Hyper-parameters/Tweaking

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Overview

1. Batch Normalization
   - Internal Covariate Shift
   - Mini-Batch Normalization
   - Key Points in Batch Normalization
   - Experiments and Results

2. Importance of Initialization and Momentum
   - Overview of first-order method
   - Momentum & Nesterov's Accelerated Gradient(NAG)
   - Deep Autoencoders & RNN - Echo-State Networks

Challenges to be solved

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Reference paper: Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift

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When we are faced with training a Deep Network with saturating nonlinearities:

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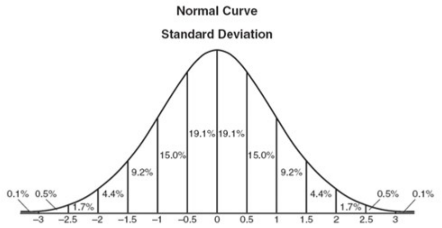

figure credit: www.regentsprep.org

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Reasons behind the problem:

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- Input distributions of each layer changes

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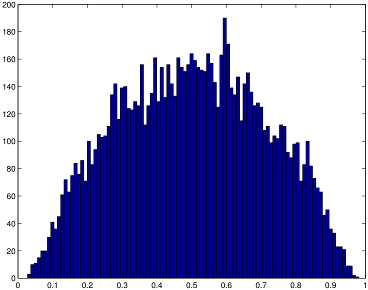

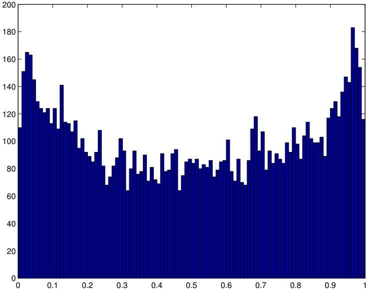

Sigmoid's output distribution before and after parameter updates

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Internal Covariate Shift

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Covariate Shift

Change of input distributions to a Learning System

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Extension to part or sub-networks

$$\ell = F_2(F_1(u, \Theta_1), \Theta_2)$$

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$$\ell = F_2(F_1(u, \Theta_1), \Theta_2)$$

$$\ell = F_2(x, \Theta_2), \;\; where \; x = F_1(u, \Theta_1)$$

$$\Theta_2 \leftarrow \Theta_2 - \frac{\alpha}{m} \sum_{i=1}^{m} \frac{\partial F_2(x_i, \Theta_2)}{\partial \Theta_2}$$

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In terms of change in the distribution of x, Θ_2 will not need to readjust much.

Internal Covariate Shift

Change in the distributions of internal nodes of a deep network

Reducing Internal Covariate Shift

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Whitening-LeCun et al., 1998b; Wiesler&Ney, 2011

The network training converges faster if its inputs are whitened-i.e., linearly transformed to have zero means and unit variances, and decorrelated.

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Goal: Whitening the inputs of each layer to have fixed distributions in order to Reduce the ill effects of Internal Covariate Shift.

Reducing Internal Covariate Shift

Reducing Internal Covariate Shift

- Interspersal lead to reduced gradient descent

$$b \leftarrow b + \Delta b, \ \textit{where } \Delta b \propto -\frac{\partial \ell}{\partial \hat{x}} \overbrace{\cancel{\frac{\partial \hat{x}}{\partial b}}}^{\textit{Ignored}}$$

$$\hat{x} = x - E[x] = u + (b + \Delta b) - E[u + (b + \Delta b)] = u + b - E[u + b]$$

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- Normalizations are NOT taken into account in Gradient Descent Optimization.

Reducing Internal Covariate Shift

Reducing Internal Covariate Shift

Introducing Normalization

$$\hat{x} = Norm(x, \mathcal{X})$$

and Jacobians in backpropagation

$$\frac{\partial Norm(x, \mathcal{X})}{\partial x} \quad and \quad \frac{\partial Norm(x, \mathcal{X})}{\partial \mathcal{X}}$$

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New challenges: expensive to compute covariance matrix and its inverse square root.

Covariance matrix

$$Cov[x] = E_{x \in \mathcal{X}}[xx^T] - E[x]E[x]^T$$

Whitening

$$Cov[x]^{-1/2}(x - E[x])$$

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Two simplifications and Identity Transform

- Normalize each scalar feature independently
- Use mini-batch to estimate the mean and variance instead of whole population
- Ensure Identity Transform can be represented

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$$y^{(k)} = \gamma^{(k)} \hat{x}^{(k)} + \beta^{(k)}$$

Two new parameters for each activation are introduced for learning.

