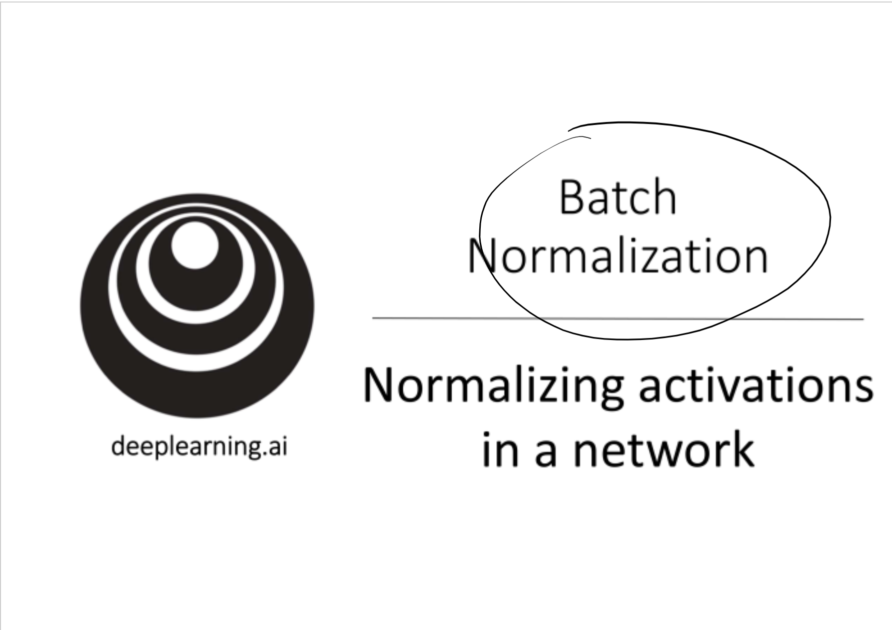
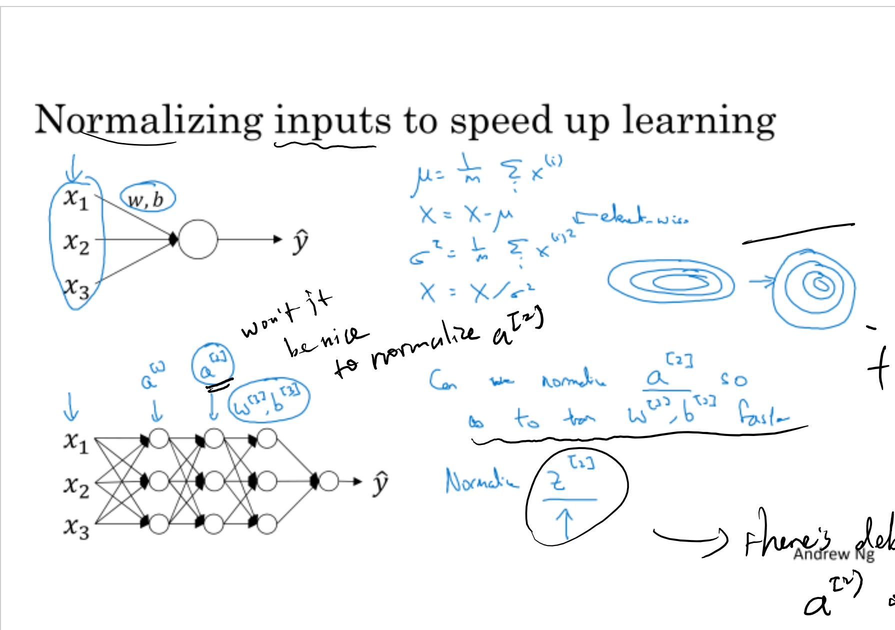
Batch normalization

Monday, June 4, 2018 9:32 PM

batchnorm1



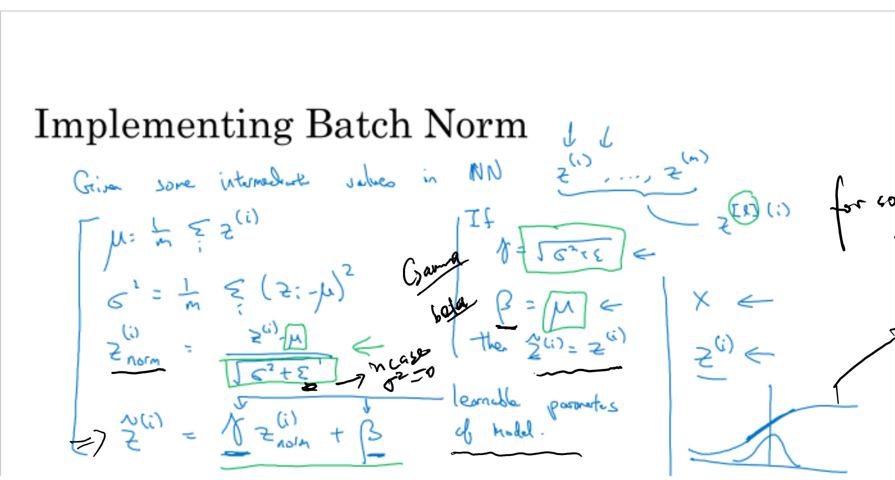


from elongated to ..

