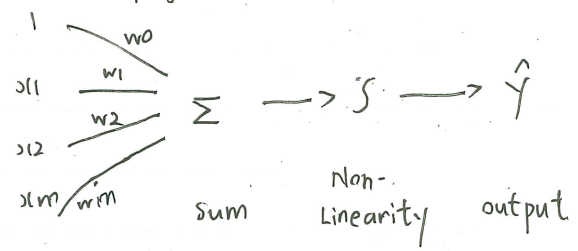
Stanford ML Note f.t. Andrew Ng

Deep Learning.

AI - machine Learning: learn without being explicitly being programmed

- Deep Learning: Extract patterns from data using neural networks

Forward Propagation.

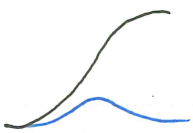


Activation Functions.

$$\hat{y} = g(w_0 + x^T w) = g(w_0 + \sum_{i=1}^{m} x_i w_i)$$

Common Activation Functions.

Sigmoid

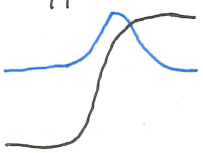


$$g(z) = \frac{1}{1+e^{-z}}$$

$$g'(z) = g(z)(1-g(z))$$

tf.nn.sigmoid(z)

Hyperbolic Tangent



$$g(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$$

$$g'(z) = 1 - g(z)^2$$

tf.nn.tanh(z)

Rectified Linear Unit

$$g(z) = \max(0, z)$$

$$g'(z) = \begin{cases} 1 & z > 0 \\ 0 & z \leq 0 \end{cases}$$

tf.nn.relu(z)

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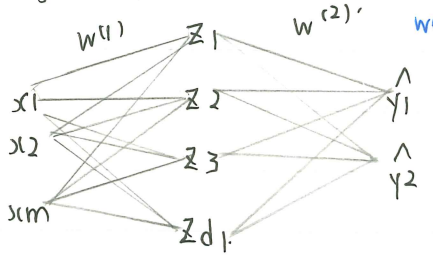
Three steps to compute the output of perceptron.

1. Dot product
2. Add a biases
3. Take non-linearity

Single Layer Neural Network.



Inputs Hidden. Output.

$$z_i = w_{0i}^{(1)} + \sum_{j=1}^{m} x_j w_{j,i}^{(1)} \qquad \hat{y}_i = g\left(w_{0,i}^{(2)} + \sum_{j=1}^{d1} z_j w_{ji}^{(2)}\right)$$

Multi Output Peceptron.

```
from tf.keras.layers import
inputs = Inputs(m)
hidden = Dense(d1)(inputs)
outputs = Dense(2)(hidden)
model = Model(inputs, outputs)
```

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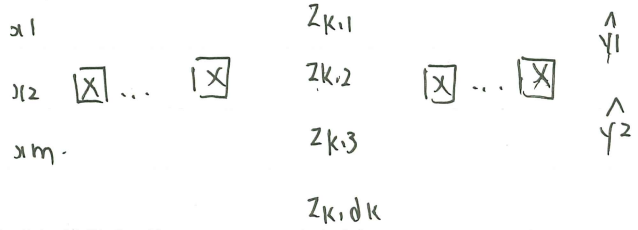
Deep Neural Network.



$$z_{k,i} = w_{0,i}^{(k)} + \sum_{j=1}^{d_{k-1}} g(z_{k-1,j})\, w_{j,i}^{(k)}$$

The model must be trained!

Quantifying loss

The loss of our network measures the cost incurred from incorrect predictions

$L(\underbrace{f(x^{(i)}; w)}_{\text{Predicted}}, \underbrace{y^{(i)}}_{\text{Actual}})$

Empirical Loss: measures the total loss over our entire data set.

$$J(w) = \frac{1}{n}\sum_{i=1}^{n} L(f(x^{(i)}; w), y^{(i)})$$

Binary Cross Entropy Loss: used when output is probability between [0, 1]

$$J(w) = \frac{1}{n}\sum_{i=1}^{n} y^{(i)} \log(f(x^{(i)}; w)) + (1-y^{(i)}) \log(1 - f(x^{(i)}; w))$$

Mean Squared Error Loss:

Used with regression models that output continuous real numbers.

$$J(w) = \frac{1}{n}\sum_{i=1}^{n} (y^{(i)} - f(x^{(i)}; w))^2$$

Define the loss is an art.

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Loss optimization.:

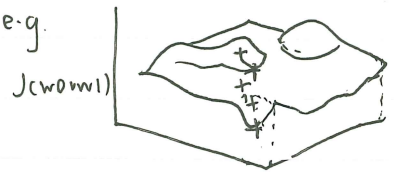
To achieve the lowest loss.

$$w^* = \arg\min_w \frac{1}{n} \sum_{i=1}^{n} L(f(x^{(i)}; w), y^{(i)})$$

$$= \arg\min_w J(w).$$

Loss is a function of the network weights!

e.g.



1. Randomly pick an (w_0, w_1)
2. Compute gradient $\frac{\partial J(w)}{\partial w}$
3. Take small step in opposite direction
4. Repeat until convergence

No guarantee it's a global mininum.
But we only need to optimize local mininum.
otherwise too expensive to compute.

Gradient Descent.

