Regularizing your neural network

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Regularizing your neural network

Regularization

prevent over-fitting
reduce variation

we usually $w \in \mathbb{R}^{n_x}$, $b \in \mathbb{R}$

Logistic regression

$w \in \mathbb{R}^{n_x}$, $b \in \mathbb{R}$

λ = regularization parameter
lambda lambd

$$\min_{w,b} J(w,b)$$

$$J(w,b) = \underbrace{\frac{1}{m}\sum_{i=1}^{m} \mathcal{L}(\hat{y}^{(i)}, y^{(i)})} + \frac{\lambda}{2m}\underbrace{\|w\|_2^2}$$

$\cancel{+\frac{\lambda}{2m} b^2}$ omit

→ why doing this? w high dim
b. one param. won't make much
difference. Don't bother to
include it.

L_2 regularization $\|w\|_2^2 = \sum_{j=1}^{n_x} w_j^2 = w^T w$ ←

L_1 regularization $\frac{\lambda}{2m}\sum_{j=1}^{n_x} |w_j| = \frac{\lambda}{2m}\|w\|_1$

w will be sparse

if not for compress of model
won't be very helpful.

m or 2m only a normalizing const

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Neural network

$$J(w^{[1]}, b^{[1]}, \dots, w^{[L]}, b^{[L]}) = \frac{1}{m}\sum_{i=1}^{n} \mathcal{L}(\hat{y}^{(i)}, y^{(i)}) + \frac{\lambda}{2m}\sum_{l=1}^{L} \|w^{[l]}\|_F^2$$

$$\|w^{[l]}\|_F^2 = \sum_{i=1}^{n^{[l]}}\sum_{j=1}^{n^{[l-1]}} (w_{ij}^{[l]})^2$$

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

"Frobenius norm"

$\|\cdot\|_2^2$ $\|\cdot\|_F^2$

$$dw^{[l]} = \boxed{(\text{from backprop}) + \frac{\lambda}{m} w^{[l]}}$$

$$\frac{\partial J}{\partial w^{[l]}} = dw^{[l]}$$

back propagation.

$$w^{[l]} := w^{[l]} - \alpha\, dw^{[l]}$$

"Weight decay"

$$w^{[l]} := w^{[l]} - \alpha\left[(\text{from backprop}) + \frac{\lambda}{m} w^{[l]}\right]$$

$$= w^{[l]} - \frac{\alpha\lambda}{m} w^{[l]} - \alpha\,(\text{from backprop})$$

$$= \underbrace{\left(1 - \frac{\alpha\lambda}{m}\right)}_{<1} w^{[l]} - \alpha\,(\text{from backprop})$$

make it smaller.

L2 regularization = weight decay

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Neural network

$$J(w^{[1]}, b^{[1]}, \dots, w^{[L]}, b^{[L]}) = \frac{1}{m}\sum_{i=1}^{n} \mathcal{L}(\hat{y}^{(i)}, y^{(i)}) + \frac{\lambda}{2m}\sum_{l=1}^{L} \|w^{[l]}\|^2$$

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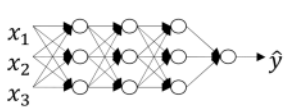
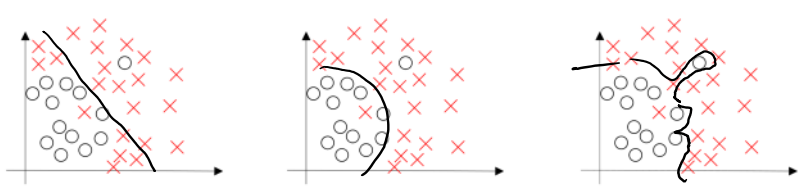
How does regularization prevent overfitting?



$$J(w^{[l]}, b^{[l]}) = \frac{1}{m}\sum_{i=1}^{n} \mathcal{L}(\hat{y}^{(i)}, y^{(i)}) + \frac{\lambda}{2m}\sum_{l=1}^{L} \|w^{[l]}\|_F^2$$



zero out lots of inputs of the hidden unit $\Rightarrow$ reduce impact of lots of hidden unit. $\Rightarrow$ $w^{[l]} = 0$.

not an accurate description though.

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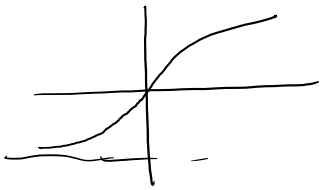
How does regularization prevent overfitting?



$\lambda \uparrow \Rightarrow w^{[l]} \downarrow \quad z^{[l]} = w^{[l]} a^{[l-1]} + b^{[l]}$

Every layer is roughly linear if regularized

$\Rightarrow$ simpler function

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Implementation tip: add term to the loss function

plot cost function — gradient decent.

$\Rightarrow$ should $\downarrow$.

