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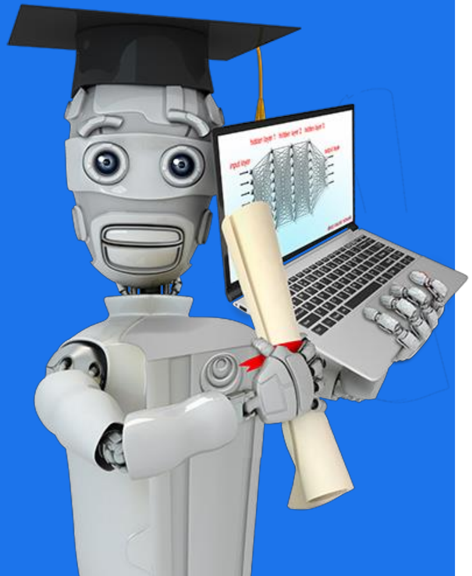

Machine Learning

Welcome!

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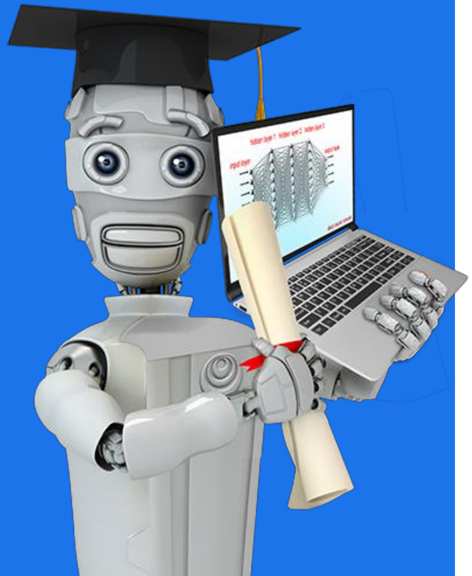


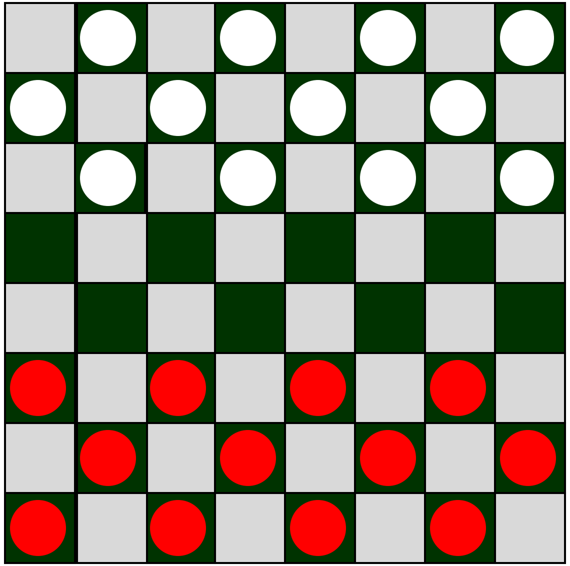
Machine Learning Overview

What is Machine Learning?

Machine learning

"Field of study that gives computers the ability to learn without being explicitly programmed."

Arthur Samuel (1959)



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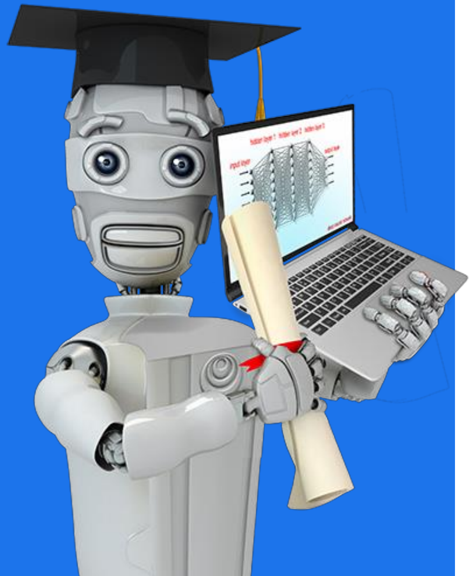