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Batch Normalization Transform, see reference paper for details

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$$E(x) \leftarrow E_{\mathcal{B}}[\mu_{\mathcal{B}}]$$

$$Var[x] \leftarrow \frac{m}{m-1} E_{\mathcal{B}}[\sigma^2_{\mathcal{B}}]$$

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- In Convolutional layers, different locations of a feature map should be normalized in the same way.

$$m' = |\mathcal{B}| = m \cdot pq, \ and \ \gamma^{(k)}, \ \beta^{(k)} \ per \ feature \ map$$

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- Batch Normalization will regularize the model with less overfitting.

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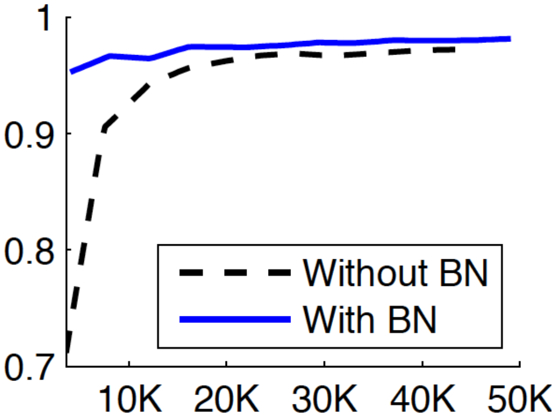

figure credit: reference paper

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Batch Normalization makes input distribution more stable.

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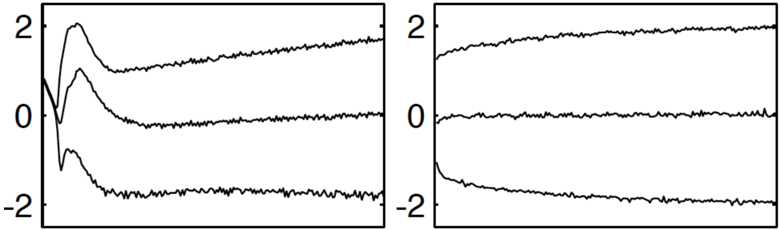

(b) Without BN (c) With BN

figure credit: reference paper

Accelerating Batch Normalization Networks

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Tricks to follow

Accelerating Batch Normalization Networks

Tricks to follow

- Increasing learning rate
- Remove or Reduce Dropout
- Reduce ℓ_2 weight regularization
- Accelerate the learning rate decay
- Remove Local Response Normalization
- Shuffle training examples more thoroughly
- Reduce the photometric distortions

Network Comparisons

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Inception, BN-Baseline, BN-x5, BN-x30, BN-x5-Sigmoid

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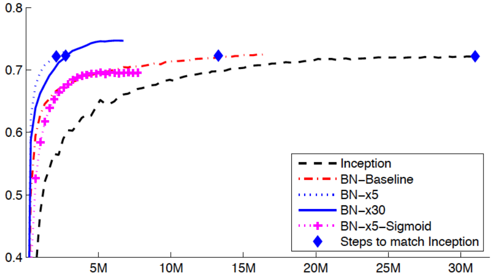

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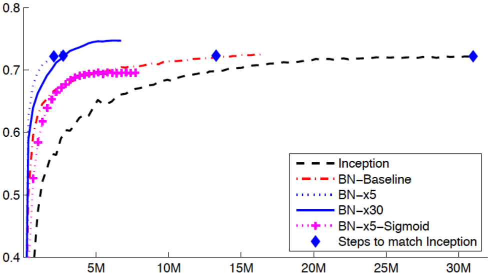

Model	Steps to 72.2%	Max accuracy
Inception	$31.0 \cdot 10^6$	72.2%
BN-Baseline	$13.3 \cdot 10^6$	72.7%
BN-x5	$2.1 \cdot 10^6$	73.0%
BN-x30	$2.7 \cdot 10^6$	74.8%
BN-x5-Sigmoid		69.8%

figure credit: reference paper

Ensemble Classification

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Top-5 validation error of 4.9% and test error of 4.82%, exceeds the estimated accuracy of human raters.

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Model	Resolution	Crops	Models	Top-1 error	Top-5 error
GoogLeNet ensemble	224	144	7	-	6.67%
Deep Image low-res	256	-	1	-	7.96%
Deep Image high-res	512	-	1	24.88	7.42%
Deep Image ensemble	variable	-	-	-	5.98%
BN-Inception single crop	224	1	1	25.2%	7.82%
BN-Inception multicrop	224	144	1	21.99%	5.82%
BN-Inception ensemble	224	144	6	20.1%	**4.9%***

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- Well-designed random initialization
- Slowly increasing schedule for momentum parameter

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- Difficult to use first-order method to reach performance previously only achievable by second-order method like Hessian-Free.

- Well-designed random initialization
- Slowly increasing schedule for momentum parameter

- No need for sophisticated second-order methods.

