ABSTRACT

Deep Neural Network (DNN) acoustic models often use discriminative sequence training that optimizes an objective function that better approximates the word error rate (WER) than frame-based training. Sequence training is normally implemented using Stochastic Gradient Descent (SGD) or Hessian Free (HF) training. This paper proposes alternative batch style optimisation frameworks that employ a Natural Gradient (NG) approach to traverse the parameter space. By correcting the gradient according to the local curvature of the KL-divergence, the NG optimisation process converges more quickly than HF. Furthermore, the proposed NG approach can be applied to any sequence discriminative training criterion. The efficacy of the NG method is shown using experiments on a Multi-Genre Broadcast (MGB) transcription task that demonstrates both the computational efficiency and the accuracy of the resulting DNN models.

Index Terms— Deep neural networks, sequence training, natural gradient, Hessian free

1. INTRODUCTION

With the advent of GPU computing and careful network initialisation [1], a hybrid of Deep Neural Networks (DNNs) combined with Hidden Markov models (HMMs) have been shown to outperform traditional Gaussian Mixture Model (GMM) HMMs on a wide range of speech recognition tasks [2]. DNNs, due to their deep and complex structure, are better equipped to model the underlying nonlinear data manifold in contrast to GMMs. However, the existence of such structures also create complex dependencies between the model parameters which can make such models difficult to train with standard Stochastic Gradient Descent (SGD).

The task of finding the best procedure to train DNNs is an active area of research that has been rendered more challenging by the availability of ever larger datasets. It is therefore necessary to develop techniques that lead to rapid convergence and are also stable in training. For example, second order optimisation methods can help to alleviate the problems of vanishing and exploding gradients by rescaling the gradient direction to adjust for the high non-linearity and ill-conditioning of the objective function. For convex optimisation problems [3], such methods have been shown to improve the convergence of both batch and stochastic methods. Martens [4] was one of the first researchers to successfully apply second order methods to train DNNs. Instead of rescaling the gradients with a ‘local’ curvature matrix directly, the author advocated using a ‘Hessian-Free’ (HF) approach which generates an approximate update by the iterative Conjugate Gradient (CG) algorithm. Such a method has been shown to be effective for lattice-based discriminative sequence training [5] when applied with large batch sizes. When training on speech data, it is advantageous to randomly select the frames in each mini-batch when using SGD training with the frame-based Cross Entropy (CE) objective function. However, for lattice-based discriminative sequence training, information from a forward-backward pass through the complete lattice of individual utterances is required to be calculated. Hence, data randomisation can only be effectively performed at the utterance level. In this context, [6] found that second order methods like HF that accumulate gradients over large batches, perform better than utterance-based mini-batch SGD.

However, as an optimiser, the HF method is slow and suffers from drawbacks. In a stochastic HF approach, where we employ only a single batch to compute the gradient estimate, the optimisation process has been seen to often converge to a sub-optimal solution. To address these drawbacks, in [7], the authors proposed combining the HF optimiser with the Stochastic Average Gradient (SAG), where at each iteration, the CG algorithm is initialised with a weighted sum of the current and previous gradient estimates. On a large amount of data, the proposed modification was shown to improve both the speed and convergence of HF. However, when faced with moderate sized training sets, we have found that such an approach can suffer from over-fitting due to the mismatch of training criteria between the DNN sequence discriminative objective function and the true objective which is to reduce the Word Error Rate (WER).

In this work, we propose an alternative optimisation framework for sequence training that is more effective with large batch sizes than HF. Instead of minimising a local second order model, it is shown that substantial improvements in both training speed and convergence can result from using CG to derive an approximation to the Natural Gradient (NG) direction. In NG, the update direction chosen at each iteration is the product of the inverse of the empirical Fisher Information (FI) matrix with the gradient estimate. Essentially this amounts to performing gradient descent on the space of densities \( p_{\theta}(u, H) \), captured by different parameterisations of \( \theta \). In Automatic Speech Recognition (ASR), this approach has previously been applied for frame-based classification under a different optimisation framework. In [8], the authors assume a block diagonal structure for the FI matrix and computes a stochastic estimate of the NG direction directly. By contrast, this paper makes no such assumptions about the structure of the empirical FI matrix and computes an approximation to the NG direction by running a few iterations of CG. Unlike the framework described in [8], our optimisation framework is more flexible and can be used to train DNNs with respect to any sequence classification criterion.