Algorithm

1. Initialize weights randomly $\sim N(0, \sigma^2)$
2. Loop until convergence:
3. Compute gradient $\frac{\partial J(w)}{\partial w}$
4. Update weights $w \leftarrow w - \eta \frac{\partial J(w)}{\partial w}$.
5. Return weights

Backpropagation $x \xrightarrow{w_1} z_1 \xrightarrow{w_2} \hat{y} \longrightarrow J(w)$

$$\frac{\partial J(w)}{\partial w_2} = \frac{\partial J(w)}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial w_2} \qquad \frac{\partial J(w)}{\partial w_1} = \frac{\partial J(w)}{\partial \hat{y}} \cdot \frac{\partial \hat{y}}{\partial z_1} \cdot \frac{\partial z_1}{\partial w_1}$$

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Setting learning rate.

Too small: — converge slowly, get stuck in false local minima

Too large: — overshoot, become unstable and diverge.

Adaptive Learning Rates: not fixed.

e.g. Momentum / Adagrad / Adadelta / Adam / RMS Prop

Stochastic Gradient Descent.

$\frac{\partial J_i(W)}{\partial W}$ is easy to compute but very noisy and stochastic

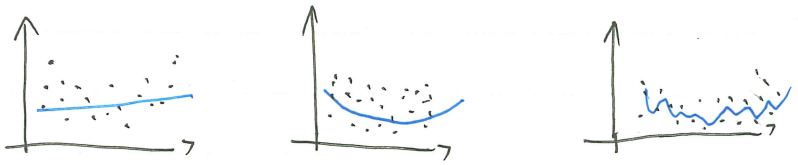
Batch data into mini batches $\frac{1}{B}\sum_{k=1}^{B}\frac{\partial J_k(W)}{\partial W}$

- faster and more accurate.

parallelized computation. send batches across GPU

compute simultaneously

aggregate them back.



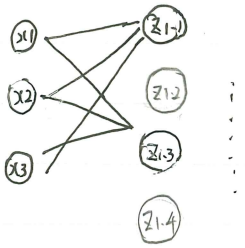
Regularization.

Technique that constrains our optimization problem to discourage complex models.

- Improve generalization of model on unseen data.

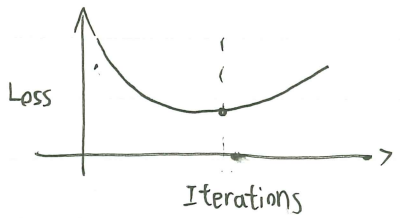
Regularization I : Dropout.

- During training, radomly set some activations to 0.
  - Typically 'drop' 50% of activation in layer
  - Force network to not rely on any I node.



II: Early Stopping

- Stop training before we have chance to overfit.



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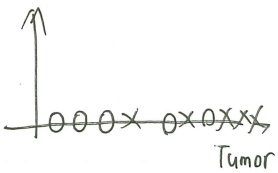
Stanford Machine Learning

Supervised Learning – input→output mappings

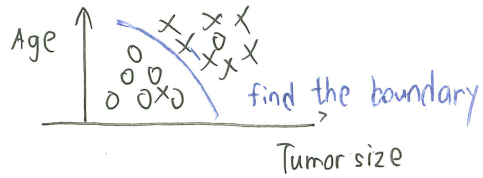
1. Regression (回归) – predict infinite possible numbers
2. Classification algorithom – predict categories

e.g



Breast cancer

malignant or benign?



Learn from the right numbers.

Unsupervised learning - Data only comes with inputs x but not output labels y.

Find some structure/ pattern in unlabeled data

1. Clustering e.g Google News / DNA micro array / Grouping Customers.

— Group similar data points together

Anomaly detection

Dimensionality reduction

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Linear Regression.

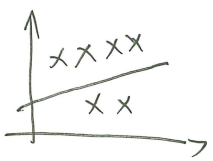
Terminology

x = "Input" variable : feature.

y : "output" variable : "target" variable.

m : number of training examples.

(x, y) = single training example



$f_{w,b}(x) = wx + b$ w = weight b = bias

$f(x) = wx + b$

Univariate linear regression

one

training set

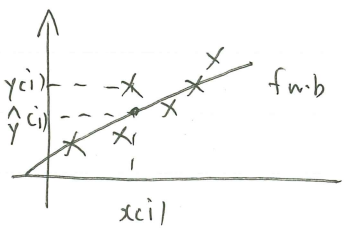
↓

learning algorithm.

↓

$x \longrightarrow [f] \longrightarrow \hat{y}$

feature — model — prediction (estimated target)



Cost Function

$$J(w,b) = \frac{1}{2m}\sum_{i=1}^{m}(\hat{y}^{(i)} - y^{(i)})^2 = \frac{1}{2m}\sum_{i=1}^{m}(f_{w,b}(x^{(i)}) - y^{(i)})^2$$

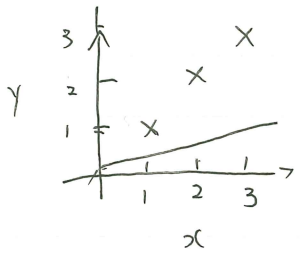
coefficients

Squared error cost function

For a simplified version.....