Overview of first-order method

First-order Methods

- Vanilla Stochastic Gradient Descent
- SGD + Momentum
- Nesterov's Accelerated Gradient(NAG)
- AdaGrad
- Adam
- Rprop
- RMSProp
- AdaDelta

slide credit: Ishan Misra

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Notation:

- θ - Parameters of network, f - Objective function, ϵ - Learning rate
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Vanilla SGD

$$v_{t+1} = \epsilon \nabla f(\theta_t)$$

$$\theta_{t+1} = \theta_t - v_{t+1}$$

slide credit: Ishan Misra

Several First-order Methods

Several First-order Methods

Rprop Update

if $\nabla f_t \nabla f_{t-1} > 0$

$$v_t = \eta^+ v_{t-1}$$

else if $\nabla f_t \nabla f_{t-1} < 0$

$$v_t = \eta^- v_{t-1}$$

else

$$v_t = v_{t-1}$$

$$\theta_{t+1} = \theta_t - v_t$$

where $0 < \eta^- < 1 < \eta^+$

slide credit: Ishan Misra

Several First-order Methods

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AdaGrad

$$r_t = \theta_t^2 + r_{t-1}$$
$$v_{t+1} = \frac{\alpha}{\sqrt{r_t}} \nabla f(\theta_t)$$
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RMSProp = Rprop + SGD

$$r_t = (1-\gamma)\theta_t^2 + \gamma r_{t-1}$$
$$v_{t+1} = \frac{\alpha}{\sqrt{r_t}} \nabla f(\theta_t)$$
$$\theta_{t+1} = \theta_t - v_{t+1}$$

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Several First-order Methods

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AdaDelta

$$v_{t+1} = H^{-1}\nabla f,$$
$$\propto \frac{f'}{f''}$$
$$\propto \frac{1/units\ \ of\ \ \theta}{(1/units\ \ of\ \ \theta)^2}$$
$$\propto units\ \ of\ \ \theta$$

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Adam

$$r_t = (1-\gamma_1)\nabla f(\theta_t) + \gamma_1 r_{t-1}$$
$$p_t = (1-\gamma_2)\nabla f(\theta_t)^2 + \gamma_2 p_{t-1}$$
$$\hat{r}_t = \frac{r_t}{(1-(1-\gamma_1)^t)}$$
$$\hat{p}_t = \frac{p_t}{(1-(1-r_2)^t)}$$
$$v_t = \alpha\frac{\hat{r}_t}{\sqrt{\hat{p}_t}}$$
$$\theta_{t+1} = \theta_t - v_t$$

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Classical Momentum

$$v_{t+1} = \mu v_t - \epsilon \nabla f(\theta_t)$$

$$\theta_{t+1} = \theta_t + v_{t+1}$$

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$$v_{t+1} = \mu v_t - \epsilon \nabla f(\theta_t)$$

$$\theta_{t+1} = \theta_t + v_{t+1}$$

Nesterov's Accelerated Gradient

$$v_{t+1} = \mu v_t - \epsilon \nabla f(\theta_t + \mu v_t)$$

$$\theta_{t+1} = \theta_t + v_{t+1}$$

Relationship between CM and NAG

Relationship between CM and NAG

NAG uses $\theta_t + \mu v_t$ but MISSING the yet unknown correction. Thus when the addition of μv_t results in an immediate undesirable increase in the objective f, NAG uses $\theta_t + \mu v_t$ but MISSING the yet unknown correction. Thus when the addition of μv_t results in an immediate undesirable increase in the objective f,

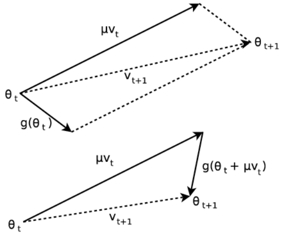

Figure 1. **(Top)** Classical Momentum **(Bottom)** Nesterov Accelerated Gradient

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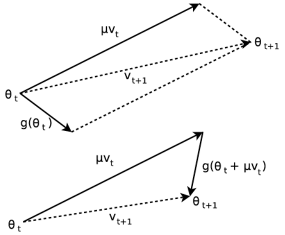

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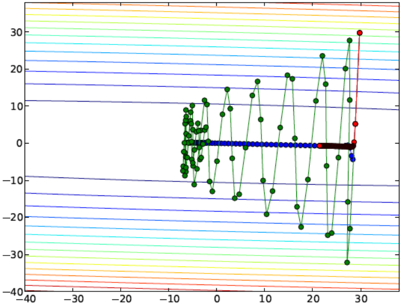

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Relationship between CM and NAG

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Apply CM and NAG to a positive definite quadratic objective $q(x) = x^T Ax/2 + b^T x$.