This paper is organised as follows. Section 2 provides a brief review of HMM-DNN systems in ASR. Section 3 introduces NG and provides a derivation of the empirical FI matrix for use in sequence training. In Sec. 4, a slight detour is taken to discuss 2nd order methods and discuss the model that is minimised at each iteration. In sec. 5, NG is formulated for sequence training within the same framework as HF. Section 6 discusses CG while in Sec. 7, it is shown how NG improves MBR training. The experimental setup for ASR experiments on Multi Genre Broadcast (MGB) data is presented in Sec. 8, results in Sec. 9, followed by conclusions.

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2. BACKGROUND

Large Vocabulary Continuous Speech Recognition (LVCSR) is an application of sequence to sequence modelling where given a continuous acoustic waveform \( O' = \{ a_1^r, a_2^r, \cdots a_N^r \} \), the objective is to generate its most likely word sequence, \( H = \{ w_1^r, w_2^r, \cdots w_M^r \} \). The problem can be essentially cast as a general problem of supervised learning where given some seen examples \( \{ O', H' \}_{i=1}^R \), the goal is to learn the relationship between the input space \( X \) and the output space \( \mathcal{Y} \) from the training data. In parametric inference, we model this relationship by a statistical model \( P_{\theta}(H|O) \). For speech processing and a range of other sequential modelling tasks, this currently normally corresponds to using HMMs [9] with output scaled likelihoods computed using DNNs. HMMs belong to the class of generative discrete latent variable graphical models that model the joint distribution \( p(H,O) \) with a parametric model \( p_{\Omega}(H,O) \). By assuming \( p(O) \) is independent of \( \theta \), such models can be effectively used to yield a conditional distribution \( P_{\Omega}(H|O) \) for each setting \( \theta \) in the parameter space.

In ASR, the training of DNNs is normally conducted in two phases: frame-based training followed by sequence training. The first phase trains the DNN model parameters w.r.t the CE criterion, an objective function that is particularly suited for frame-level classification. In contrast, the second phase, employs a discriminative sequence criterion to further train the model. Since ASR is a sequence to sequence modelling task, using this pipeline has been found to achieve reductions in the WER [10]. At present, for discriminative sequence training, two popular classes of objective functions are used:

1. Maximum Mutual Information (MMI) [11] which maximises the sentence-level posterior probability of the correct utterance.

\[
F_{\text{MMI}}(\theta) = \frac{1}{R} \sum_{r=1}^{R} \log P_{\theta}(H'|O') \tag{1}
\]

This also includes the popular ‘boosted’ variant [12] which is inspired by margin-based objective functions.

2. Minimum Bayes’ Risk (MBR) [13] corresponds to a family of methods which minimises the average expected loss computed over the hypothesis space for a given observation sequence when the posterior distribution \( P(H|O) \) is modelled by \( P_{\Omega}(H|O) \). This corresponds to the following objective function:

\[
F_{\text{MBR}}(\theta) = \frac{1}{R} \sum_{r=1}^{R} \sum_{H'} P_{\theta}(H'|O') L(H', H') \tag{2}
\]

Here \( L(H', H') \) denotes the mismatch between the proposed hypothesis and the correct hypothesis. To assist generalisation, this is often computed at a finer level of granularity such as at the phone or ‘physical’ context-dependent state level. For string sequences of arbitrary length, the Levenshtein distance [14] is the usual metric that is used to measure the mismatch between them. However, the cost of employing such a metric increases with the length of the sequences. Due to this computational overhead, in practice, we annotate arcs that we follow in the recognition trellis with a local loss. When this local loss assignment is done at the phone level, this corresponds to the Minimum Phone Error (MPE) objective function [15]. While, when the loss assignment is done at the physical state level, this is the state-level MBR (sMBR) objective function.