How about a deeper model

This is what batch norm like

→ there's debate about whether you should normalize $a^{[2]}$ or $z^{[2]}$ Andrew Ng prefers $z^{[2]}$



for some hidden layer
[l] omitted in this slide.

→ You don't always want to want your hidden layer value forced to mean 0.

how to rescale?

e.g. if you have ... activation

$\hookrightarrow \tilde{z}^{(i)} = \gamma z^{(i)}_{norm} + \beta$ learnable parameters of model.

Use $\tilde{z}^{[l](i)}$ instead of $z^{[l](i)}$.

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how to rescale?

forced ...

eg. if you have sigmoid activation

adjust $\gamma . \beta$

batchnorm2

Batch Normalization

Fitting Batch Norm into a neural network

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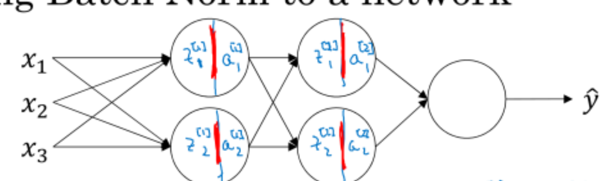
Adding Batch Norm to a network



$X \xrightarrow{w^{[1]}, b^{[1]}} z^{[1]} \xrightarrow[\text{Batch Norm (BN)}]{\beta^{[1]}, \gamma^{[1]}} \tilde{z}^{[1]} \rightarrow a^{[1]} = g^{[1]}(\tilde{z}^{[1]}) \xrightarrow{w^{[2]}, b^{[2]}} z^{[2]} \xrightarrow[\text{BN}]{\beta^{[2]}, \gamma^{[2]}} \tilde{z}^{[2]} \rightarrow a^{[2]} \rightarrow \dots$

Parameters: $w^{[1]}, b^{[1]}, w^{[2]}, b^{[2]}, \dots, w^{[L]}, b^{[L]}$ $\quad d\beta^{[l]} \quad \beta^{[l]} = \beta^{[l]} - \alpha \, d\beta^{[l]}$ ← these can be updated ..

$\rightarrow \beta^{[1]}, \gamma^{[1]}, \beta^{[2]}, \gamma^{[2]}, \dots, \beta^{[L]}, \gamma^{[L]}$ $\quad$ tf.nn.batch-normalization ← tensorflow

$\rightarrow \beta$

$\alpha \rightarrow$ distinguish from the hyperparam of momentum etc.

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Working with mini-batches

$X^{\{1\}} \xrightarrow{W^{[1]}, b^{[1]}} z^{[1]} \xrightarrow[BN]{\beta^{[1]}, \gamma^{[1]}} \tilde{z}^{[1]} \rightarrow g^{[1]}(\tilde{z}^{[1]}) = a^{[1]} \xrightarrow{W^{[2]}, b^{[2]}} z^{[2]} \rightarrow \dots$

$\boxed{X^{\{2\}}} \rightarrow z^{[1]} \xrightarrow[BN]{\beta^{[1]}, \gamma^{[1]}} \tilde{z}^{[1]} \rightarrow \dots$

Just using minibatch

$X^{\{3\}} \rightarrow \dots$

Parameters: $W^{[l]}$, $\cancel{b^{[l]}}$, $\beta^{[l]}$, $\gamma^{[l]}$.

$(n^{[l]}, 1)$ $(n^{[l]}, 1)$ $(n^{[l]}, 1)$

$z^{[l]}$ $(n^{[l]}, 1)$

$\rightarrow z^{[l]} = W^{[l]} a^{[l-1]} + \boxed{\cancel{b^{[l]}}}$

$z^{[l]} = W^{[l]} a^{[l-1]}$

$z^{[l]}_{norm}$

$\rightarrow \tilde{z}^{[l]} = \gamma^{[l]} z^{[l]}_{norm} + \boxed{\beta^{[l]}}$

# of layers

第 l 层节点 y normalization

$a^{[l](1)}$ $a^{[l](2)}$ $a^{[l](3)}$

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important

within batch normalization

$b^{[l]}$ not necessary

=> will be canceled out by normalization

or set $b^{[l]} = 0$

batch normal zero out the mean of $z^{[l]}$

=> so set $b^{[l]} = 0$.

Implementing gradient descent

BN = batch normalization

for $t = 1 \dots$ num MiniBatches

Compute forward prop on $X^{\{t\}}$.

In each hidden layer, use BN to replace $z^{[l]}$ with $\tilde{z}^{[l]}$.

Use backprop to compute $dW^{[l]}$, $\cancel{db^{[l]}}$, $d\beta^{[l]}$, $d\gamma^{[l]}$

Update params
$W^{[l]} := W^{[l]} - \alpha\, dW^{[l]}$
$\beta^{[l]} := \beta^{[l]} - \alpha\, d\beta^{[l]}$
$\gamma^{[l]} := \dots$

Works w/ momentum, RMSprop, Adam.