Difference in effective momentum coefficient

- Classical Momentum: μ
- NAG: $\mu(1 - \lambda\epsilon)$, where λ is the eigenvalue of A.

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- Classical Momentum: μ
- NAG: $\mu(1 - \lambda\epsilon)$, where λ is the eigenvalue of A.

- ϵ small, CM and NAG are equivalent
- ϵ large, NAG gives smaller $\mu(1 - \lambda_i\epsilon)$ to stop oscillations.

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Deep Autoencoders

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Structure of Deep Autoencoder

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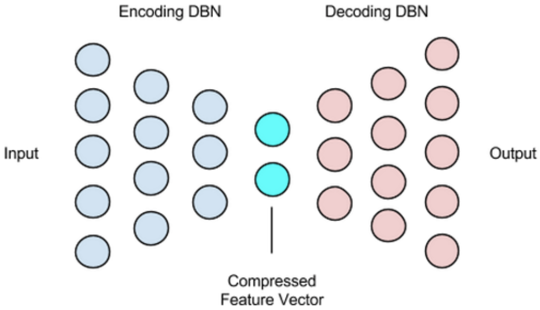

figure credit: http://deeplearning4j.org/deepautoencoder.html

Deep Autoencoders

Deep Autoencoders

- **Sparse Initialization**-each random unit connected to 15 randomly chosen units in the previous layer, drawn from a unit Gaussian
- **Schedule for Momentum Coefficient**

$$\mu_t = min(1 - 2^{-1-log_2(\lfloor t/250 \rfloor + 1)}, \mu_{max})$$

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  - $\mu_t = 1 - 3/(t+5)$, not strongly convex - Nesterov(1983)
  - constant μ_t, strongly convex - Nesterov(2003)

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task	$0_{(SGD)}$	0.9N	0.99N	0.995N	0.999N	0.9M	0.99M	0.995M	0.999M	SGD_C	HF[†]	HF[*]
Curves	0.48	0.16	0.096	0.091	**0.074**	0.15	0.10	0.10	0.10	0.16	0.058	0.11
Mnist	2.1	1.0	**0.73**	0.75	0.80	1.0	0.77	0.84	0.90	0.9	0.69	1.40
Faces	36.4	14.2	8.5	7.8	**7.7**	15.3	8.7	8.3	9.3	NA	7.5	12.0

table credit: reference paper

RNN - Echo-State Networks

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Echo-State Networks(a family RNNs)

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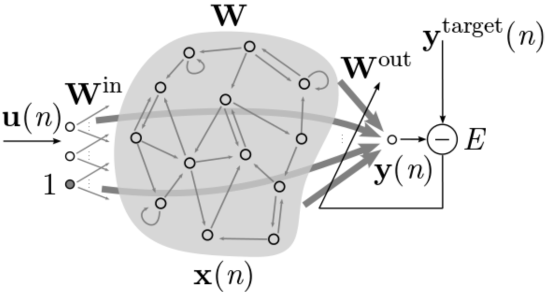

figure credit: Mantas Lukoevicius

- Hidden-to-output connections learned from data
- Recurrent connections fixed to a random draw from a specific distribution

RNN - Echo-State Networks

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ESN-based Initialization

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Schedule of Momentum coefficient μ

- $\mu = 0.9$ for the first 1000 parameters;
- $\mu = \mu_0 \in \{0, 0.9, 0.98, 0.995\}$ afterwards;

RNN - Echo-State Networks

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- $\mu = 0.9$ for the first 1000 parameters;
- $\mu = \mu_0 \in \{0, 0.9, 0.98, 0.995\}$ afterwards;

problem	biases	0	0.9N	0.98N	0.995N	0.9M	0.98M	0.995M
add $T = 80$	0.82	0.39	0.02	0.21	**0.00025**	0.43	0.62	0.036
mul $T = 80$	0.84	0.48	0.36	0.22	**0.0013**	0.029	0.025	0.37
mem-5 $T = 200$	2.5	1.27	1.02	0.96	**0.63**	1.12	1.09	0.92
mem-20 $T = 80$	8.0	5.37	2.77	0.0144	**0.00005**	1.75	0.0017	0.053

Table credit: reference paper

Overview

1. Batch Normalization
   - Internal Covariate Shift
   - Mini-Batch Normalization
   - Key Points in Batch Normalization
   - Experiments and Results
2. Importance of Initialization and Momentum
   - Overview of first-order method
   - Momentum & Nesterov's Accelerated Gradient(NAG)
   - Deep Autoencoders & RNN - Echo-State Networks

Questions?

Chris Dusold's Part

- Variance-SGD(No More Pesky Learning Rates)
- Adam(Adam: A Method for Stochastic Optimization)
- AdaGrad(Adaptive Subgradient Methods for Online Learning and Stochastic Optimization)