3. NATURAL GRADIENT

One particular approach for training DNNs that has recently experienced renewed popularity is the method of Natural Gradient (NG) [16, 17, 18]. This method was first proposed by Amari [19], as an effective optimisation method for training parametric density models. Instead of formulating gradient descent in the Euclidean parameter space, we establish a geometry on the space of density functions and perform steepest descent on that space. Amari showed [20], that by inherently doing optimisation on the space of density models, these models can be trained in a more effective way than with standard gradient descent. This work extends its application to the domain of sequence training. In this section, the geometry is developed that is needed to traverse through the functional manifold of joint distributions \( p_{\Omega}(H,O) \).

3.1. Fisher Information Matrix for sequence to sequence modelling

Let \( \mathcal{F} \) be the family of densities \( p_{\Omega}(H,O) \) that can be captured by different parameterisations of \( \theta \). To formulate gradient descent on the functional manifold \( \mathcal{F} \), it is necessary to quantify how the density \( p_{\Omega}(H,O) \) changes when one adds a small quantity \( \Delta \theta \) to \( \theta \).

For probability distributions, such changes in behaviour can be captured by the KL-divergence, \( KL(p_{\Omega}(H,O)||p_{\Omega+\Delta\theta}(H,O)) \). The KL-divergence is a functional that maps the space of distributions \( \mathcal{F} \) to \( \mathbb{R} \). Since each distribution itself is a function of \( \theta \), the KL-divergence can also be expressed as a smooth function of \( \theta \) through compositionality. Using a Taylor approximation, within a convex neighbourhood of any given point \( \theta_k \), its behaviour can be bounded as follows:

\[
KL(p_{\Omega}(H,O)||p_{\Omega+\Delta\theta}(H,O)) \\
\approx -\frac{1}{2} \Delta \theta^T E_{p_{\Omega}(H,O)}[\nabla^2 \log p_{\Omega}(H,O)] \Delta \theta \tag{3}
\]

Using the fact that each candidate \( p_{\Omega}(H,O) \) is a valid probability distribution, it can be shown that the first term in the quadratic approximation \( E_{p_{\Omega}(H,O)}[\nabla^2 \log p_{\Omega}(H,O)] \) equates to zero. This allows the KL divergence to be locally approximated by the bilinear form:

\[
KL(p_{\Omega}(H,O)||p_{\Omega+\Delta\theta}(H,O)) \\
\approx -\frac{1}{2} \Delta \theta^T E_{p_{\Omega}(H,O)}[\nabla^2 \log p_{\Omega}(H,O)] \Delta \theta \tag{4}
\]

Since \( p(O) \) is independent of \( \theta \), \( \nabla \log p_{\Omega}(H,O) = \nabla \log p_{\Omega}(H|O) \). Thus,

\[
KL(p_{\Omega}(H,O)||p_{\Omega+\Delta\theta}(H,O)) \\
\approx -\frac{1}{2} \Delta \theta^T E_{p_{\Omega}(H,O)}[\nabla^2 \log p_{\Omega}(H|O)] \Delta \theta \tag{5}
\]

The Fisher Information \( I_{\theta} \), for the random variable \( \theta \) is the expectation of the squared score of the likelihood \( p_{\Omega}(H,O) \), which here equates to

\[
I_{\theta} = E_{p_{\Omega}(H,O)}[\langle \nabla \log p_{\Omega}(H|O) \rangle^T (\nabla \log p_{\Omega}(H|O))] \tag{6}
\]

In scenarios where (4) holds, \( I_{\theta} \) can be shown to be equal to the negative of the expectation of the Hessian w.r.t the distribution...
Thus by substituting (6) into (5), we can now locally approximate the KL divergence by the inner product:

$$\text{KL}(p_{\theta}(H, O)||p_{\theta_{k+1}}(H, O)) \approx \frac{1}{2} \Delta \theta^T R \Delta \theta$$

(7)

Instead of computing the expectation of (6) directly, in this work we approximate $I_{\theta}$ with the following Monte-Carlo estimate:

$$I_{\theta} = \frac{1}{N} \sum_{r=1}^{N} \left[ (\nabla \log P_\theta(H'|O')) (\nabla \log P_\theta(H'|O'))^T \right]$$

(8)

The matrix $I_{\theta}$ is the empirical FI matrix and in this case corresponds to the outer product of the Jacobian of the MMI criterion. By assigning an inner product of the form $I_{\theta}$ which is dependent on $\theta$, we have assigned a Riemannian metric on the functional manifold $F$. Such a formulation now allows us to define a notion of a local ‘distance’ measure in the space of joint distributions $p_{\theta}(H, O)$.

