CUED-RNNLM – An Open-Source Toolkit for Efficient Training and Evaluation of Recurrent Neural Network Language Models

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Overview

- RNNLM Overview
- Introduction of CUED-RNNLM
- Experiments on AMI corpus
Overview of Statistical Language Models

• Language Model (LM): Estimate probability of word sequence

\[ P(W) = P(w_1, w_2, \ldots w_K) = \prod_{k=1}^{K} P(w_k | w_{k-1}, \ldots w_1) \]

• Three widely used language models
  – N-Gram Language Models (from 1980s)
  – Feed Forward Neural Network Language Models (from 2001)
  – Recurrent Neural Network Language Models (from 2010)
N-Gram Language Models

• Only related to previous $N - 1$ words, ML used to estimate parameter

$$P(w_k|w_{k-1},...w_1) \approx P(w_k|w_{k-1},...w_{k-N-1})$$

• Most popular LM over two decades

• Easy to implement

• Drawbacks
  – Data sparsity, e.g. $|V| = 1000$, a 4-gram LM needs $1000^4 = 10^{12}$ parameter
  – smoothing is necessary
  – Cannot model long term history, only consider last $N - 1$ words
Recurrent Neural Network LMs

- 1-of-K coding for word in input layer
- Each word projected to a low and continuous space – solve data sparsity
- Long term history to be modeled
Class based Recurrent Neural Network LMs

- Use factorized output layer
- Computation reduced significantly
Existing toolkits for RNNLM

- Toolkits for RNNLM training
  - RNNLM toolkit – by Tomas Mikolov
  - RWTHLM – by RWTH Aachen University
    * Trained on CPU
    * Class based output layer used to reduce computation
    * Lack of parallel implementation

- Popular Toolkits for deep learning
  - Theano – by University of Montreal
  - Tensorflow – by Google
  - CNTK – by Microsoft
    * Support RNN implementation using GPU
    * Designed for general deep learning, not optimized for language model

- Issue: slow to train on large data and model size for RNNLM
ICASSP 2016

Highlights of CUED-RNNLM

• CUDA
  – class and full output layer
  – minibatch training with GPU implementation

• Efficient training/evaluation criteria
  – standard cross entropy based training
  – variance regularization
  – noise contrastive estimation

• RNNLM Lattice rescoring integration with HTK 3.5
  – n-gram approximation and history vector clustering
  – support HTK lattice directly
  – conversion tools provided to support Kaldi lattice
Spliced Sentence Bunch

- Enable RNNLMs to be trained using bunch (i.e. minibatch) mode
- The number of NULL token is minimized
Network Configuration Support

- Model structure
  - full output layer
  - class based output layer
  - additional feature in the input layer
  - multiple hidden layers

- Specified input and output list

- OOV node in the input layer, OOS node in the output layer
Train Criteria in CUED-RNNLM

• Cross entropy (CE)

\[
J_{CE}^{\theta} = - \frac{1}{N_w} \sum_{i=1}^{N_w} \ln P_{RNN}(w_i|h_i)
\]

• Variance regularization (VR)

\[
J_{VR}^{\theta} = J_{CE}^{\theta} + \gamma \frac{1}{2 N_w} \sum_{i=1}^{N_w} (\ln(Z_i) - \overline{\ln Z})^2
\]

• Noise contrastive estimation (NCE)

\[
J_{NCE}^{\theta} = - \frac{1}{N_w} \sum_{i=1}^{N_w} (\ln P(C_{w_i}^{RNN} = 1|w_i, h_i) + \sum_{j=1}^{k} \ln P(C_{w_i,j}^{n} = 1|\hat{w}_{i,j}, h_i))
\]
Additional Feature in CUED-RNNLM

- Perplexity calculation
- N-best rescoring
  - unnormalized probability to be applied (for VR and NCE trained model)
- Sampling sentences from well-trained RNNLMs
- Appended feature in input layer, e.g. LDA based topic representation
- ReLU for hidden node
  - faster convergence and slightly better performance
Experiments Setup

• Acoustic Model
  – AMI Kaldi recipe used
  – 78 hours data
  – sequence training for DNN
  – DNN: 6 hidden layers, each layer with 2048 hidden nodes, 4000 targets
  – Lattice generated from Kaldi, and converted to HTK format

• Language Model
  – 1M AMI transcription + 13M fisher data
  – 49k word decoding vocabulary
  – 33k RNNLM input vocabulary, 22k RNNLM output vocabulary
  – 512 hidden nodes
  – Full output layer RNNLMs (F-RNNLMs) trained by CUED-RNNLM
  – Class based RNNLM (C-RNNLMs) trained by Mikolov’s RNNLM Toolkit
  – RNNLMs are interpolated with \( n \)-gram LM using weight 0.5
## Experiments on 1M AMI transcription