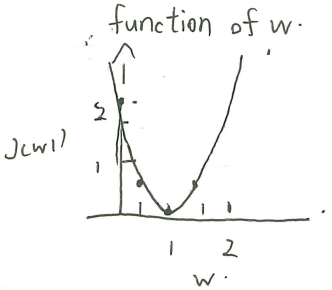
$f_w(x)$

function of x



$J(w)$

function of w.



$$J(0.5) = \frac{1}{2m}\left[(0.5-1)^2 + (1-2)^2 + (1.5-3)^2\right] = \frac{7}{12}$$

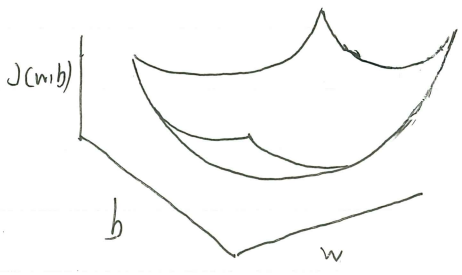
$$J(0) = \frac{14}{6}$$

Goal of linear regression.

- choose w to minimize $J(w)$

General case.

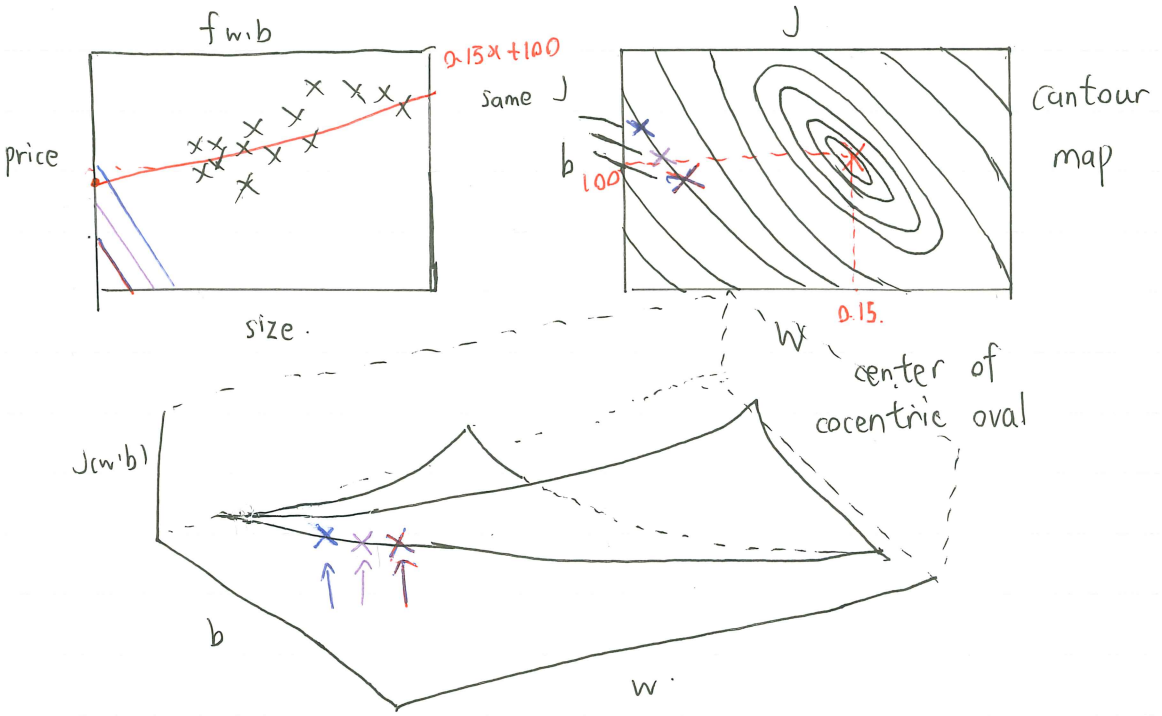
minimize $J(w,b)$
w b



Use contour map.

Square error cost always leads to a bowl-shaped graph.

convex function


f w,b
0.13x+100
price
size
same J
J
b
100
0.15
w
contour
map
center of
cocentric oval
J(w,b)
b
w

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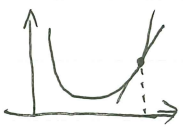
Gradient descent (one feature)

Algorithm: repeat until convergence

$w = w - a\frac{\partial}{\partial w}J(w,b)$ a is Learning rate.

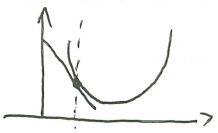
$b = b - a\frac{\partial}{\partial b}J(w,b)$

Simultaneously update w and b.



$w = w - a\frac{d}{dw}J(w)$

$w = w - a \cdot (\text{positive number})$ $\therefore$ w moves left



$w = w - a\frac{d}{dw}J(w)$

$w = w - a(\text{negative number})$ $\therefore$ w moves right

Learning rate

If a is too small.... Gradient descent too slow.

If a is to large Gradient descent may diverge.

- Can reach local minimum with fixed learning rate a.

  Near a l.m., - Derivative becomes smaller

  - Update step becomes smaller.