Machine Learning Overview

Supervised Learning Part 1

Supervised learning

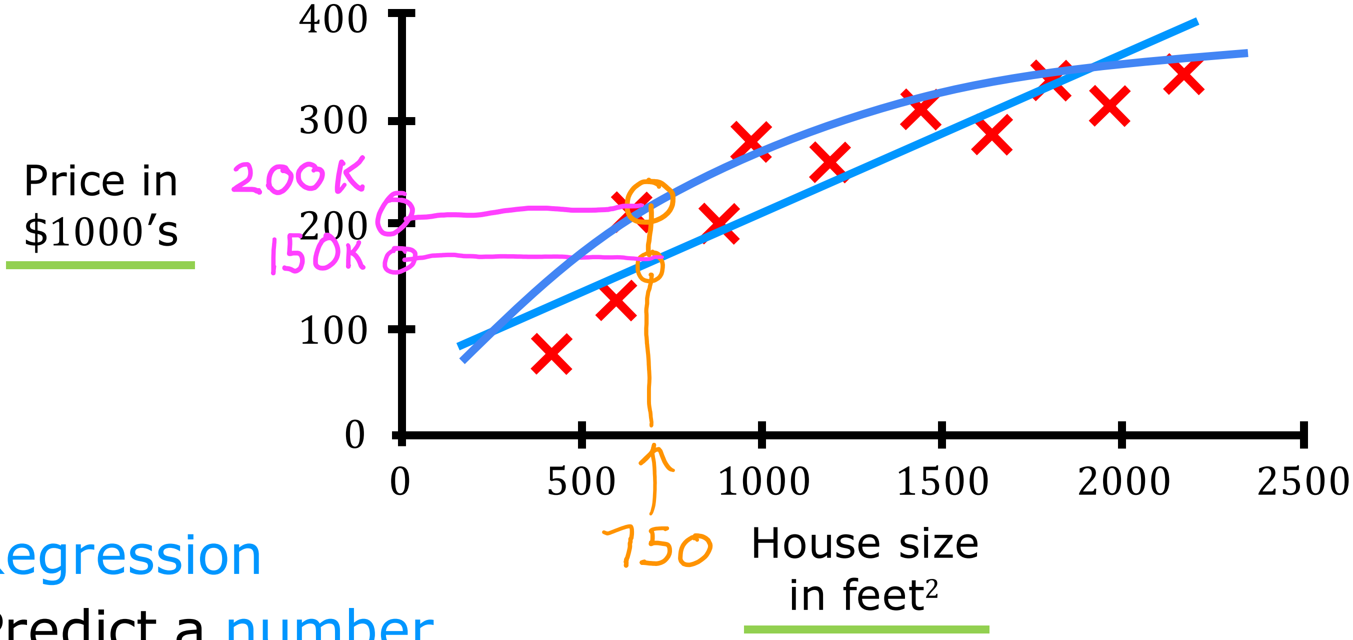
$X \longrightarrow Y$

input $\longrightarrow$ output label

Learns from being given "right answers"

Input (X)	Output (Y)	Application
email →	spam? (0/1)	spam filtering
audio →	text transcripts	speech recognition
English →	Spanish	machine translation
ad, user info →	click? (0/1)	online advertising
image, radar info →	position of other cars	self-driving car
image of phone →	defect? (0/1)	visual inspection

