Improved Optimization of Neural Networks

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Outline

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Introduction

Mean-Normalized Stochastic Gradient Descent

Experimental Results

Implementation of Neural Networks in RASR

Conclusion

Motivation

- Deep Neural Networks (DNNs) outperform Gaussian mixtures on large-scale speech recognition tasks [Mohammed$^+$, NIPS 2009], [Seide$^+$, Interspeech 2011], [Hinton$^+$, SPM 2012], ...
- The training of DNNs is a difficult non-convex optimization problem. Even with the use of GPUs, training time of DNNs is high.
- Improving optimization algorithms can accelerate training.

Motivation

- Deep Neural Networks (DNNs) outperform Gaussian mixtures on large-scale speech recognition tasks [Mohammed^{+}, NIPS 2009], [Seide^{+}, Interspeech 2011], [Hinton^{+}, SPM 2012], ...
- The training of DNNs is a difficult non-convex optimization problem. Even with the use of GPUs, training time of DNNs is high.
- Improving optimization algorithms can accelerate training.
- For large-scale tasks: limited computation time
  $\Rightarrow$ Better optimization algorithms can improve accuracy of DNNs, see [Bouttou^{+}, NIPS 2007] .

Conventional Training of DNNs

- Typically, DNNs are trained according to the cross-entropy criterion:

$$F(W) = -\sum_{t=1}^{T} \ln p_W(s_t|x_t).$$

Here, $(x_t, s_t)_{t=1,\ldots,T}$ denotes the training sample, x_t an acoustic observation, s_t an HMM state, and $p_W(s_t|x_t)$ the output of the softmax-layer of a DNN with parameters W.

- F is optimized with stochastic gradient descent (SGD):

$$W_n = W_{n-1} - \gamma_n \nabla F_{\mathcal{B}_n}(W_{n-1}) \ .$$

The stochastic gradient $\nabla F_{\mathcal{B}_n}$ is computed on a small random subset of the training data $\mathcal{B}_n$ ("mini-batch").

Second-Order Optimization: The Problem

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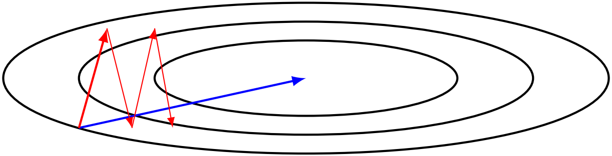
- SGD scales well to large datasets due to its stochastic nature.
- But no use of second-order information
  $\Rightarrow$ May converge very slowly ("zig-zag behavior").



- Second-order algorithms use a better search direction than the steepest descent, typically an approximation to the Newton direction:

$$W_n = W_{n-1} - \gamma_n C_n \nabla F_{\mathcal{B}_n}(W_{n-1}) \, .$$

Second-Order Optimization: Related Work

Batch algorithms:

- L-BFGS [Byrd$^+$, J.Sc.Comp. 1995],
- Rprop [Riedmiller$^+$, ICNN 1993],
- Hessian-Free [Martens, NIPS 2010], [Kingsbury$^+$, Interspeech 2012], [Wiesler$^+$, Interspeech 2013].

Stochastic algorithms:

- diagonal Hessian approximation [LeCun$^+$, 1998],
- online L-BFGS [Schraudolph$^+$, AIStats 2007],
- AdaGrad [Duchi$^+$, JMLR 2010], [Dean$^+$, NIPS 2012], ...

Here: present new stochastic second-order algorithm:

S. Wiesler, A. Richard, R. Schlüter, H. Ney: Mean-Normalized Stochastic Gradient for Large-Scale Deep Learning. In ICASSP 2014 (to appear).

IBM Research Spoken Language Processing Student Paper Award

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Mean-Normalized SGD: Idea

- It is known that the convergence behavior of NN training depends on mean, variance, and correlation of the features. [LeCun^{+}, NIPS 1991], [Wiesler^{+}, NIPS 2011]
- Feature normalization makes the gradient closer to the optimal search direction.

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- Feature normalization makes the gradient closer to the optimal search direction.
- For deep networks: Impact of feature normalization is limited.
- Basic idea: Apply mean normalization to input of all layers.
- But: Normalization can not be performed beforehand.

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- For deep networks: Impact of feature normalization is limited.
- Basic idea: Apply mean normalization to input of all layers.
- But: Normalization can not be performed beforehand.
- Solution: Perform normalization implicitly in optimization algorithm.
- Mean statistics are computed as running averages.