4. SECOND ORDER OPTIMISATION

Before proceeding to formulate NG for sequence training, a slight detour is taken to discuss how methods like HF minimise a given objective criterion. Assuming that the objective function $F(\theta)$ is sufficiently smooth, for a given point $\theta$, in the parameter space, there exists an open convex neighbourhood where its behaviour can be locally approximated as:

$$F(\theta_k + \Delta \theta) \approx F(\theta_k) + \nabla F(\theta_k) \Delta \theta + \frac{1}{2} \Delta \theta^T H \Delta \theta$$

(9)

Instead of minimising $F(\theta)$, second order methods aim to minimise this approximate quadratic at each iteration.

4.1. Approximating the Hessian with the Gauss-Newton matrix

Within a convex neighbourhood of $\theta$, the critical point $\Delta \theta = H^{-1} \nabla F(\theta)$ corresponds to a unique minimiser only when the Hessian $H$ is positive definite. However, when we restrict our choice of predictive functions $F$ to DNN models, the optimisation problem is no longer guaranteed to be convex. This means that within a convex neighbourhood of $\theta$, the Hessian associated with the 2nd order Taylor model is no longer guaranteed to be positive definite. In such a scenario, minimisation of (9) no longer guarantees a decrement in the true objective function. To overcome this issue, the general practice is to replace the 2nd order model by an approximate model in which the Hessian is replaced by a positive definite matrix $B$.

$$F(\theta_k + \Delta \theta) \approx F(\theta_k) + \nabla F(\theta_k) \Delta \theta + \frac{1}{2} \Delta \theta^T B \Delta \theta$$

(10)

In work by Sainath and Kingsbury [6], the authors claimed to achieve reductions in WER on large datasets when they employ a Gauss Newton (GN) approximation of the Hessian matrix. For convex loss functions defined on DNN output activations, this approximation always yields a positive semi-definite matrix. In neighbourhoods where the neural network objective $F(\theta)$ can be locally modelled by its first order approximation, it can be shown that the GN matrix represents the Hessian exactly.

The GN matrix takes the form $J_{\theta}^T \nabla^2 L_{\theta} J_{\theta}$, where $J_{\theta}$ is the Jacobian of the linear output activations w.r.t $\theta$ and $\nabla^2 L_{\theta}$ is the Hessian of the loss with respect to the DNN linear output activations at time $t$. For MBR loss functions, $\nabla^2 L_{\theta}$ takes the following form:

$$\nabla^2 L_{\theta} = \frac{\kappa^2}{R} \left[ \text{diag}(\gamma_i^2) - \gamma_i^2 \gamma_i^T \right]$$

(11)

with $\gamma_i^T = \gamma_i \otimes L(s)$. Here,

- $L(s)$ is a vector whose $ith$ entry corresponds to the difference between $L(i)$, the posterior weighted sum of the local losses computed over all the lattice paths that pass through arcs containing the state $i$, and $\xi_{\text{avg}}$, the posterior weighted sum of the loss computed over all the lattice paths.
- $\gamma_i^T$ is a vector whose entries correspond to the posterior probability associated with the states (DNN output nodes) at time $t$ within the consolidated lattice.
- $\kappa$ is the acoustic scaling factor. To assist generalisation, when propagating through the trellis, acoustic probabilities are often raised to a power less than unity to allow less likely sentences to become more important during discriminative sequence training.

In the next section, we show that we can formulate NG in a similar way where at each iteration we minimise a function of the form of (10).

5. FORMULATING NATURAL GRADIENT FOR SEQUENCE TRAINING

Having established a notion of a local distance on the space of joint distributions $F$, an algorithm is required that minimises a functional $L : p_\theta(H, O) \in F \rightarrow \mathbb{R}$. In Sec. 2, it has been suggested that this can be achieved by either using one of the MBR loss functions or the negation of the MMI criterion. Each iteration of a typical iterative optimisation algorithm computes an iterate $p_{\theta_{k+1}}(H, O)$ on the basis of information pertaining to the current iterate $p_{\theta_k}(H, O)$. Since the Riemannian geometry describes only the local behaviour around $p_{\theta_{k+1}}(H, O)$, to generate a candidate function, the following greedy strategy is formulated:

$$p_{\theta_{k+1}}(H, O) = \arg \min_{p_{\theta} \in F} F(p_{\theta}) \quad \text{s.t} \quad \text{KL}(p_{\theta} || p_{\theta_k} + \Delta \theta) \leq \epsilon_k$$

(12)

where we use $F$ to represent the chosen sequence classification criterion.