Regression: Housing price prediction



150,000
70,000
183,000

Regression

Predict a number

infinitely many possible outputs

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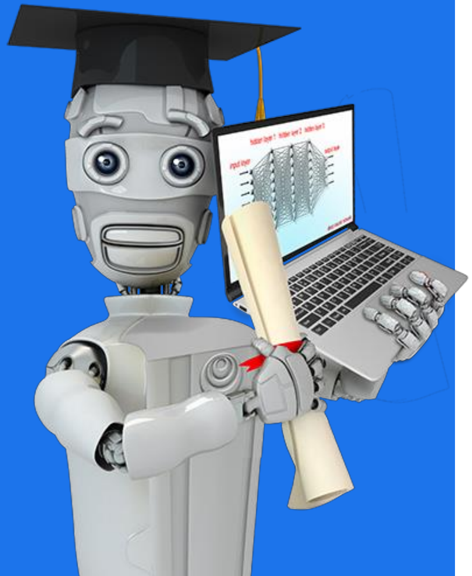
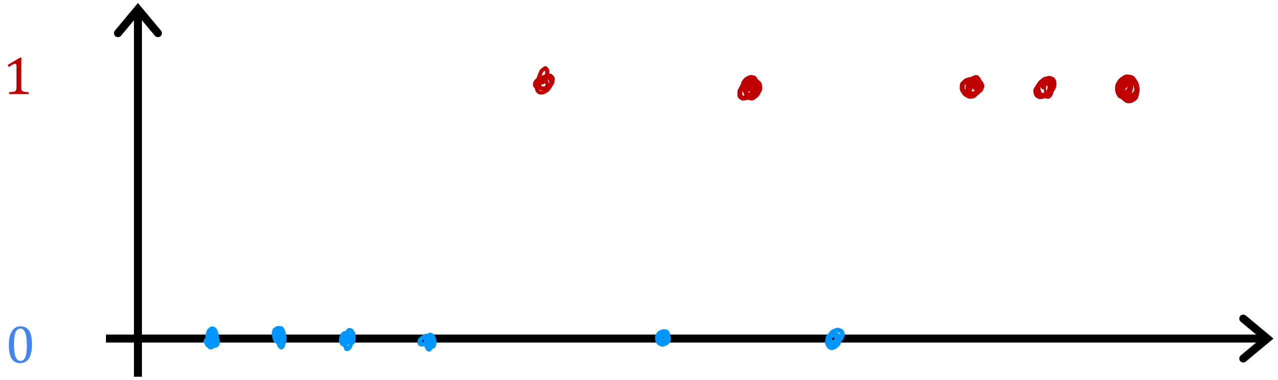


Machine Learning Overview

Supervised Learning Part 2

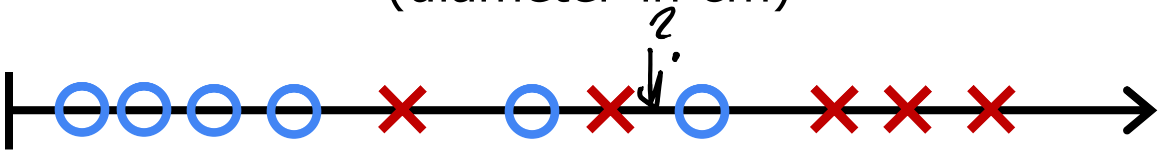
Classification: Breast cancer detection

malignant benign



tumor size x
(diameter in cm)

