Promising Accurate Prefix Boosting for Sequence-to-sequence ASR

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**Premilinaries**

- What is Prefix?
  - In the context of ASR, prefix refers to a partial sequence
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  – In the context of ASR, prefix refers to a partial sequence

• Why boost accurate prefix??
  – Training by boosting correct prefixes (accurate) over wrong prefixes will help model to rectify its own errors
Encoder - Decoder

- **Encoder:**
  - recurrent layers
  - entire input sequence to fixed-length vector

- **Decoder:**
  - recurrent layers with final softmax layer
  - predict probability for the next symbol of the output sequence in an auto-regressive fashion
  - learns an implicit language model for the output sequences
Problem Overview

- **Exposure bias**
  - **Training**: output character is conditioned on the previous true character
  - **Testing**: the model needs to rely on its own previous predictions

- **Error criterion mismatch**
  - **Training**: the objective is the conditional maximum likelihood (cross entropy) for maximizing the probability of the correct sequence
  - **Testing**: Character error rate (CER) or word error rate (WER)
Mismatch during train and decode

**Training**: Minimize cross-entropy loss of each target token $y_i^*$ (character)

$$\log p(y^* | X) = \sum_i \log p(y_i^* | X)$$

**Teacher-forcing**: Feed previous token from ground-truth as auxiliary info to predict current token

True seq : ABB

True labels

Hypothesis
Mismatch during train and decode

Decoding:

- Previous token from hypothesis is fed to predict current token
- Output sequence is predicted in two ways
  - Greedy (argmax) search
  - Beam search

True seq: ABB
Argmax seq: BAB
Mismatch during train and decode

True seq: ABB
Argmax seq: BAB
Modify training procedure ??

Decrease the training loss for both reference and predicted paths !!

Training is matched to testing
Scheduled sampling

Recognition performance on Voxforge-Italian (14 hours) corpus

Scheduled sampling (SS) performance

<table>
<thead>
<tr>
<th>% WER</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline (Teacher-forcing)</td>
</tr>
<tr>
<td>52</td>
</tr>
</tbody>
</table>
Is there a technique to train only with predictions as previous tokens?
Decoding:

- Previous token from hypothesis is fed to predict current token
- Output sequence is predicted in two ways
  - Greedy (argmax) search
  - Beam search
Beam search

- Heuristic approach where only the most promising (S) nodes at each step of the search are retained for further branching
- B – beam size / width (S = 2 in the figure)
- Efficient Memory usage
- Used to generate N-best list of paths

True seq : ABB
Beam search seq : ABB
How to match beam-search decoding with training??

- Need to consider multiple hypothesis generated during beam-search.
- Training objective must keep prefix at top of the beam.
- Helps to survive pruning by keeping scores higher in the beam.

Beam width = 3

Correct prediction
How to match beam-search decoding with training??

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Beam width =3

```
P T S I A E T C K
```

Correct prediction
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Prefixes that participate in loss:

Beams width = 3:

Correct prediction:

- P
- I
- T
- A
- C
- S
- E
- K
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Prefixes that participate in loss: P I T A S, Prefix width = 3.

Correct prediction: K

Beam search
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Prefixes that participate in loss

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Prefixes that participate in loss:

```
P I T A S O
T A C E L L
S E K M A S
K E
```

Correct prediction:

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Prefixes that participate in loss

Correct prediction
Choose weights

score of true label is better than predicted label by a specific margin

$$L_{MM} = \sum_l -s(y^*_l, X) + \max_y (s(y, X) + \alpha \text{Acc}(y^*_l, y))$$
Choose weights

score of true label is better than predicted label by a specific margin

weight \cdot (true\ label\ score) \geq (Margin) + weight \cdot (scores\ of\ other\ labels)

\[ L_{MM} = \sum_l -s(y^*_l, X) + \max_y (s(y, X) + \alpha \text{Acc}(y^*_l, y)) \]
Maximum margin objective

Choose weights

Score of true label is better than predicted label by a specific margin:

\[ \text{weight} \cdot (\text{true label score}) \geq (\text{Margin}) + \text{weight} \cdot (\text{scores of other labels}) \]

\[
\mathcal{L}_{MM} = \sum_{l} -s(y^*_l, X) + \max_y (s(y, X) + \alpha \text{Acc}(y^*_l, y))
\]

Label → Prefix

**True label score**

**Predicted label score**

**Margin**
Maximum margin objective

Choose weights

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Label → Prefix

Better for training the encoder-decoder because they contain more informative training signals at each step
Maximum margin objective