<table>
<thead>
<tr>
<th>LM Type</th>
<th>Train Crit</th>
<th>Re score</th>
<th>PPL dev</th>
<th>PPL eval</th>
<th>WER dev</th>
<th>WER eval</th>
</tr>
</thead>
<tbody>
<tr>
<td>3g</td>
<td>-</td>
<td>-</td>
<td>93.6</td>
<td>82.8</td>
<td>25.2</td>
<td>25.4</td>
</tr>
<tr>
<td>+CRNN</td>
<td>CE</td>
<td>lattice 50 best</td>
<td>83.3</td>
<td>75.2</td>
<td>24.0</td>
<td>24.1</td>
</tr>
<tr>
<td>+FRNN</td>
<td>CE</td>
<td>lattice 50 best</td>
<td>81.0</td>
<td>71.7</td>
<td>24.0</td>
<td>23.9</td>
</tr>
<tr>
<td></td>
<td>VR</td>
<td>lattice 50 best</td>
<td>80.4</td>
<td>71.6</td>
<td>23.9</td>
<td>24.0</td>
</tr>
<tr>
<td></td>
<td>NCE</td>
<td>lattice 50 best</td>
<td>81.1</td>
<td>72.8</td>
<td>24.1</td>
<td>24.1</td>
</tr>
</tbody>
</table>

- RNNLMs give significant improvement over 3-gram LM
- F-RNNLMs are slightly better than C-RNNLMs
- F-RNNLMs trained by CE, VR and NCE give comparable performance
## Experiments on 14M (AMI+Fisher) data

<table>
<thead>
<tr>
<th>LM Type</th>
<th>Rescore</th>
<th>PPL</th>
<th>WER</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>dev</td>
<td>eval</td>
</tr>
<tr>
<td>3g</td>
<td>-</td>
<td>84.5</td>
<td>79.6</td>
</tr>
<tr>
<td>4g</td>
<td>lattice</td>
<td>80.3</td>
<td>76.3</td>
</tr>
<tr>
<td>+CRNN</td>
<td>lattice</td>
<td>70.5</td>
<td>67.5</td>
</tr>
<tr>
<td></td>
<td>50 best</td>
<td></td>
<td></td>
</tr>
<tr>
<td>+FRNN</td>
<td>lattice</td>
<td>69.8</td>
<td>67.0</td>
</tr>
<tr>
<td></td>
<td>50 best</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

- Similar trend observed on 14M data
- RNNLMs give significant performance improvement over *n*-gram LM
- F-RNNLMs are slightly better than C-RNNLMs
- Lattice (6g approximation) and N-best rescoring give comparable performance
Experiments on 14M data using various criteria

- Data shuffled for training of RNNLMs
  - give slight performance gain

- N-Best results reported

<table>
<thead>
<tr>
<th>Train Crit</th>
<th>PPL dev</th>
<th>PPL eval</th>
<th>WER dev</th>
<th>WER eval</th>
</tr>
</thead>
<tbody>
<tr>
<td>CE</td>
<td>67.5</td>
<td>63.9</td>
<td>22.1</td>
<td>22.4</td>
</tr>
<tr>
<td>VR</td>
<td>68.0</td>
<td>64.4</td>
<td>22.1</td>
<td>22.4</td>
</tr>
<tr>
<td>NCE</td>
<td>68.5</td>
<td>65.1</td>
<td>22.1</td>
<td>22.4</td>
</tr>
</tbody>
</table>

- F-RNNLMs trained with CE, VR, NCE give comparable performance
Training and testing speed of RNNLMs

<table>
<thead>
<tr>
<th>Toolkit</th>
<th>Train Crit</th>
<th>Train Speed (kw/s)</th>
<th>Test (CPU) Speed (kw/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RNNLM</td>
<td>CE</td>
<td>0.45</td>
<td>6.0</td>
</tr>
<tr>
<td>CUED-RNNLM</td>
<td>CE</td>
<td>11.5</td>
<td>0.32</td>
</tr>
<tr>
<td></td>
<td>VR</td>
<td>11.5</td>
<td>15.3</td>
</tr>
<tr>
<td></td>
<td>NCE</td>
<td>20.5</td>
<td>15.3</td>
</tr>
</tbody>
</table>

- CUED-RNNLM is much faster than RNNLM Toolkit from Mikolov
- NCE almost double train speed compared with VR and CE
- VR and NCE are much faster than CE due to unnormalized probability in test
Train Speed (kw/s) against number of hidden nodes

<table>
<thead>
<tr>
<th>Toolkit</th>
<th># Hidden node</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>128</td>
</tr>
<tr>
<td>RNNLM Toolkit</td>
<td>4.1</td>
</tr>
<tr>
<td>CUED-RNNLM</td>
<td>19.8</td>
</tr>
</tbody>
</table>

- RNNLM Toolkit slow down quickly with the increase of hidden layer.

- CUED-RNNLM is more suitable for training of RNNLM with large model size.
Toolkit Download and Future Work

- Available at http://mi.eng.cam.ac.uk/projects/cued-rnnlm/
  - Source code (implemented by C++)
  - Document
  - Lattice conversion tool
  - AMI recipe

- License: BSD license

- Future work
  - CTS recipe
  - LSTM based RNNLM
  - Bidirectional RNNLM
Thanks!

Q & A