size	diagnosis
2	0
5	1
1	0
7	1
⋮	



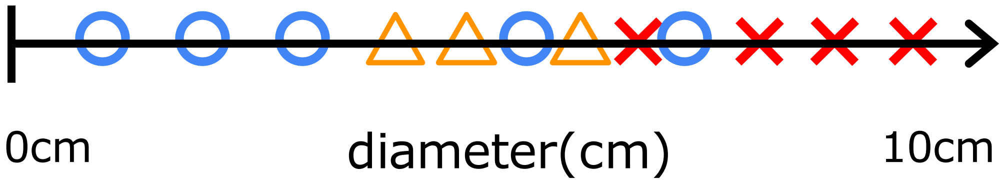
○ benign
× malignant

Classification: Breast cancer detection

○ benign

× malignant type1

△ malignant type 2



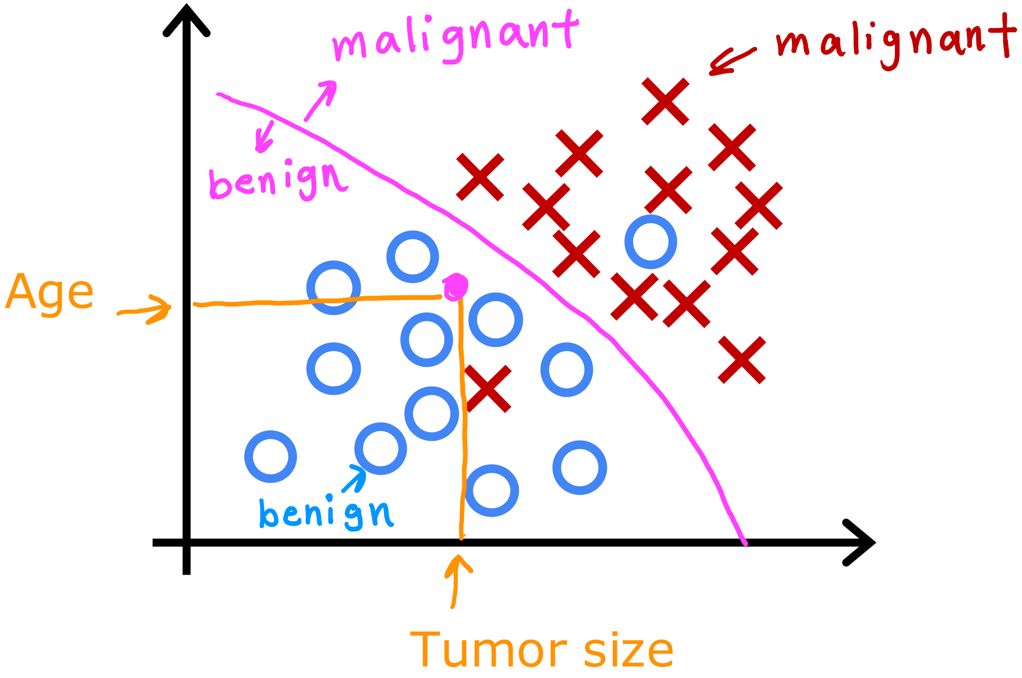
class category

Classification

predict categories cat dog benign malignant 0, 1, 2

small number of possible outputs

Two or more inputs



Supervised learning

Learns from being given "right answers"

Regression

Predict a number

infinitely many possible outputs

Classification

predict categories

small number of possible outputs

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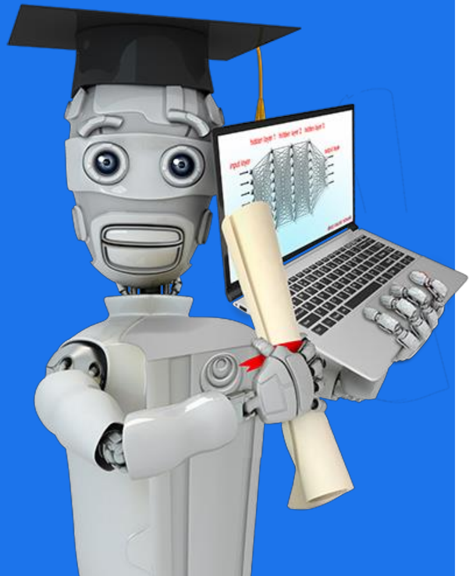
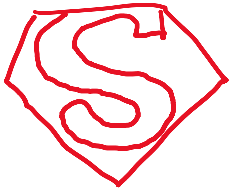