★ With regularization remember to use the new def of $J = \sum L(\,) + \boxed{\lambda / m \, \| w \|}$. remember to include this part in plotting.

dropout

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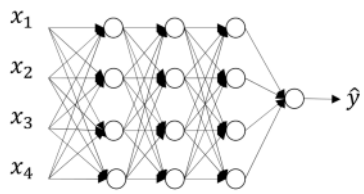
Regularizing your neural network

Dropout regularization

Dropout regularization



0.5 0.5 0.5

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Implementing dropout ("Inverted dropout")

Illustrate with layer $l=3$. keep-prob $= 0.8$ 0.2

$d3 = np.random.rand(a3.shape[0], a3.shape[1]) < keep\text{-}prob$

activation $a3 = np.multiply(a3, d3)$ # $a3 *= d3$.

$a3 /= \cancel{0.8}\ keep\text{-}prob$

true/false or 1/0.

50 units. ⇝ 10 units shut off example

$z^{[4]} = W^{[4]} \cdot a^{[3]} + b^{[4]}$

reduced by 20%

$/= 0.8$

scale it up.

Divide by keep-prob.

so it won't change the expected value of $z^{[4]}$

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layer $l=3$

keep-prob. $=0.8$.

np.random.rand

$\mathbb{I}(<0.8)$

0.8 ⇒ prob 0.2 drop.

At test time, the inverted dropout is easier ⟶ has less scaling problem

Making predictions at test time

test time NO Drop out

$a^{[0]} = X$

No drop out.

$z^{[1]} = W^{[1]} a^{[0]} + b^{[1]}$

$a^{[1]} = g^{[1]}(z^{[1]})$

$z^{[2]} = W^{[2]} a^{[1]} + b^{[2]}$

$a^{[2]} = \ldots$

$\hat{y}$

$/= keep\text{-}prob$ ⟶ the fact that we do this in training makes sure that there's no scaling problem even if we don't implement dropout at test time

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Regularizing your neural network

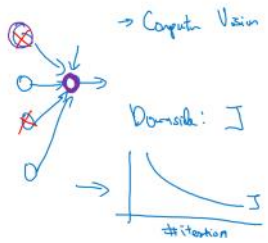
Understanding dropout

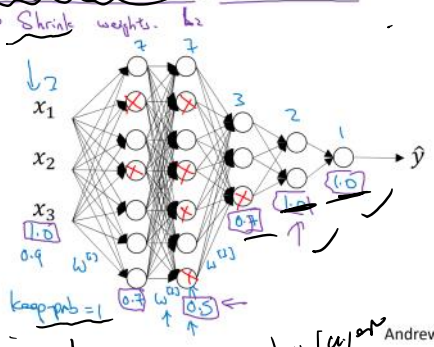
any feature could go away at random.
reluctant to put weight on any one particular input

Why does drop-out work?

Intuition: Can't rely on any one feature, so have to spread out weights. ⇝ Shrink weights. L_2

for each node toss a coin.
with some probability. remove it
"Diminished network"





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$Z_3(12)$ 的 Z_3. param ...
⇒ keep-prob ?

more worry about overfitting ⇒ lower keep prop.

can vary keep-prop by layer

similar to playing with λ.

★ Occasionally, dropout on input feature
but this is not common practice

★ Many dropout has to do with CV
cuz so many input.

Unless the application has over-fitting problem ⇒ Don't use dropout

Another problem of Dropout: Loss function J not well defined.