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Gradient descent algorithm.

repeat until convergence:

$$w = w - \alpha \cdot \left[\frac{1}{m} \sum_{i=1}^{m} (f_{w,b}(x^{(i)}) - y^{(i)}) x^{(i)} \right]$$

$$b = b - \alpha \cdot \left[\frac{1}{m} \sum_{i=1}^{m} (f_{w,b}(x^{(i)}) - y^{(i)}) \right]$$

$$\frac{\partial}{\partial w} J(w,b) = \frac{\partial}{\partial w} \frac{1}{2m} \sum_{i=1}^{m} (f_{w,b}(x^{(i)}) - y^{(i)})^2 = \frac{\partial}{\partial w} \frac{1}{2m} \sum_{i=1}^{m} (wx^{(i)} + b - y^{(i)})^2$$

$$= \frac{1}{2m} \sum_{i=1}^{m} (wx^{(i)} + b - y^{(i)}) 2x^{(i)}$$

$$\frac{\partial}{\partial b} J(w,b) = \frac{\partial}{\partial b} \frac{1}{2m} \sum_{i=1}^{m} (wx^{(i)} + b - y^{(i)}) \cdot 2$$

"Batch" Each step of gradient descent uses all the training examples

Multiple features (variables)

x_j = j^{th} feature

n = number of features

$\vec{x}^{(i)}$ = features of i^{th} training example

$x_j^{(i)}$ = value of feature j in i^{th} training example.

$$f_{w,b}(x) = w_1 x_1 + w_2 x_2 + \dots + w_n x_n + b = \vec{w} \cdot \vec{x} + b$$

multiple linear regression.

parameters: $\vec{w} = [w_1 \; w_2 \; \dots \; w_n]$, b

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Vectorization

* linear algebra count from 1 but code count from 0.

$$f_{\vec{w},b}(\vec{x}) = \sum_{i=1}^{n} w_j x_j + b$$

Without Vectorization

```
f = 0
for j in range(n):
    f = f + x[j] * w[j]
f = f + b
```

Vectorization.

```
f = np.dot(w, x) + b
```

☺

1. shorter
2. Faster

Numpy dot function can use Parellel hardware. — more efficient.

to $f + w[0] * x[0]$

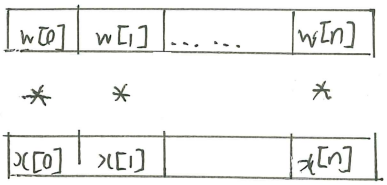
t1 $f + w[1] * x[1]$

. . . . . .

tn $f + w[n] * x[1]$

— Step by step. one step at a time.

to



in parallel

t1

$w[0] * x[0] + \ldots\ldots + w[n] * x[n]$

Parellel hardware is efficient when scale to large data set.

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Gradient descent.

$\vec{w} = (w_1\ w_2\ \dots\ w_n)$ $\quad \vec{d} = (d_1\ d_2\ \dots\ d_n)$

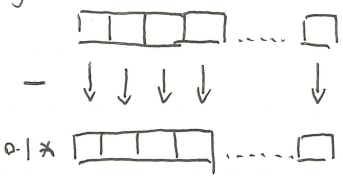
$w = np.array([w_1, w_2, \dots w_n])$

$d = np.array([d_1, d_2, \dots d_n])$.

compute $w_j = w_j - 0.1\, d_j$

a = learning rate

Vectorization: $\vec{w} = \vec{w} - 0.1\vec{d}$



code: $w = w - 0.1 * d$

When we have n features $(n \geq 2)$

repeat {

$j=1$ $\quad w_1 = w_1 - a\frac{1}{m}\sum_{i=1}^{m}(f_{\vec{w},b}(\vec{x}^{(i)}) - y^{(i)})\, x_1^{(i)}$

$\vdots$

$j=n$ $\quad w_n = w_n - a\frac{1}{m}\sum_{i=1}^{m}(f_{\vec{w},b}(\vec{x}^{(i)}) - y^{(i)})\, x_n^{(i)}$

$b = b - a\frac{1}{m}\sum_{i=1}^{m}(f_{\vec{w},b}(\vec{x}^{(i)}) - y^{(i)})$

> simultaneously update w_j (for $j = 1 \dots n$) and b.

* An alternative to gradient descent — Normal equation.

sometimes used in machine learning libraries.

- Only for linear regression.
- Solve for w, b without iterations.

Disadvantage: • Doesn't generalize to other learning algorithms

• Slow when number of features is large ($> 10{,}000$)

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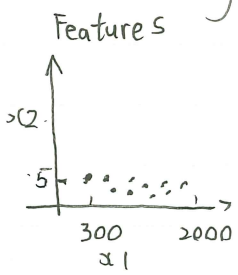
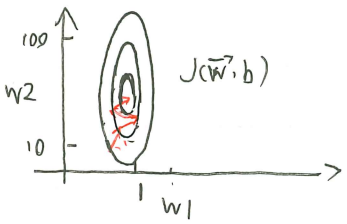
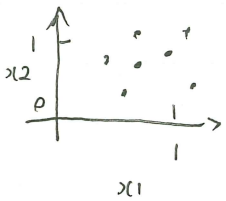
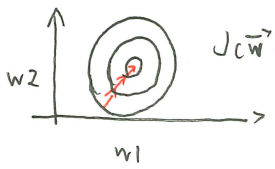
Feature Scaling — can help converge faster



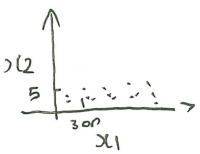




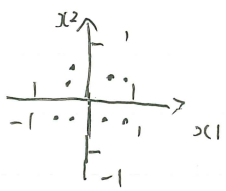


more direct path to minimum.