Machine Learning Overview

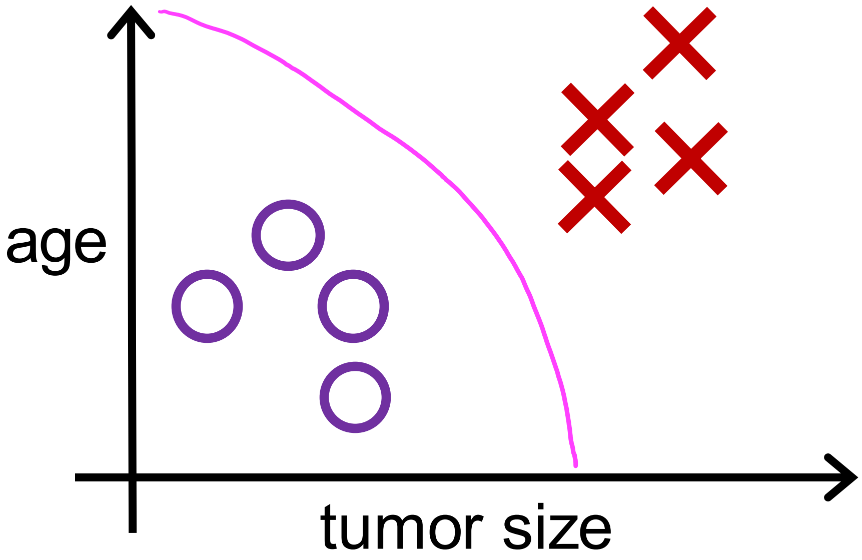
Unsupervised Learning Part 1

Previous: Supervised learning

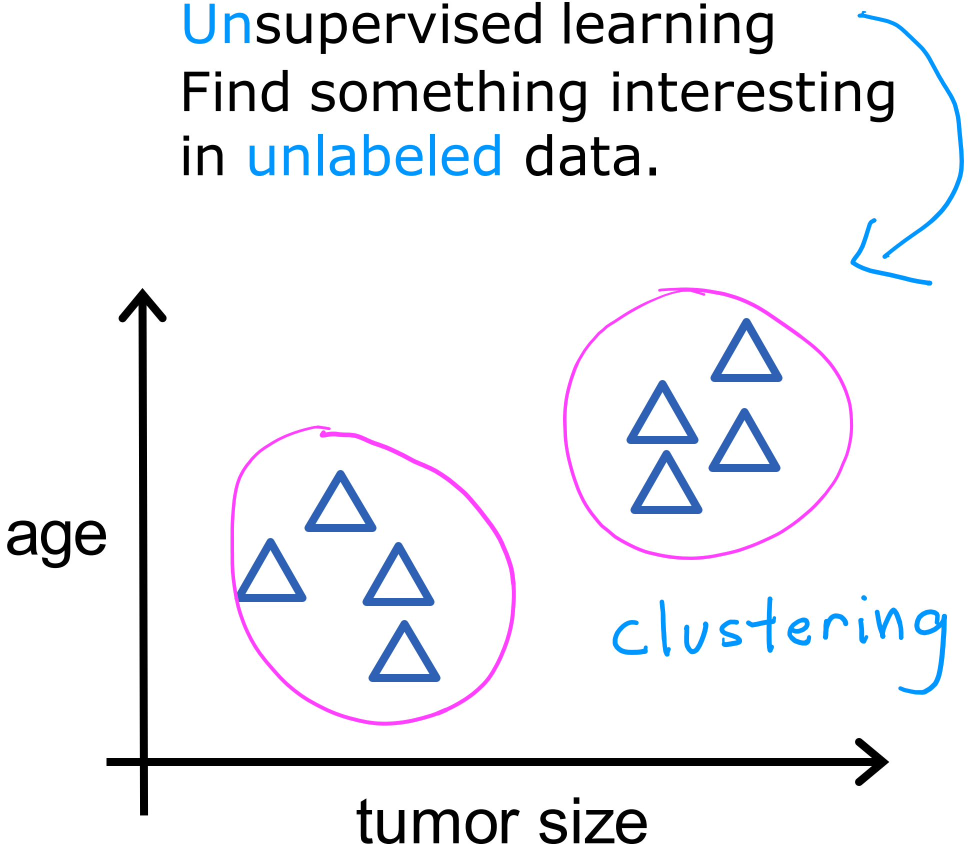
Now: Unsupervised learning



Supervised learning
Learn from data labeled
with the "right answers"