Mean-Normalized SGD: Derivation

- Consider a single layer of a NN for simplicity.
- Let $W \in \mathbf{R}^{D' \times D}$ be the weight matrix, $a \in \mathbf{R}^{D'}$ the bias, and $y \in \mathbf{R}^{D}$ an input to the layer. Then:

$$F : \mathbf{R}^{D' \times (D+1)} \to \mathbf{R}, \quad (W, a) \mapsto \mathcal{G}(W\,y + a)\ .$$

- Mean normalization is a shift by a vector b:

$$\begin{aligned}\tilde{F} : \mathbf{R}^{D' \times (D+1)} \to \mathbf{R}, \quad (W, a) &\mapsto \mathcal{G}(W(y + b) + a) \\ &= \mathcal{G}(W\,y + W\,b + a) = F(W, W\,b + a)\ .\end{aligned}$$

$\Rightarrow$ Normalization can be performed on model side.

- Mapping from original to new parameter space:

$$\phi(W, a) := (W, a - W\,b)\ ,$$
$$F(W, a) = (\tilde{F} \circ \phi)(W, a)\ .$$

Mean-Normalized SGD: Derivation

- Define the MN-SGD update rule as:

$$(\hat{W}, \hat{a}) = \phi^{-1}\Big(\phi(W, a) - \gamma \cdot (\nabla \tilde{F})\big(\phi(W, a)\big)\Big) \ .$$

- Application of chain rule yields ...

$$\begin{aligned}\hat{W} &= W - \gamma \cdot \left(\nabla_W F(W, a) + b \cdot \nabla_a F(W, a)^T\right) \\ \hat{a} &= a - \gamma \cdot \left(\nabla_W F(W, a) b + (1 + b^T b) \nabla_a F(W, a)\right) \ .\end{aligned}$$

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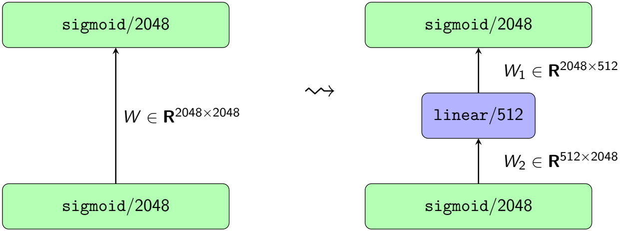
- Rule is expressed in terms of the gradient of F.
- Computing the update is cheap.
- Can be written in the form of a second-order algorithm.
- Convergence proof in [Wiesler$^+$, ICASSP 2014].

Second-Order Optimization and Regularization

- Problem: Improved optimization can lead to overfitting.
- Conventional ℓ_2- or ℓ_1-regularization is typically not very effective for NN acoustic models.
- Alternative: Limiting number of parameters.
- Additional positive effect: Reduces time and memory requirements in training and recognition.

Linear Bottlenecks

- Specific network structure proposed by [Sainath⁺, ICASSP 2013] for speeding up NN training.
- Example:



- Question: Consequence for performance?
- Note: Equivalent to a low rank approximation: $W \approx W_1 W_2$.

Linear Bottlenecks: Problems

- Observation of [Sainath$^+$, ICASSP 2013]: Training NNs with linear bottlenecks from scratch: works only for output layer, performance degradation for hidden layers.
- [Xue$^+$, Interspeech 2013] showed: linear bottlenecks are possible between all layers when
  1. training a full network,
  2. factorizing the weight matrices with SVD and reducing their rank,
  3. fine-tuning the smaller network.
- Only beneficial for recognition.
- Conclusion: optimization problem!

Outline

Experimental Setup

- Corpus: Quaero English (English broadcast conversations)
- Experiments on 50h subset and full corpus.

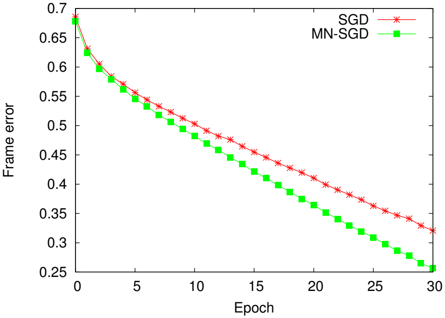
	#Running Words	Duration
Train50h	300k	50h
TrainComplete	1.7M	268h
dev (quaero-eval10)	41k	3.7h
test (quaero-eval11)	35k	3.3h

- Lexicon size: 150k words.
- OOV rate:
  - 0.39% on dev,
  - 0.44% on test.
- 4-gram LM with perplexity
  - 123.0 on dev,
  - 135.6 on test.