Mean normalization



$300 \leq x_1 \leq 2000$ $\quad 0 \leq x_2 \leq 5$



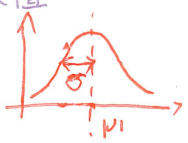
$$x_1 = \frac{x_1 - \mu_1}{2000 - 300} \qquad x_2 = \frac{x_2 - \mu_2}{5 - 0}$$

$-0.18 \leq x_1 \leq 0.82$ $\quad -0.46 \leq x_2 \leq 0.54$

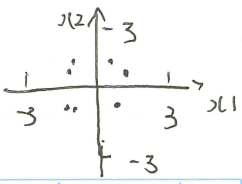
消除量极给分析带来的不便. 但数据的真实意义需还原值

with a similar scale

Z-score deviation — feature center at 0.



standard deviation σ



$$x_1 = \frac{x_1 - \mu_1}{\sigma_1 = 450} \qquad x_2 = \frac{x_2 - \mu_2}{\sigma_2 = 1.4}$$

$-0.67 \leq x_1 \leq 3.1$ $\quad -1.6 \leq x_2 \leq 1.9$.

$$\mu_j = \frac{1}{m} \sum_{i=0}^{m-1} x_j^{(i)} \qquad \sigma_j^2 = \frac{1}{m} \sum_{i=0}^{m-1} (x_j^{(i)} - \mu_j)^2$$

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(divide maximum)

Feature scaling aim for about $-1 \leq x_j \leq 1$ for each feature x_i

$(-3, 3)$ / $(-0.3, 0.3)$ acceptable

$[0, 3]$ / $[-2, 0.5]$ ok

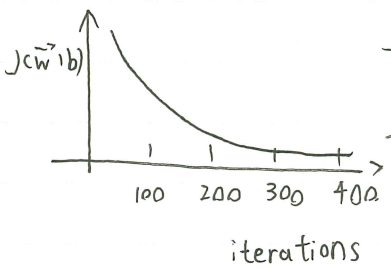
$[-100, 100]$ too large

$[-0.001, 0.001]$ too small → rescale

$98.6 \leq x \leq 105$ too large

Make sure gradient descent is working correctly

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



$J(\vec{w}, b)$ should decrease after every iteration

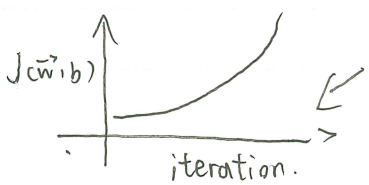
likely converged by 400 iterations

Automatic convergence test

If $J(\vec{w}, b)$ decreases by $\leq \varepsilon = 10^{-3}$ in one iteration.

declare convergence.

(check the graph is always the best way!)



There's a bug / α is too large.

* Use a very small learning rate to check whether there's a bug.

Values of α to try

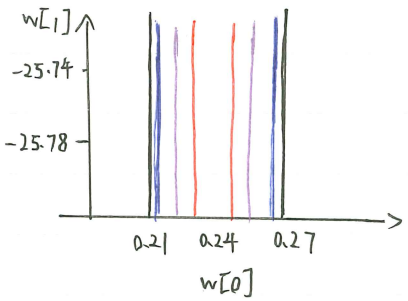
0.001 0.003 0.01 0.03 0.1 0.3 1 .... 3 times bigger every time

pick a suitable α according to graph.

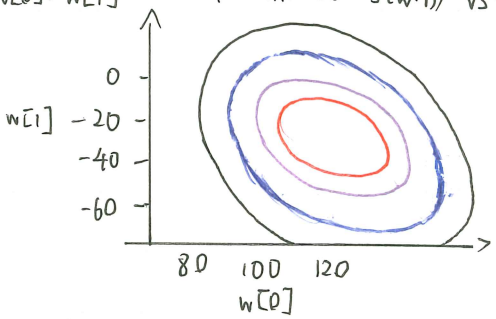
* Any predictions using the parameters learned from a normalized training set must also be normalized

Cost contour with equal scale.

Unnormalized $J(w,b)$ vs $w[0]$, $w[1]$



Normalized $J(w,b)$ vs. $w[0]$, $w[1]$



Feature Engineering:

Using intuition to design new features, by transforming or combining original features.

e.g. x_1 (length) * x_2 (width) = x_3 (area)

Polynomial regression. x = size

$f_{\vec{w},b}(x) = w_1 x + w_2 x^2 + b$

$f_{\vec{w},b}(x) = w_1 x + w_2 x^2 + w_3 x^3 + b$

It's important to combine it with feature scaling!

$f_{\vec{w},b}(x) = w_1 x + w_2 \sqrt{x} + b$

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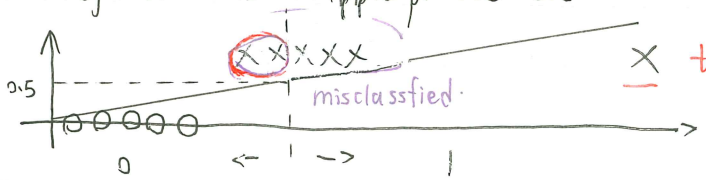
Classification.

Linear regression is inappropriate here.

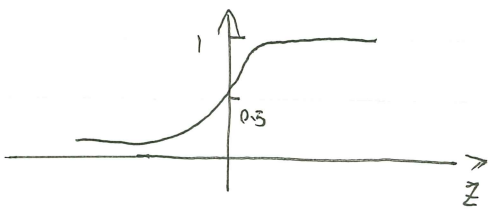


× this cause the line to shift.