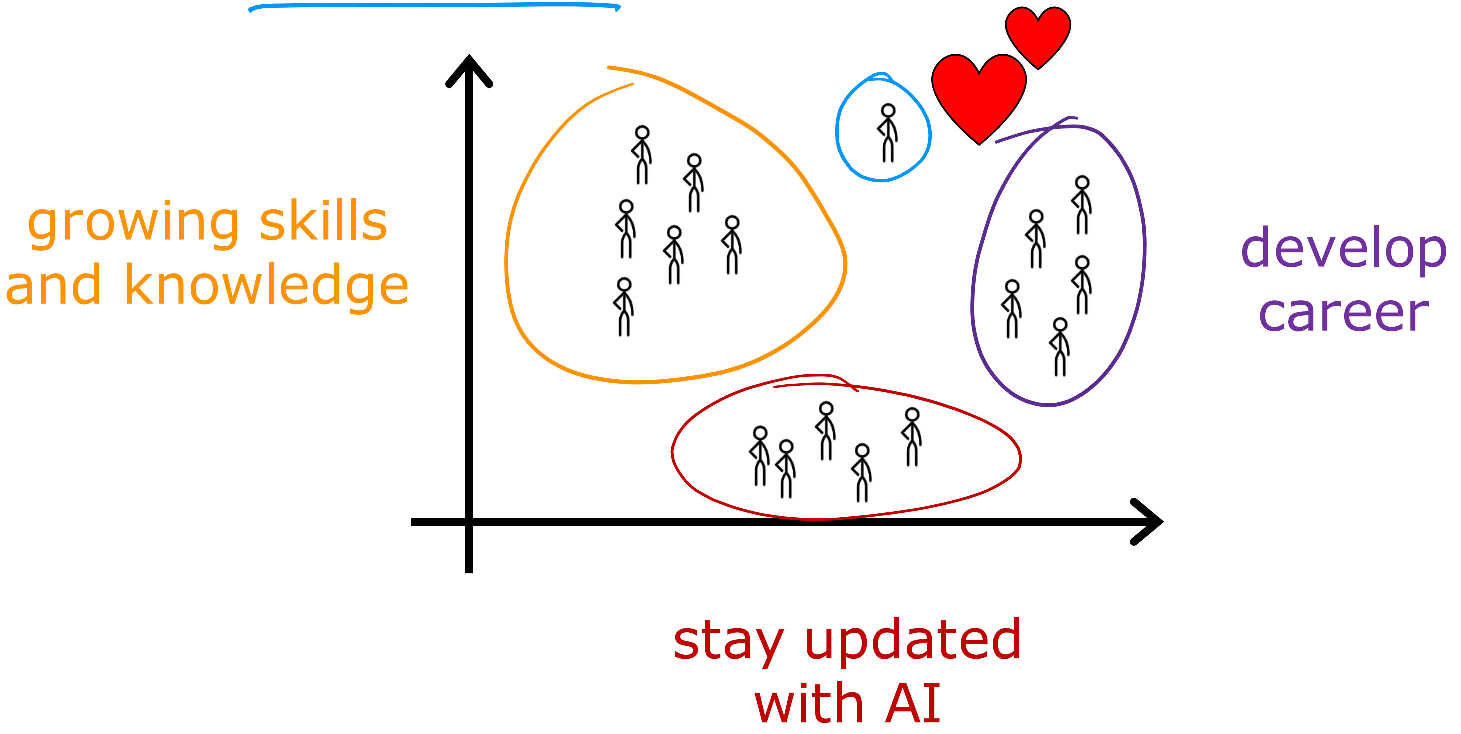


Unsupervised learning
Find something interesting
in unlabeled data.