Using (7) and (8), this can be reformulated as an optimisation problem in the parameter space:

$$\theta_{k+1} = \arg \min_{\theta} \frac{1}{2} \text{tr} (\theta - \theta_k) + \frac{1}{2} \Delta \theta^T B \Delta \theta$$

(13)

In this work, the probing of the parameter space is restricted to within a convex neighbourhood of $\theta_k$, where the first order approximation to $F(\theta)$ can be used: $F(\theta) \approx F(\theta_k) + \nabla F(\theta_k) \Delta \theta$. In doing so, the optimisation problem can now be cast as a first order minimisation problem within a trust region. Since the minimum of the first order approximation is at infinity, the optimisation dynamics will always jump to the border of the trust region. Thus, at each iteration the following constrained optimisation problem is solved:

$$F(\theta_k + \Delta \theta) \approx F(\theta_k) + \nabla F(\theta_k) \Delta \theta + \frac{\lambda}{2} \Delta \theta^T I_{\theta_k} \Delta \theta$$

(14)

Hence it can be seen that under such a formulation, at each iteration of NG, a function of the form of (10) is minimised.

6. CONJUGATE GRADIENT

Differentiating (10) and setting it to zero yields the Newton direction $\Delta \theta = B^{-1} \nabla F(\theta)$, where $B$ now corresponds to either GN or $I_{\theta_k}$. However, the Newton direction does not scale well with the
dimension \( D \) of the optimisation problem. Computing this direction directly is expensive in terms of both computation and storage as storing \( B \) requires \( \mathcal{O}(D^2) \) storage and inverting it incurs a cost of \( \mathcal{O}(D^3) \). These obstacles however, can be overcome if we employ inexact Newton methods. In particular, rather than computing the Newton direction exactly through matrix factorisation techniques, we solve the system \( B\Delta \theta = \nabla F(\theta) \) using the iterative linear Conjugate Gradient (CG) algorithm [21]. When \( B \) represents the GN matrix, such a method is called Hessian-Free.

Like many iterative linear system techniques, CG applied to (11) does not require access to \( B \) itself but only its vector products. Pearlmutter [22] has shown that such matrix-vector products can be computed efficiently through appropriate modifications of the forward and backward pass. By iteratively solving the linear system, the CG algorithm minimises the local quadratic of (10) by continuously improving the search direction it initially starts with. In our implementation, CG is initialised with an estimate of the gradient. It can be shown that if this estimate is accurate then CG in its initial iterations will be able to find updates that immediately improves upon this direction. This proves to be quite an advantage, especially when there is hard limit of the maximum number of allowed iterations.

Within this framework, using only a small number of CG iterations is also desirable for computational reasons. Within each iteration of CG, the computation of each matrix-vector product is expensive as a gradient evaluation. This means that as the size of the dataset increases, the cost of running a single CG iteration also increases linearly. To address this issue, in practice, a subsampled approximation to the candidate \( B \) is used when (10) is minimised. It was found that this approach is actually quite reasonable, as the training iterations were found to be more tolerant to noise in the estimate of \( B \) than to noise in the gradient estimate. Following Kingsbury’s approach [5], our default recipe consists of sampling 1% of the training set to do matrix-vector products for each run of CG. Effectively, by using such a setup, an optimisation algorithm has been framed where the CG iterations contribute only a small percentage of the total cost and the gradient computations are inherently data parallel.