Logistic Regression.

We want outputs between 0 and 1

Sigmoid function (logistic function)



$$g(z) = \frac{1}{1+e^{-z}} \qquad (0 < g(z) < 1)$$

$$f_{\vec{w},b}(\vec{x}) = g(\vec{w}\cdot\vec{x}+b) = \frac{1}{1+e^{-(\vec{w}\cdot\vec{x}+b)}}$$

"Probability"

$f_{\vec{w},b}(\vec{x}) = 0.7 \longrightarrow$ 70% chance that y is 1.

$\therefore f_{\vec{w},b}(\vec{x}) = P(y=1 \mid \vec{x}; \vec{w}, b)$

Probability that y is 1, given input $\vec{x}$, parameters $\vec{w}, b$

Is $f_{\vec{w},b}(\vec{x}) \geq 0.5$? (threshold)

Yes: $\hat{y} = 1$ No: $\hat{y} = 0$

$g(z) \geq 0.5$?

$z \geq 0$?

$\vec{w}\vec{x}+b \geq 0$?

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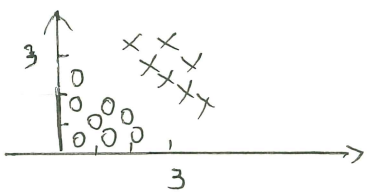
Decision boundary



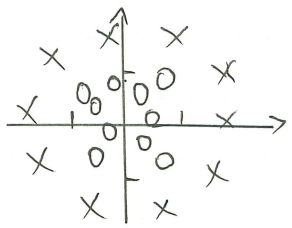
$f_{\vec{w},b}(\vec{x}) = g(z) = g(w_1x_1 + w_2x_2 + b)$

if $w_1 = w_2 = 1$, $b = -3$

Decision boundary is $z = 0$

$x_1 + x_2 = 3$

Non-Linear decision boundaries



$f_{\vec{w},b}(\vec{x}) = g(w_1x_1^2 + w_2x_2^2 + b)$

Let $w_1 = w_2 = 1$, $b = -1$

$x_1^2 + x_2^2 = 1$

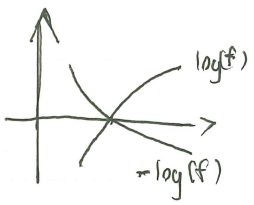
logistic regression $f_{\vec{w},b}(\vec{x}) = \dfrac{1}{1+e^{-(\vec{w}\cdot\vec{x}+b)}}$

$J(\vec{w},b) = \frac{1}{m}\sum_{i=1}^{m}\frac{1}{2}(f_{\vec{w},b}(\vec{x}^{(i)}) - y^{(i)})^2$

non-convex

Logic loss function.

$$L(f_{\vec{w},b}(\vec{x}^{(i)}), y^{(i)}) = \begin{cases} -\log(f_{\vec{w},b}(\vec{x}^{(i)})) & \text{if } y^{(i)} = 1 \\ -\log(1 - f_{\vec{w},b}(\vec{x}^{(i)})) & \text{if } y^{(i)} = 0 \end{cases}$$



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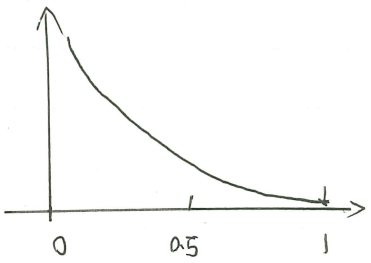
$L(f_{\vec{w},b}(\vec{x}^{(i)}), y^{(i)})$:

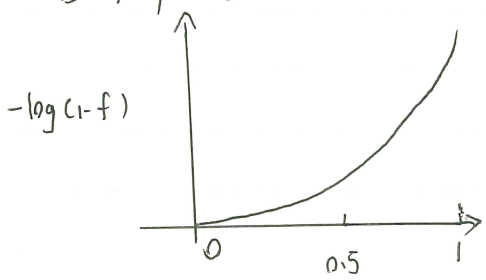
① If $y^{(i)}=1$



As $f_{\vec{w},b}(\vec{x}^{(i)}) \to 1$, then loss $\to 0$ ☺

As $f_{\vec{w},b}(\vec{x}^{(i)}) \to 0$ then loss $\to \infty$ ☹

② If $y^{(i)}=0$



As $f_{\vec{w},b}(\vec{x}^{(i)}) \to 0$ then loss $\to 0$ ☺

As $f_{\vec{w},b}(\vec{x}^{(i)}) \to 1$ loss $\to \infty$ ☹

∴ If model get answer wrong, we penalize model with high loss

Cost $\therefore J(\vec{w},b) = \frac{1}{m}\sum_{i=1}^{m} \underbrace{L(f_{\vec{w},b}(x^{(i)}), y^{(i)})}_{\text{loss}}$

it's convex now! $\text{loss} = \begin{cases} -\log(f_{\vec{w},b}(\vec{x}^{(i)})) & \text{if } y^{(i)}=1 \\ -\log(1-f_{\vec{w},b}(\vec{x}^{(i)})) & \text{if } y^{(i)}=0 \end{cases}$

find the w.b that minimize the cost

$\therefore L(f_{\vec{w},b}(\vec{x}^{(i)}), y^{(i)}) = \boxed{-y^{(i)}\log(f_{\vec{w},b}(\vec{x}^{(i)})) - (1-y^{(i)})\log(1-f_{\vec{w},b}(\vec{x}^{(i)}))}$

$J(\vec{w},b) = -\frac{1}{m}\sum_{i=1}^{m}\left[y^{(i)}\log(f_{\vec{w},b}(\vec{x}^{(i)})) + (1-y^{(i)})\log(1-f_{\vec{w},b}(\vec{x}^{(i)}))\right]$

Campus The function is picked out by maximum likelihood. to reach single global maximum.

