to the model and/or decoding
  - Require generates from external data

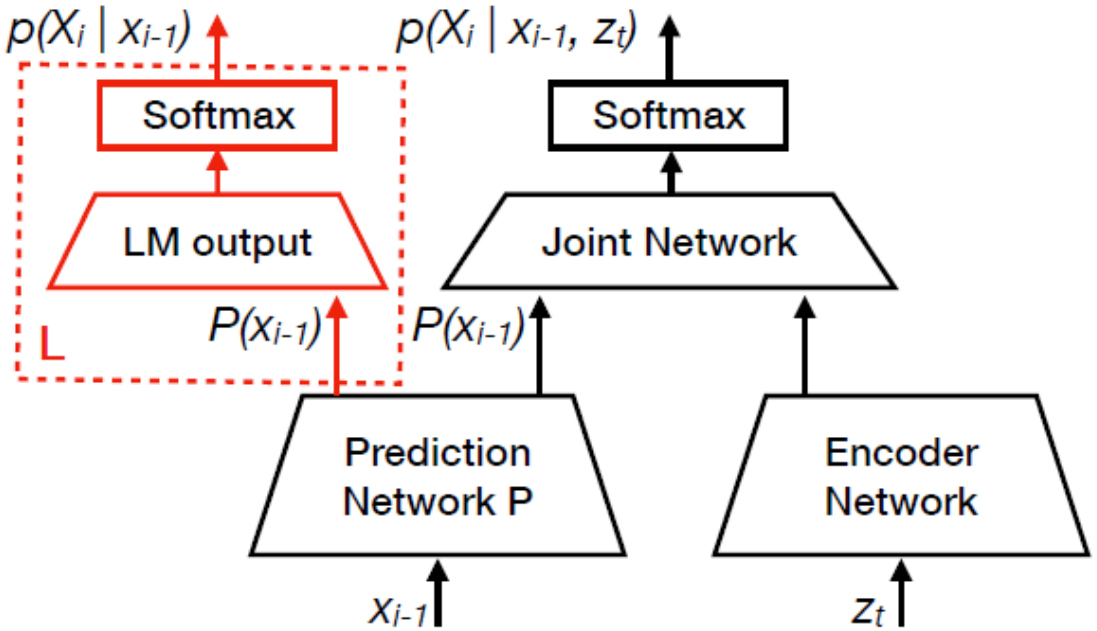
- In this paper ..
  - They present a simple yet effective RNN-T adaptation method
  - Require only textual data

# Proposed Methods

- Overview
  - (Initializing networks)
  - (RNN-T training)

  - Pre-processing step
    - Attach $L$
    - Transcription $D_t \rightarrow p(X_i|x_{i-1})$
    - While keeping $P$ fixed

  - Adapation step
    - Transcription $D_a \rightarrow$ fine-tune
    - While keeping $L$ fixed
    - Detach $L$



# Proposed Methods

- Regularization
  - Only used in the adaption step … to prevent $P$ from over-fitting to the corpus $D_a$
  - Penalize changes in the predictions observed with common utterances
    - $P^*$: non-adapted prediction network → $p^*(X_i|x_{i-1}) = L(P^*(x_{i-1}))$
    - $D_b$: set of sampled utterance $\hat{x}$ for each adaptation example $x$ in $D_a$ (similar length)

$$\ell_b(x, P) = \frac{1}{n}\sum_{i=1}^{n} \mathrm{KLD}\left(p(X_i \mid x_{i-1}), p^*(X_i \mid x_{i-1})\right)$$

  - Penalizes the drifting of the weights of $P$ from their original values in $P^*$

$$\ell_n(P) = \|P - P^*\|_2$$

  - Therefore ..

$$\ell(P) = \sum_{x \in D_a} \frac{\mathrm{CE}(x, P)}{|D_a|} + \frac{w_b}{|D_b|} \sum_{x \in D_b} \ell_b(x, P) + w_n \ell_n(P)$$

# Setup

- ASR systems
  - Encoder: 32 dimensional filterbank energies, a convolution layer, 7 LSTM layers
  - Prediction network: 2 LSTMs
  - Joint network: a feed-forward layer, softmax activation (1000 word pieces and a blank symbol)

  + SpecAugment, beam-search decoder

  + Each encoder and prediction network is pre-initialized.