\[ F_{\text{MBR}}(\theta) = \sum_{r=1}^{R} \frac{1}{Z} \sum_{q} \alpha_{q} \beta_{q} L(q, q') \quad (15) \]

where
- \( \alpha_{q} \) represents the forward probability traversing through arc \( q \) in the recognition lattice. This in turn can be un-rolled in a recursive fashion:
  \[ \alpha_{q} = \sum_{r} \text{preceeding } q \alpha_{r} t^{\text{arc}}_{r,q} p(O^{r,q}\{M_{r}, \theta\}) \]
  \( p(O^{r,q}\{M_{r}, \theta\}) \) here represents the arc likelihood and \( O^{r,q} \) corresponds to the frames observed between the start and end times of the arc \( q \).
- \( \beta_{q} \) represents the backward probability of traversing from the arc \( q \) to the end of the recognition trellis. Like the forward probability, this too can be recursively defined as:
  \[ \beta_{q} = \sum_{s} \text{following } q t^{\text{arc}}_{s,q} p(O^{s,q}\{M_{s}, \theta\}) \beta_{s} \]
- the partition function \( Z \) represents the sum of joint probabilities of transversing through all paths through the lattice.

In a lattice-based framework, the individual local losses are initially computed using a CE trained model and do not change during the course of training. What does change are the weights we assign to them. For arcs where \( L(q, q') \) is high, at each iteration, we adapt the model parameters to decrease \( p(O^{r,q}\{M_{r}, \theta\}) \) which in (16) can be seen to reduce the weights associated with these arcs. Under both HF and NG, at each iteration, an update is generated by re-scaling the gradient direction:

\[ \Delta \theta = B^{-1} \nabla F_{\text{MBR}}(\theta) \]

Since by definition \( B \) is real and symmetric, under a change of basis, the above expression reduces to:

\[ \Delta \theta = \sum_{i} \frac{1}{\mu_{i}} (v_{i}^{T} \nabla F_{\text{MBR}}) v_{i} \quad (16) \]

Here the basis vectors \( \{v_{i}\} \) correspond to the eigen vectors of the matrix. Under this formulation, it can be seen how the choice of the matrix \( B \) impacts the steps taken by the optimiser in the parameter space. In HF, the eigen values \( \mu_{i} \) encode the curvature of the loss function w.r.t the DNN output activations. The HF optimizer uses this information to rescale the steps it takes in each eigen direction. However, since GN does not encode the curvature w.r.t the model parameters (whose optimisation is the main objective), it is not always guaranteed for such scalings to be always optimal.

By contrast, when \( B \) corresponds to \( \lambda I_{\theta} \), the scaling factor is \( \mu_{i} = \lambda \bar{\mu}_{i} \), where \( \bar{\mu}_{i} \) is the respective eigenvalue associated with direction \( v_{i} \). Under such rescaling, the optimisation process will now move more cautiously along directions which have a significant impact on \( P_{\theta}(O^{r}\{M_{r}\}) \) of each utterance \( r \). With respect to MBR training, this tries to ensure that the probability \( p(O^{r,q}\{M_{r}, \theta\}) \) associated with the reference arcs does not change while the model parameters are adapted to reduce \( p(O^{r,q}\{M_{r}, \theta\}) \) of the hypotheses arcs. The Lagrange multiplier \( \lambda \) controls the leverage between minimising the objective and enforcing this constraint. Through suitably adjusting \( \lambda \), the optimisation process will follow a path where minimising the MBR criterion correlates well with achieving reductions in WER.

\[ F_{\text{MBR}}(\theta) = \sum_{r} \frac{1}{Z} \sum_{q} \alpha_{q} \beta_{q} L(q, q') \quad (15) \]
8. EXPERIMENTAL SETUP
The DNN training techniques were evaluated on data from the 2015 Multi-Genre Broadcast ASRU challenge task (MGB1) [23]. The full audio data consists of seven weeks of BBC TV programmes covering a wide range of genres, e.g. news, comedy, drama, sports, etc. Systems were trained using a 200hr training set and a smaller 50hr subset. The data were collected by randomly sampling audio from 2,180 broadcast episodes. All utterances collected had a phone matched error rate of $< 20\%$ between the sub-titles and the distributed MGB1 lightly supervised output. The official dev.sub set was employed as a validation set and consists of 5.5 hours of audio data from across 12 episodes. A separate evaluation set was used to estimate the generalisation performance of each candidate model. For our experiments we took the remaining 35 shows from the MGB1 dev.full and denote this set as dev.sub2 for evaluation purposes. The segmentations used for all experiments were taken from the reference transcriptions. Further details of the data preparation are in [24]. All experiments were conducted using the HTK 3.5 toolkit [25, 26] with supports DNN and HMM training including discriminative sequence training. This work focuses on training hybrid DNN HMMs using traditional fully-connected feed-forward layers. The input to the DNN was produced by splicing together 40 dimensional log-Mel filter bank (FBK) features extended with their delta coefficients across 9 frames to give a 720 dimensional input per frame. These features were normalised at the utterance level for mean and at the show-segment level for variance [24]. The DNN used an architecture of 5 hidden layers each with 1000 nodes with sigmoid activation functions. The output softmax layer had context dependent phone targets formed by conventional decision tree context dependent state tying. The output layer contained 4k/6k nodes for the 50hr/200hr training sets.