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Gradient descent for logistic regression

repeat {

$$w_j = w_j - \alpha \left[\frac{1}{m} \sum_{i=1}^{m} (f_{\vec{w},b}(\vec{x}^{(i)}) - y^{(i)}) x_j^{(i)} \right]$$

$$b = b - \alpha \left[\frac{1}{m} \sum_{i=1}^{m} (f_{\vec{w},b}(\vec{x}^{(i)}) - y^{(i)}) \right]$$

} simultaneous updates.

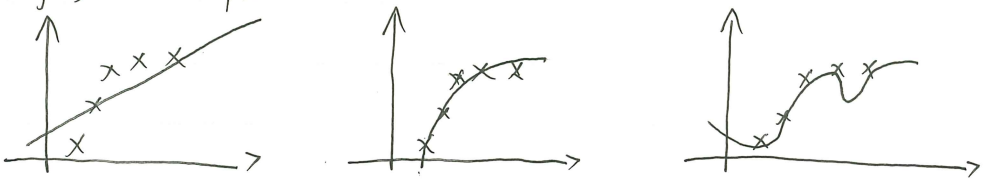
Seemingly same with linear regression

but $f_{\vec{w},b}(\vec{x}) = \frac{1}{1+e^{-(\vec{w}\cdot\vec{x}+b)}}$ here.

- Monitor gradient descent (learning curve) for convergence
- Using vectorization to make gradient descent faster
- Feature scaling also help converge faster.

(Bias and Variances - take minutes to learn
take life to master.

Regression example.



underfit (high biases)
- size: $w_1 x + b$

generalization
size: $w_1 x + w_2 x^2 + b$

overfit (high variance)
size: $w_1 x + \dots + w_4 x^4 + b$

If you have too many features, it might fit too well

Our goal is to predict outcomes correctly for new examples.

A model which does this is said to generalize well.

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Address overfitting

1: collect new data

2. select features

throw away unnecessary feature

disadvantage: useful information might be lost

3. regularization

keep all the features, shrink the parameters

$f(x) = 28x - 385x^2 + 39x^3 - 174x^4 + 100$

eliminate

$f(x) = 13x - 0.23x^2 + 0.0000014x^3 - 0.0001x^4 + 100$

small values for w_j

normally no need to regularize b (just $w_1 \cdots w_j$!)

makes a difference!

*extreme examples can increase overfitting

Regularization.

for $x_1 \cdots\cdots x_{100}$

Penalize all the features;

$$J(\vec{w}, b) = \frac{1}{2m} \sum_{i=1}^{m} (f_{\vec{w},b}(\vec{x}^{(i)}) - y^{(i)})^2 + \frac{\lambda}{2m} \sum_{j=1}^{n} w_j^2 \quad (+ \frac{\lambda}{2m} b^2)$$

"lamda" λ: regularization parameter

mean square error regularization term

$$\min_{\vec{w},b} J(\vec{w},b) = \min_{\vec{w},b}\left[\frac{1}{2m}\sum_{i=1}^{m}(f_{\vec{w},b}(\vec{x}^{(i)})-y^{(i)})^2 + \frac{\lambda}{2m}\sum_{j=1}^{n} w_j^2\right]$$

fit data keep w_j small

λ balance both goals.

$\lambda = 0$ → overfit

$\lambda = 10^{10}$ → underfit

Gradient descent.

repeat {

$w_j = w_j - \alpha\frac{\partial}{\partial w_j}J(\vec{w},b)$

$b = b - \alpha\frac{\partial}{\partial b}J(\vec{w},b)$ } simultaneous update.

$$\frac{\partial}{\partial w_j}J(\vec{w},b) = \frac{1}{m}\sum_{i=1}^{m}(f_{\vec{w},b}(\vec{x}^{(i)})-y^{(i)})x_j^{(i)} + \boxed{\frac{\lambda}{m}w_j}$$

$$\frac{\partial}{\partial b}J(\vec{w},b) = \frac{1}{m}\sum_{i=1}^{m}(f_{\vec{w},b}(\vec{x}^{(i)})-y^{(i)}) \quad \text{(don't have to regularize } b\text{)}$$

$$w_j = w_j\left(1-\alpha\frac{\lambda}{m}\right) - \alpha\frac{1}{m}\sum_{i=1}^{m}(f_{\vec{w},b}(\vec{x}^{(i)})-y^{(i)})x_j^{(i)}$$

slightly smaller than 1

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Regularized logistic regression.

$$f_{\vec{w},b}(\vec{x}) = \frac{1}{1+e^{-z}}$$

$$z = w_1x_1 + w_2x_2 + w_3x_1^2x_2 + w_4x_1x_2^2 + w_5x_1^2x_2^3 + \dots + b.$$

Cost function

$$J(\vec{w},b) = -\frac{1}{m}\sum_{i=1}^{m}\left[y^{(i)}\log\left(f_{\vec{w},b}(\vec{x}^{(i)})\right) + (1-y^{(i)})\log\left(1-f_{\vec{w},b}(\vec{x}^{(i)})\right)\right] + \frac{\lambda}{2m}\sum_{j=1}^{m} w_j^2$$

$$\min J(\vec{w},b) \rightarrow w_j \downarrow$$

$$\left(f_{\vec{w},b}(\vec{x}^{(i)}) - y^{(i)}\right)x_j^{(i)}$$

looks same as the algorithm for linear regression.

except the $f_{\vec{w},b}(\vec{x})$ is different here.