Neural Network Training

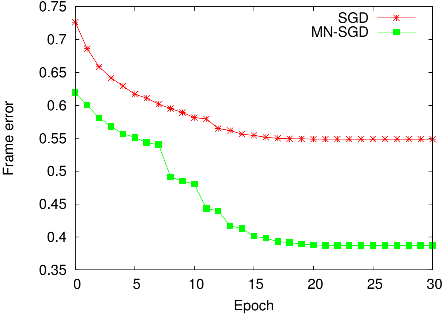
- Feature extraction: 16-dim MFCC vector, sliding window of size 17, $\Delta + \Delta\Delta \Rightarrow$ 493-dim feature vector, global mean and variance normalization.
- Model: six hidden layers of size 2048 with sigmoid activation, softmax-output layer of size 4498.
- Training criterion: cross-entropy.
- Optimization: SGD vs. MN-SGD with mini-batch size 512, supervised pretraining [Seide$^+$, ASRU 2011].
- Initial baseline with learning rate schedule Newbob: 19.8% WER on dev, 25.7% WER on test.
- Improved baseline with better learning rate strategy: optimize on train, use early stopping for regularization: 18.7% WER on dev, 24.7% WER on test.

Training Error of SGD and MN-SGD



- Training frame error of SGD and MN-SGD for full-sized models.

Training Error of SGD and MN-SGD



- Training frame error of SGD and MN-SGD for models with bottlenecks of size 256.
- Note: Already the pre-training results of SGD and MN-SGD differ strongly.

Recognition Results: 50h

Algorithm	Bottleneck	#Parameters	WER (dev)	WER (test)
SGD	-	31.2M	18.7	24.7
	512	14.8M (47.7%)	18.9	25.0
	256	7.9M (25.5%)	19.7	25.7
MN-SGD	-	31.2M	19.0	25.5
	512	14.8M (47.7%)	18.7	24.7
	256	7.9M (25.5%)	18.4	24.2
	128	4.9M (15.7%)	18.6	24.2
	64	2.8M (8.9%)	19.3	25.3

- 0.5% WER improvement with only 25.5% parameters
- Even with only 15.7% parameters an improvement in WER is observed.

Recognition Results: Full Training Set

Algorithm	Bottleneck	#Parameters	WER (dev)	WER (test)
SGD	-	31.2M	15.1	20.3
	512	14.8M (47.7%)	15.8	21.0
MN-SGD	-	31.2M	15.0	20.2
	512	14.8M (47.7%)	14.9	19.8
	256 (depth 8)	10.0M (32.0%)	14.9	19.9

- 0.4% WER improvement with only 32.0% parameters.

Outline

The RWTH NN Toolkit for Speech Recognition

- RWTH RASR is the open source version of the RWTH speech recognition toolkit.
- Development started by Max Bisani and Stephan Kanthak in 2001, and further developed since then.
- At RWTH, RASR is used for all project evaluations and research.

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- Development started by Max Bisani and Stephan Kanthak in 2001, and further developed since then.
- At RWTH, RASR is used for all project evaluations and research.
- Previous versions of RASR did not have support for NNs.
- In collaboration with Alexander Richard and Pavel Golik: Wrote the RASR NN module.
- Part of the latest version of RASR, available at `http://www-i6.informatik.rwth-aachen.de/rwth-asr`
- S. Wiesler, A. Richard, P. Golik, R. Schlüter, H. Ney: RASR/NN : The RWTH Neural Network Toolkit for Speech Recognition. In ICASSP 2014 (to appear).

RASR/NN: Features

- Highly efficient GPU and CPU-multithreading implementation.
- Directly integrated in speech recognition software.
- Generic code basis, clean interfaces.

Support for

- feed-forward NNs of a very general form: must be representable by a DAG,
- many activation functions: sigmoid, tanh, softmax, RLU,
- various training criteria: cross-entropy, squared-error, binary divergence,
- regularization: ℓ_1, ℓ_2, dropout,
- different optimization algorithms: SGD, MN-SGD, momentum, Rprop.
- ...

All components can be configured independently.

Experimental Comparison with QuickNet

- Experiments with a DNN with 493 inputs, six 2048-dim. hidden layers, 4498 outputs. Word error rates in %.