To make fair comparisons between different optimisation frameworks all models were trained using lattice-based MPE training. Prior to sequence training, the DNN model parameters were initialised using frame-level CE training. To check the efficacy of each optimisation method, decoding was performed on the validation set at intermediate stages of training using the same weak pruned biased bigram LM that we initially used to create the initial MPE lattices. Having such a framework is advantageous as it also allows us to investigate over-fitting due to training criterion mismatch between the MPE criterion and the WER.

8.1. Training configuration for SGD
From initial experimental runs, it was found that the best learning rate was $1 \times 10^{-4}$. As an optimiser, SGD on its own can be fairly unstable with network topologies where the gradient has to propagate through many layers. To stabilise training, sequence training with SGD was accompanied by layer dependent gradient clipping to prevent network saturation and ensure smooth propagation of gradients during the training process.

8.2. Training configuration for NG & HF-variants
From preliminary experiments it was found that using batch sizes of roughly 25 hrs gave a good balance between the number of updates and using good gradient estimates. When the number of CG iterations is limited, initialising CG with a good estimate of the gradient is desirable, as within a few iterations a good descent direction can be found. However this comes at the cost of fewer HF/NG updates per epoch as larger batch sizes are needed to reduce the variance associated with the gradient estimates. In preliminary tests, it was found that increasing the batch sizes beyond 25hrs yielded no significant improvements. To make up the NG/HF minibatch, we followed Kingsbury’s approach [5] and sampled only 1% of the training set.

9. EXPERIMENTS
9.1. Experiments on 50hr MGB1 dataset
On the 50hr setup, we investigated the efficacy of the proposed optimisation framework and compared to both SGD and HF. Table 1 summarises the results.

| method | #epochs | #updates | phone acc. | WER dev.sub |
|--------|---------|----------|------------|-------------|
| CE     | N/A     | N/A      | 0.7988     | 0.8549      | 45.2        |
| SGD    | 8       | $2.62 \times 10^4$ | 0.8476     | 0.7044      | 42.0        |
| HF     | 40      | 80       | 0.8461     | 0.6967      | 42.2        |
| NG     | 30      | 60       | 0.8677     | 0.7089      | 41.6        |

Table 1: Sequence training and dev.sub MPE phone accuracy/WER for the 50hr training set. The WERs shown at the last column were computed using the weak pruned biased LM used in MPE training.

It can be seen from Table 1 that of all the sequence training approaches the NG method produces the highest training and validation (dev.sub) MPE phone accuracies and the lowest WER using the MPE weak biased LM. The NG approach replaces the ‘Hessian’ component of the HF optimiser with the empirical FI matrix and this leads to both faster and improved convergence which makes the proposed optimisation framework more effective where only a relatively few updates are performed with large batch sizes. The NG optimiser requires just 60 updates to both better model the training data and improve the WER on the validation set. In comparison to the SGD baseline, both HF and NG training were observed to be highly stable and did not require any form of additional update clipping. This is attributed to the fact that at each iteration, the direction explored is a modified gradient estimate that has been appropriately rescaled using the local KL curvature information.

While both the HF and NG optimisers use more training epochs than SGD, each epoch has fewer updates and is somewhat more efficient in constructing a geodesic in the parameter space. Furthermore since the batch gradient computations are inherently data parallel, a batch style optimisation framework such as HF/NG becomes time efficient in a distributed setting where the gradient calculations can be easily parallelised and still yield identical updates. The relative contribution to the total computational cost from the CG iterations were 15% for HF and 18% NG. It should be noted that the overall run-times per epoch of both the baseline and the large batch sized methods on a single GPU are all within 10% of each other.