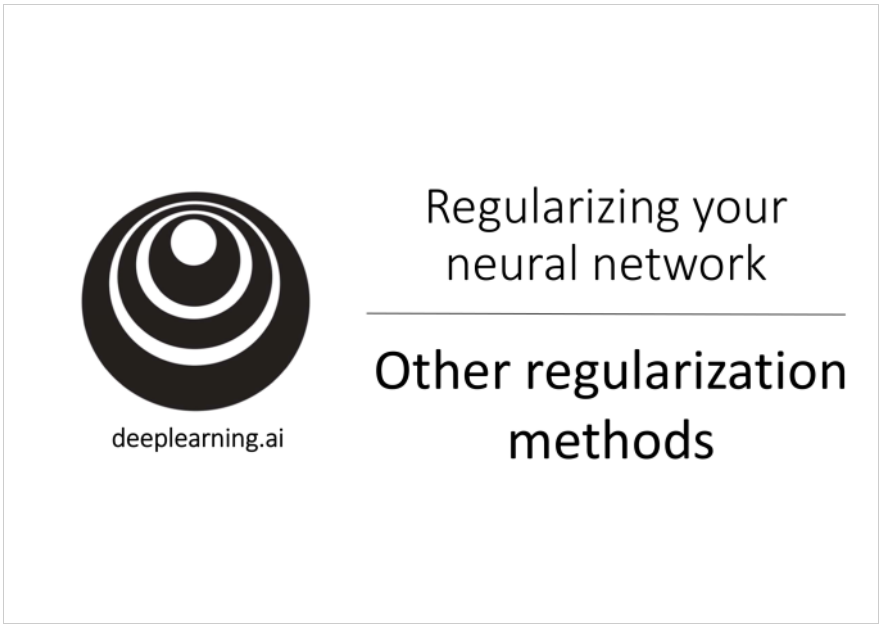
random J

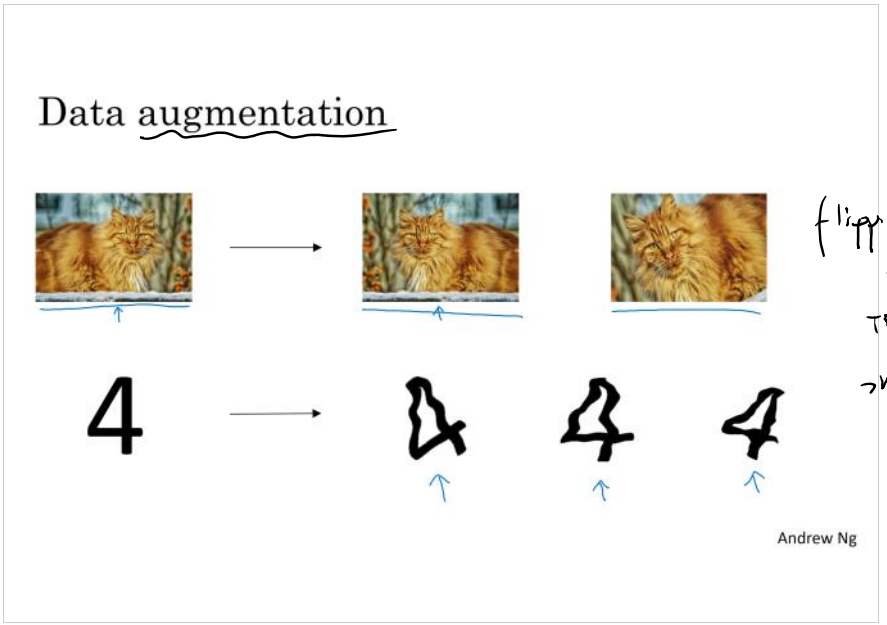
no longer monotonically decreasing.

(What to do?) Do it without dropout, if works then

⇒ ~~these~~ add dropout.

other regularization



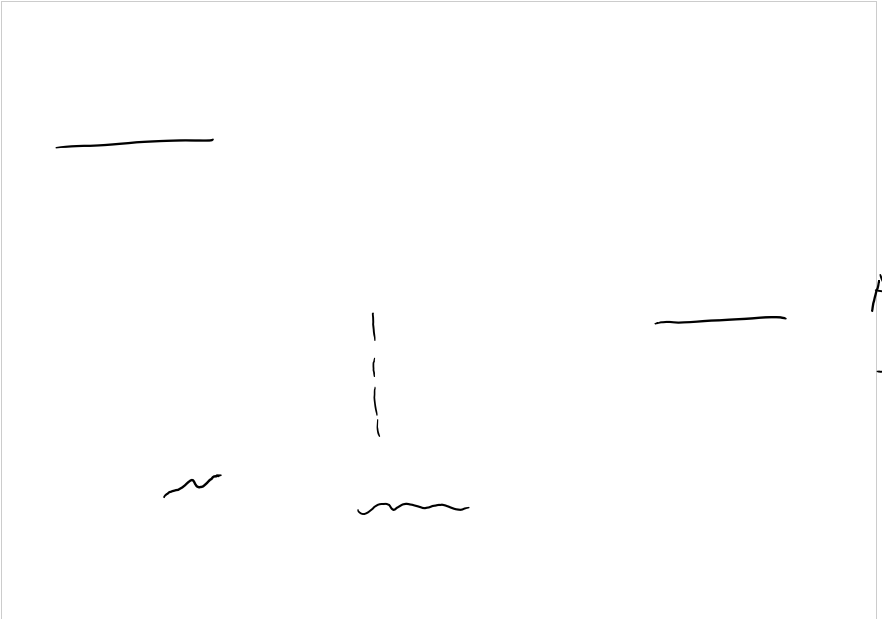


flipping images

transform

inexpensive way to get more data.

random rotation & distortion.



Also plot dev set error.

find: Dev set error ↓ => ↑.

stop halfway

Downside of early stopping [- Optimize J => J(w, b)
- avoid overfitting.] a different tool for this task
solo

Orthogonalization → 用同一个机制分别两个任务.

work on two tasks independently

不独立

→ alternative — L2 regularization

↳ Downside: computationally expensive

searching for λ.

will talk about it later.

7. With the inverted dropout technique, at test time:

- (selected) You do not apply dropout (do not randomly eliminate units), but keep the 1/keep_prob factor in the calculations used in training.

  This should not be selected

- You do not apply dropout (do not randomly eliminate units) and do not keep the 1/keep_prob factor in the calculations used in training
- You apply dropout (randomly eliminating units) and do not keep the 1/keep_prob factor in the calculations used in training
- You apply dropout (randomly eliminating units) but keep the 1/keep_prob factor in the calculations used in training.

4. You are working on an automated check-out kiosk for a supermarket, and are building a classifier for apples, bananas and oranges. Suppose your classifier obtains a training set error of 0.5%, and a dev set error of 7%. Which of the following are promising things to try to improve your classifier? (Check all that apply.)

- [x] Increase the regularization parameter lambda

Correct

- [ ] Decrease the regularization parameter lambda

Un-selected is correct

- [ ] Get more training data

This should be selected

- [ ] Use a bigger neural network

Un-selected is correct