The skill of reduce overfitting is very valuable in real world!

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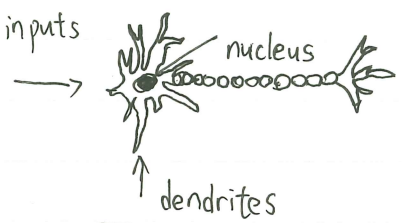
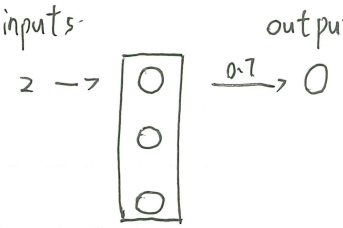
Neural networks

Biological neuron.

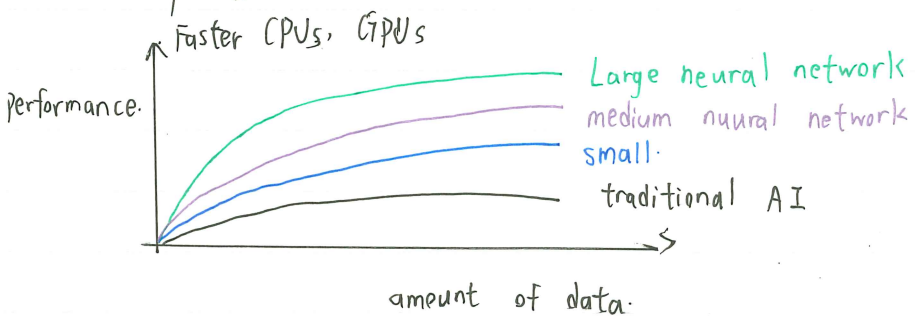


Simplified mathematical model

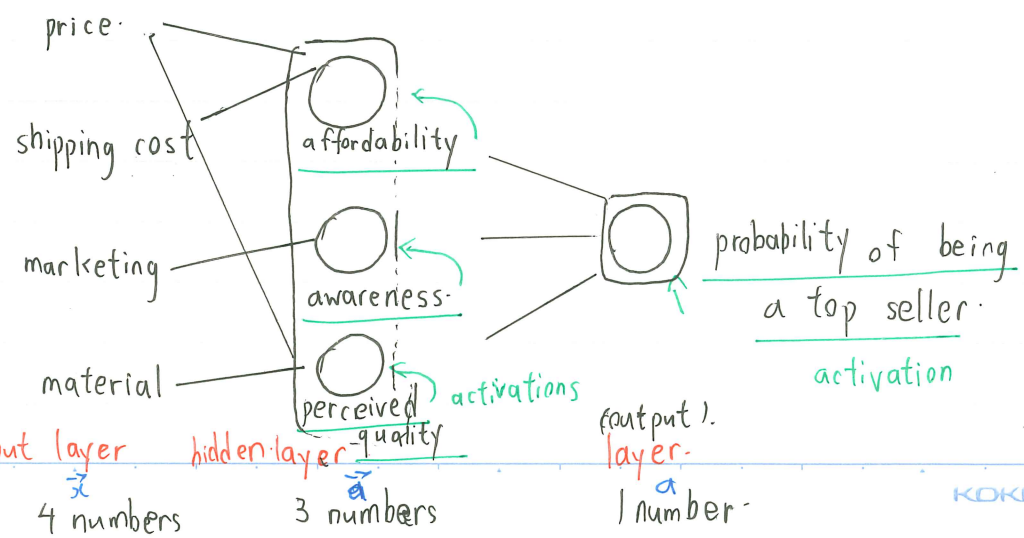


(How brain exactly works is yet to be discovered)

Why Now?



Demand Prediction.



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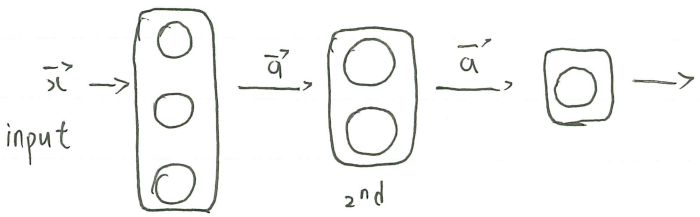
Why neural network is powerful?

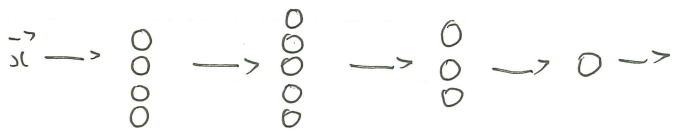
It can Learn its own features that makes it easier to accurately predict

human doesn't need to explicitly decide the features

Multiple hidden layers:



or.



(neural network architecture)

e.g. Face recognition