To investigate whether the WER reductions still hold with stronger LMs, decoding passes on the dev.sub validation set were run with 158k vocabulary bigram and trigram LMs used in [24] and the results are presented in Table 2.

| LM | SGD | HF | NG |
|----|-----|----|----|
| 158k Bigram | 39.2 | 39.4 | 39.0 |
| 158k Trigram | 32.8 | 33.0 | 32.6 |

Table 2: %WER differences between different optimisers on dev.sub with 158k vocabulary bigram/trigram LMs on dev.sub (50hr training set).

These gains were found to be consistent when we re-ran training with different sampling schemes. The extra CG cost associated with NG is attributed to doing more CG iterations. With HF, in our preliminary runs, running CG beyond 5 iterations was not found to yield any significant improvement in the quality of the updates. Since NG is effectively a first order method, we found that in its case we needed to do slightly more iterations for each update.
From Table 2, it can be seen that the same trends on dev.sub continue with NG giving greater reductions in WER than models trained with either SGD or HF.

9.2. Experiments on 200hr MGB1 dataset

The experiments on the 200hr training set were performed to ensure that the sequence training techniques generalise to a somewhat larger training set (and output layer size) and also to present more detailed comparisons of how training proceeds. The use of the proposed NG method was also compared to the Dynamic Stochastic Average Gradient HF variant (DSAG-HF), presented in [7]. Table 3 provides a summary of the results while Fig. 1 compares the performance at intermediate stages of training.

Table 3: Performance achieved with different optimisers on the 200hr setup. The WERs shown at the last column were computed using the weak pruned biased LM used in MPE training.

| method | #epochs | #updates | phone acc. | WER dev.sub |
|--------|---------|----------|------------|-------------|
| CE     | N/A     | N/A      | 0.8106     | 0.6986      | 41.2        |
| SGD    | 8       | 9.2⋅10⁴  | 0.8684     | 0.7601      | 38.2        |
| HF     | 15      | 120      | 0.8417     | 0.7365      | 38.8        |
| DSAG-HF| 15      | 120      | 0.8499     | 0.7456      | 38.5        |
| NG     | 15      | 120      | 0.8601     | 0.7534      | 37.9        |

Table 4: %WER differences between different optimisers on dev.sub with 158k vocabulary bigram/trigram LMs on dev.sub (200hr training set).

The resulting DNN acoustic models were tested with stronger LMs as for the 50hr setup and the results are shown in Table 4. It can be seen again that the NG method results in lower WERs than SGD or the HF variants.

| LM      | SGD | HF | DSAG-HF | NG |
|---------|-----|----|---------|----|
| 158k Bigram | 35.0 | 35.3 | 35.2 | 34.7 |
| 158k Trigram | 29.3 | 29.3 | 29.2 | 29.0 |

Table 5: %WER differences between different optimisers on dev.sub2 (evaluation set) with 158k trigram (200hr).

Finally, these DNNs were tested on the dev.sub2 set as an evaluation set that was not used for setting training hyper-parameters to ensure that the trends observed above generalise. Table 5 shows the WER results using the 158k trigram model and shows that again that the model trained with NG achieves the largest reductions in the WER due to sequence training. Furthermore these improvements have been fairly consistent between the validation dev.sub and evaluation dev.sub2 test sets. On average the NG method can be seen to provide approximately a 1% relative reduction in WER over both the SGD baseline and the DSAG-HF variant. While this improvement is fairly small, it is consistent and a statistical significance test (sign test of the word error rates at the episode level) showed that the improvement due to NG over each of the other methods is highly statistically significant ($p < 0.001$).

10. CONCLUSIONS

This paper has described a discriminative sequence training method based on the NG approach and has shown that it can improve the optimisation performance of the discriminative sequence training objective functions used in speech recognition systems. This novel technique provides the same advantages as large batch HF methods in terms of stability and being inherently data parallel. However it converges more quickly and finds better performing final models. It was evaluated using training and test data from the MGB1 transcription task where it was shown that as well as being effective in optimising the MPE objective function, it tends to generalise better and leads to reduced WERs on independent test data. Future work will involve extending the proposed framework to sequence training of DNN architectures with recurrent topologies.
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