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**Label → Prefix**

Better for training the encoder-decoder because they contain more informative training signals at each step

\[ \mathcal{L}_{MM} = \sum_{l} - s(y^*_{1:l}, X) + \max_{y} (s(y_{1:l}, X) + \alpha \text{Acc}(y^*_{1:l}, y_{1:l})) \]
Promising accurate prefix boosting (PAPB)

- Hard maximum is replaced by soft maximum “softmax” \((\log \sum \exp)\)
- Softmax margin* showed noticeable gains over max margin empirically

\[
\mathcal{L}_{SM} = \sum_l -s(y_{1:l}^*, X) + \log(\sum_y \exp(s(y_{1:l}, X) + \alpha \text{Acc}(y_{1:l}^*, y_{1:l})))
\]

- Generalization of boosted MMI (bMMI) criterion

* K. Gimpel and N. A. Smith, “Softmax-margin training for structured log-linear models,” 2010
Promising accurate prefix boosting (PAPB)

- CE (SS – greedy search)
- CE (SS – beam search)
- Maximum margin
- Softmax margin
% WER on held-out set with PAPB

% WER by varying beam-width

- Training beam width
- % WER

- 2
- 5
- 10
- 12
- 15
Comparison with sequence-level objective

- Sequence-level optimization technique: Minimum Bayes Risk Criterion*

\[ \mathcal{L}_{MBR} = E_p(y|x) \left[ \text{Acc}(y^*, y) \right] = \sum_{y \in Y} p(y|X) \text{Acc}(y^*, y) \]

- Obtain sequence predictions from model distribution and backpropagate a sequence-level objective

- \( Y \) denotes the N-best sequences selected using beam search

CER on held-out set with PAPB

%CER on validation set of Voxforge-Italian

- MBR
- Softmargin
- Prefix

# Epochs

0.15
0.145
0.14
0.135
0.13
0.125

1 2 3 4 5
## Impact of pretraining and CE regularization

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<thead>
<tr>
<th>CE</th>
<th>Pretraining</th>
<th>MBR (%WER)</th>
<th>% Rel. drop</th>
<th>PAPB (%WER)</th>
<th>% Rel. drop</th>
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<tr>
<td>Y</td>
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<td>10.8</td>
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<td>N</td>
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- **Pretraining is crucial** for sequence-level objective such as MBR training.
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- **Pretraining is crucial** for sequence-level objective such as MBR training
- **PAPB did show convergence without pretraining**
- **CE regularization provides 6.1 % and 16.7% relative gain for PAPB and MBR**
### Recognition performance on WSJ corpus

Effect of LM on **token level**, **sequence level** and **prefix (partial sequence)** level training.

<table>
<thead>
<tr>
<th>Model type</th>
<th>No RNNLM</th>
<th>Character RNNLM</th>
<th>Word RNNLM</th>
</tr>
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<tbody>
<tr>
<td>CE</td>
<td>%CER</td>
<td>%WER</td>
<td>%CER</td>
</tr>
<tr>
<td></td>
<td>4.6</td>
<td>12.9</td>
<td>2.5</td>
</tr>
<tr>
<td>MBR</td>
<td>%CER</td>
<td>%WER</td>
<td>%CER</td>
</tr>
<tr>
<td></td>
<td>4.3</td>
<td>11.5</td>
<td>2.5</td>
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<tr>
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<td>%CER</td>
<td>%WER</td>
<td>%CER</td>
</tr>
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<td></td>
<td>4.0</td>
<td>10.8</td>
<td>2.1</td>
</tr>
<tr>
<td>Deep-CNN*</td>
<td>-</td>
<td>10.5</td>
<td>-</td>
</tr>
<tr>
<td>OCD*</td>
<td>-</td>
<td>9.6</td>
<td>-</td>
</tr>
<tr>
<td>LF-MMI*</td>
<td>-</td>
<td>-</td>
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## Recognition performance (%WER) on Librispeech

Effect of LM on token level, sequence level and prefix (partial sequence) level training

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<tr>
<td></td>
<td>test-clean</td>
<td>test-other</td>
</tr>
<tr>
<td>CE</td>
<td>6.7</td>
<td>21.5</td>
</tr>
<tr>
<td>MBR</td>
<td>5.5</td>
<td>17.4</td>
</tr>
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<td>4.7</td>
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Conclusion and Constraints

- Prefix boosting with softmax-margin objective provides considerable gains
- **Effective** compared to sequence-level MBR objective
- Beam-search is **not an efficient** method to run with GPU
- 2-fold **increase in training time**
- Constraint in setting larger training beam-size
- Future work will be to use **sampling** approach instead of beam-search
References