	Learning rate schedule			
	QuickNet		**RASR**	
Training using	Dev	Test	Dev	Test
QuickNet	19.6	26.2	19.4	25.9
RASR	19.8	25.7	19.2	25.4

- RASR uses an improved version of the Newbob learning rate schedule.
- With the same learning rates: comparable results.

Runtime Analysis of RASR and QuickNet

- Runtime was measured on an Nvidia Tesla K20c (GPU) and a 12-core AMD processor (CPU).

Model	Hardware	Implementation	Time / Epoch	Speedup
6x2048	GPU	QuickNet	58.2m	
		RASR	37.1m	1.8
	CPU	QuickNet	1773.3m	
		RASR	549.3m	3.2

- Even larger difference for shallow networks.

Outline

Conclusion

- Developed MN-SGD, a new stochastic second-order optimization algorithm.
- Linear bottlenecks act as a regularization method, but make optimization more difficult.
- MN-SGD + linear bottlenecks outperforms baseline with 85% less parameters.
- Efficient & generic NN implementation, publicly available as part of the latest RASR release.

Thank you for your attention

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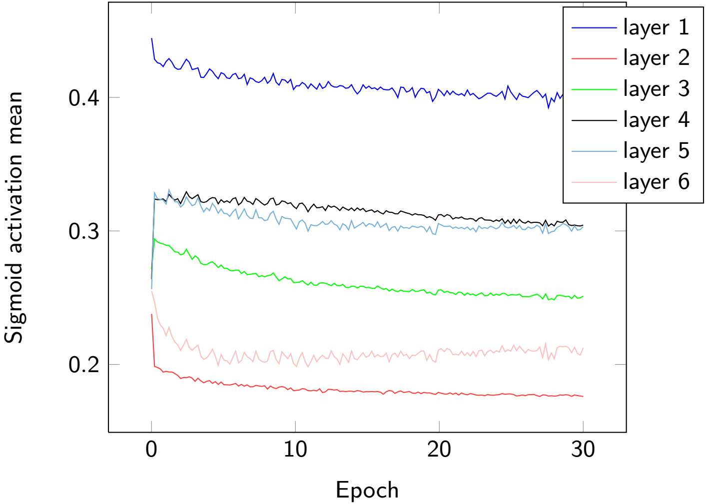
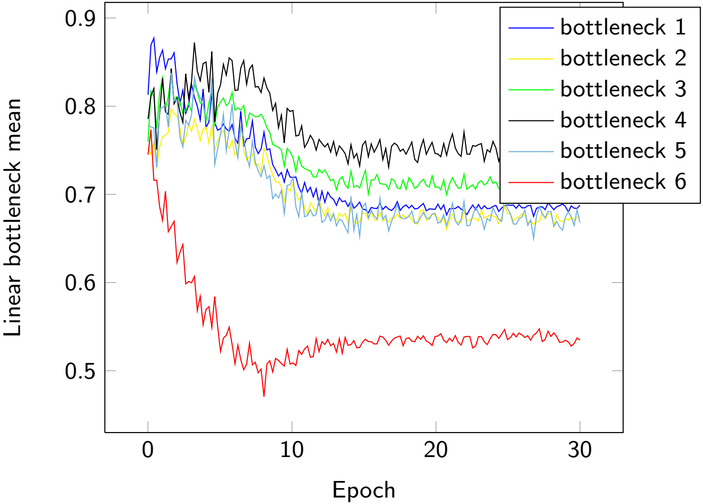
Activation Mean: Sigmoid

- Average magnitude of the activation mean per sigmoid layer (index from input to output layer).



Activation Mean: Sigmoid + Bottlenecks

- Average magnitude of the activation mean per linear bottleneck.



Results with RLUs

- Use Rectified linear units instead of sigmoid activations.
- Additional ℓ_2-regularization required.

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	7.9M (25.5%)	256	17.7	23.3
	4.9M (15.7%)	128	18.0	23.8
	2.8M (8.9%)	64	19.0	24.9

Low-Rank Factorization

Example:

- $W \in \mathbf{R}^{2048\times2048}$, $W_1 \in \mathbf{R}^{2048\times512}$, $W_2 \in \mathbf{R}^{512\times2048}$.
- Number of parameters: $2048 * 2048$ vs $2 * 2048 * 512$.
  $\Rightarrow$ Parameter reduction by a factor of 2.