Clustering: Google news

Clustering: Grouping customers



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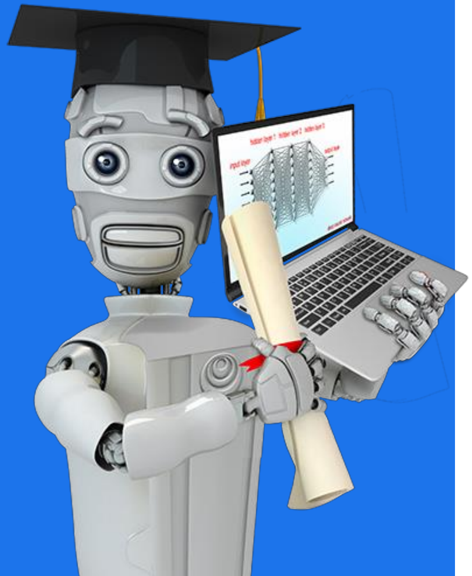

Machine Learning Overview

Unsupervised Learning Part 2

Unsupervised learning

Data only comes with inputs x, but not output labels y.
Algorithm has to find structure in the data.

<u>Clustering</u>
Group similar data points together.

<u>Dimensionality reduction</u>
Compress data using fewer numbers.

<u>Anomaly detection</u>
Find unusual data points.

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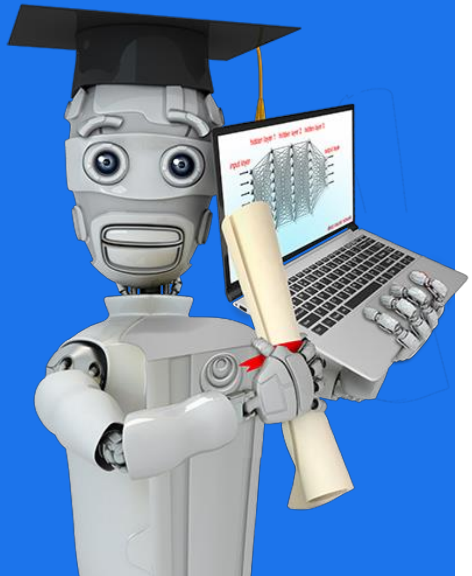

Linear Regression with One Variable

Linear Regression Model Part 1

House sizes and prices

Data table

size in feet²	price in $1000's
2104	400
1416	232
1534	315
852	178
...	...
3210	870

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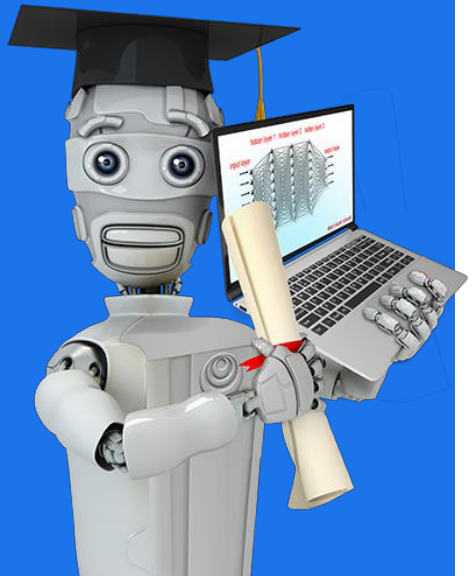


Linear Regression with One Variable

Linear Regression Model Part 2

training set

features
targets

↓

learning algorithm

↓

$x \rightarrow \boxed{f} \rightarrow \hat{y}$

"y-hat"

~~hypothesis~~ function

feature   model   prediction

(estimated y)

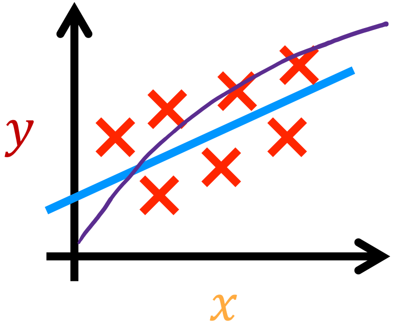
target

$\text{size} \rightarrow \boxed{f} \rightarrow \text{price}$ (estimated)

How to represent f?