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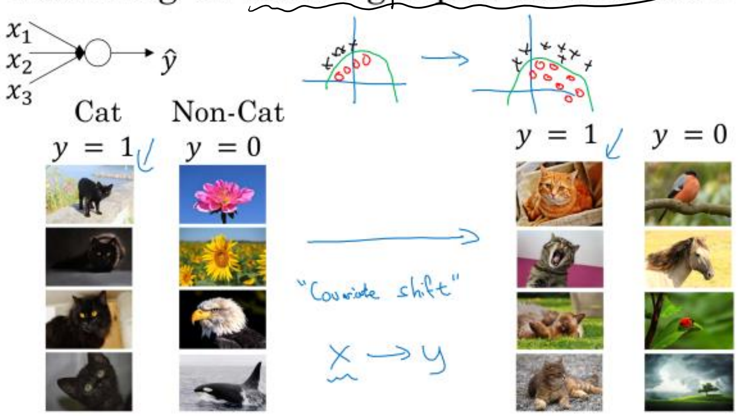
Batch Normalization

Why does Batch Norm work?

Learning on shifting input distribution



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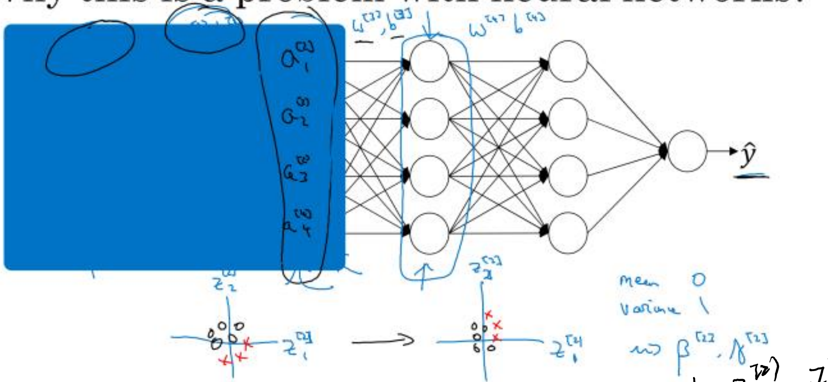
make weights robust to changes of change of weights in previous layers

model of cat detection trained on black cat picture

*-> test on colored cats. this is an example of a changed data distribution

Why this is a problem with neural networks?



mean & variance of $z_1^{[2]}$ $z_1^{[2]}$ won't change.

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Batch norm reduces the amount that the hidden-layer values change.

Batch Norm 的意义

听懂一部分吧.

Stabilize reduce the effect of input value on later layers

⇒ speed up learning

△ So does it help reusing pre-trained model

Batch Norm as regularization

- Each mini-batch is scaled by the mean/variance computed on just that mini-batch.
- This adds some noise to the values $z^{[l]}$ within that minibatch. So similar to dropout, it adds some noise to each hidden layer's activations.
- This has a slight regularization effect.

X $X^{\{t\}}$ $\tilde{z}^{[l]}$ 64, 128 $z^{[l]}$ μ, σ^2

mini-batch : 64 ⟶ 512

有点像 data augmentation 么?

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作用 ② regularization.

Add noise

Next: what to do at test time?

batchnorm4

8. Which of the following statements about γ and β in Batch Norm are true?

- [x] They can be learned using Adam, Gradient descent with momentum, or RMSprop, not just with gradient descent.

Correct

- [ ] β and γ are hyperparameters of the algorithm, which we tune via random sampling.

Un-selected is correct

- [x] The optimal values are $\gamma = \sqrt{\sigma^2 + \varepsilon}$, and $\beta = \mu$.

This should not be selected

- [x] They set the mean and variance of the linear variable $z^{[l]}$ of a given layer.

Correct

- [ ] There is one global value of $\gamma \in \Re$ and one global value of $\beta \in \Re$ for each layer, and applies to all the hidden units in that layer.

Un-selected is correct

computed at mini batches

Batch Norm at test time

$$\mu = \frac{1}{m}\sum_i z^{(i)}$$

$$\sigma^2 = \frac{1}{m}\sum_i (z^{(i)} - \mu)^2$$

$$z^{(i)}_{\text{norm}} = \frac{z^{(i)} - \mu}{\sqrt{\sigma^2 + \varepsilon}}$$

estimated

$$\tilde{z}^{(i)} = \gamma z^{(i)}_{\text{norm}} + \beta$$

μ, σ^2: estimate using exponentially weighted average (across mini-batches).

$X^{\{1\}}, X^{\{2\}}, X^{\{3\}}, \dots$

$\mu^{\{1\}[l]}$, $\mu^{\{2\}[l]}$, $\mu^{\{3\}[l]}$ → μ

θ_1, θ_2, θ_3

$\sigma^{2\{1\}[l]}$, $\sigma^{2\{2\}[l]}$, ... σ^2

每层一个 μ, σ^2

$z_{norm} = \frac{z - \mu}{\sqrt{\sigma^2 + \varepsilon}}$ $\tilde{z} = \gamma z_{norm} + \beta$

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estimate μ, σ^2

Use running average to estimate μ, σ^2

keep a running average

use the exponentiated average