  + $W_b = 0.8$, $W_n = 0.05$

- Dataset
  - English Oscar (initialization of prediction network)
  - LibriSpeech, English Common Voice, Ted-lium 3 (RNN-T training)
  - Ted-lium 3, ATIS3, Slurp (evaluation)

Table 1: *Amount of adaptation (text) and evaluation (audio) utterances, and the size of the vocabulary in the datasets used in the experiments.*

| **Dataset** | #Adaptation utts | #Eval utts | Vocabulary |
|---|---|---|---|
| ATIS3 | 6355 | 965 | 1080 |
| Slurp | 10680 | 4173 | 5168 |
| Ted-lium | – | 1155 | 3652 |

# Results

Table 2: *WER for unadapted and adapted models over evaluation corpora, and relative WER reduction.*

| **Dataset** | Unadapted | Adapted | WERR-% |
|---|---|---|---|
| ATIS3 | 15.9% | 11.9% | -25.2% |
| Slurp (pooled) | 42.8% | 38.6% | -9.8% |
| Slurp (scenario) | 42.8% | 37.3% | -12.9% |
| ATIS3 (prod) | 9.7% | 5.4% | -44.7% |
| Slurp (scen; prod) | 27.4% | 23.4% | -14.6% |

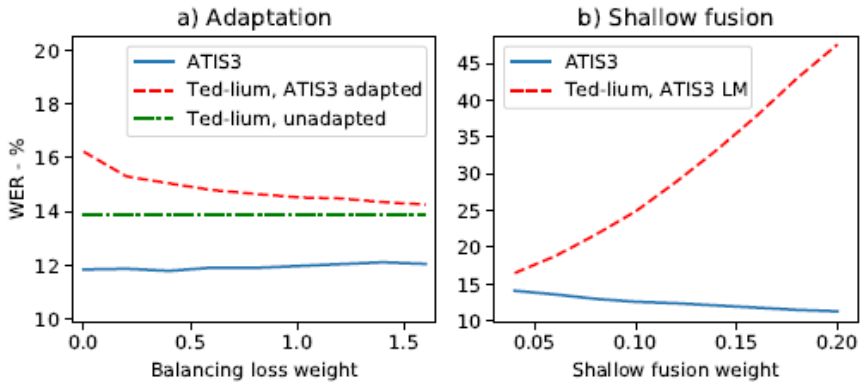



Figure 2: *Adaptation experiments with in-domain and out-of-adaptation-domain evaluation. a) The effect of the balancing loss weight to the accuracy of the adapted models. b) Shallow fusion with ATIS3 4-gram, varying the shallow fusion weight.*

# Results

Table 3: *Word-level perplexities of held-out evaluation text corpora computed with the prediction network at different stages of RNN-T training and adaptation.*

| | Perplexity | | |
|---|---|---|---|
| **Model** | Oscar | LibriSp | ATIS3 |
| #1 Initializing LM | **123.6** | 286.7 | 238.4 |
| #2 RNN-T, old LM output | 151.0 | 292.8 | 276.3 |
| #3 RNN-T, new LM output | 179.8 | **231.4** | 261.9 |
| #4 ATIS3 adapted RNN-T | 197.9 | 251.9 | **23.4** |
| RNN-T, uninitialized $P$ | 1279.2 | 400.5 | 1137.0 |
| RNN-T, internal LM | 770.5 | 1116.9 | 1055.4 |

# Discussion

- To take the full advantage of the LM property of P and L, a new LM output layer needs to be trained after the RNN-T training.
- The initialization of the prediction network can have an important role.
- The presented RNN-T adaptation provides similar accuracy gains, but outperforms shallow fusion in the generalization capability.