Large Margin Training Improves Language Models For ASR

Jilin Wang
Boston University
Boston, MA, USA

Jiaji Huang
Kenneth Ward Church
Baidu Research,
Sunnyvale, CA, USA

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Basic Structure of an Auto Speech Recognition (ASR) System
N-Best Rescoring

Language Model
Perplexity

\[ PPL = \exp \left\{ - \frac{1}{|X|} \text{Score}(X) \right\} \]

- Scores of beams candidate from decoder are given by their likelihood

- Fine-tune an LM by minimizing the **Perplexity (PPL)** on the “gold” references could fit it to the ground-truth transcriptions

- No information from ASR beam candidates utilized

- Sometimes propose “bad” hypotheses -> give a higher score on inferior hypotheses than the “gold” reference
Large Margin Language Model (LMLM)

\[ LMLM = \sum_{i=1}^{K} \sum_{j=1}^{N} \max\{0, \tau - (\text{Score}(X_i) - \text{Score}(X_{i,j}))\} \]
\[ h_t = f(h_{t-1}, x_t) \]

**Causal**

\[ h_t = g(x_t, \text{self attention}(x_t, X_{\text{context}})) \]

**Non-Causal**

**Diagram**

- **LSTM**
  - Cell state: \( C_t \)
  - Input gate: \( i_t \)
  - Forget gate: \( f_t \)
  - Output gate: \( o_t \)
  - New cell state: \( \tilde{C}_t \)
  - Output: \( h_t \)

- **Transformer**
  - **Encoder**
    - Self-Attention
    - Feed Forward
    - Add & Normalize
  - **Decoder**
    - Self-Attention
    - Encoder-Decoder Attention
    - Feed Forward
    - Add & Normalize

**Language Model**
Score (Likelihood) of a Sentence

Causal

\[ \text{Score}^c(X) = \sum_{t=1}^{X} \log P(x_t|X_{<t}; \theta) \]

\[ X_{<t} = [X_1, ..., X_{t-1}] \]

Non-Causal

\[ \text{Score}^m(X) = \sum_{t=1}^{X} \log P(x_t|X_{\backslash t}; \theta) \]

\[ X_{\backslash t} = [X_1, ..., X_{t-1}, X_{t+1}, ..., X_{|X|}] \]
Experiment

- Experiment with **LibriSpeech** benchmark.
- Baseline Decoder:
  - Acoustic model: chain system based on Factorized Time Delay Neural Network (TDNN-F)
  - Language model: Trigram LM
- Language models for rescoring:
  - **LSTM**: Causal, 4 layers, 512 hidden dimension
  - **Transformer Decoder**: Causal, 12 layers, 768 hidden dimension, 12 self-attention heads
  - **Transformer Encoder**: Non-causal, 12 layers, 768 hidden dimension, 12 self-attention heads

All neural LMs are pretrained on a joint of enWiki and bookCorpus.
Empirical Results

• Lowest WER is achieved with Transformer Encoder+LMLM training
• LMLM training significantly decreases WER for LSTM and Transformer Encoder
• Transformer Decoder without LMLM training is already very competitive.
• May be caused by the fundamental difference between causal LM score and non-causal LM score.

Published WERs*

- Without LMLM
- With LMLM

Baseline
Oracle

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Thank you!