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

$$f(x)$$



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

$f(x) = wx + b$

linear

single feature x

Linear regression with one variable.

size

Univariate linear regression.

one variable

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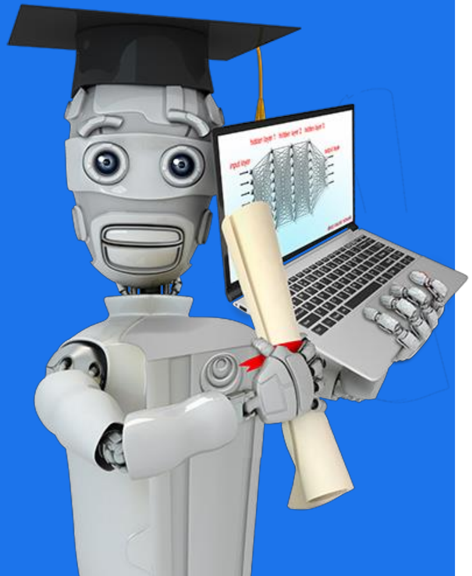


Linear Regression with One Variable

Cost Function

Training set

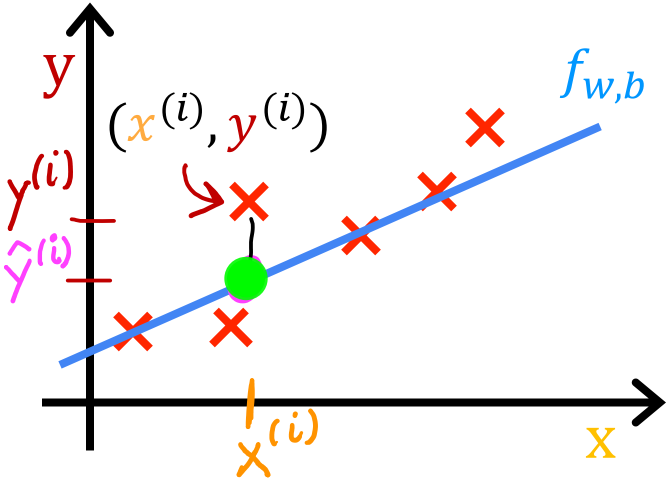
features size in feet^2 (x)	targets price \$1000's (y)
2104	460
1416	232
1534	315
852	178
...	...

Model: $f_{w,b}(x) = wx + b$

w, b: parameters

coefficients
weights

What do w, b do?



$\hat{y}^{(i)} = f_{w,b}(x^{(i)})$

$f_{w,b}(x^{(i)}) = wx^{(i)} + b$

Cost function: Squared error cost function

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

error

m = number of training examples

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

intuition (next!)

Find w, b:

$\hat{y}^{(i)}$ is close to $y^{(i)}$ for all $(x^{(i)}, y^{(i)})$.

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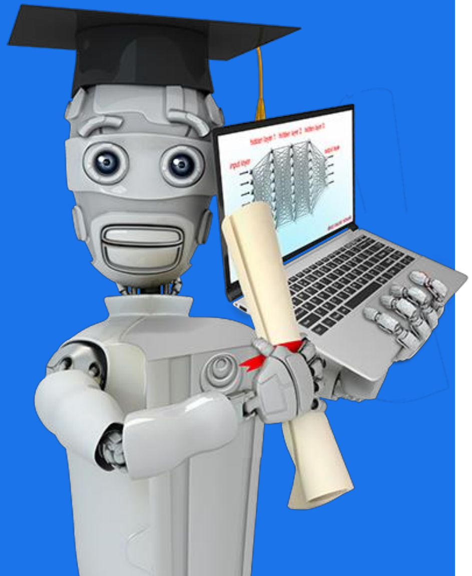


Training Linear Regression

Gradient Descent

Have some function $J(w,b)$ for linear regression or any function

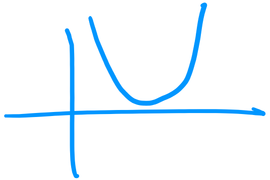
Want $\min\limits_{w,b} J(w,b)$ $\qquad \min\limits_{w_1,\dots,w_n,b} J(w_1,w_2,\dots,w_n,b)$

Outline:

- Start with some w,b (set $w=0$, $b=0$)
- Keep changing w,b to reduce $J(w,b)$
- Until we settle at or near a minimum

may have >1 minimum

J not always

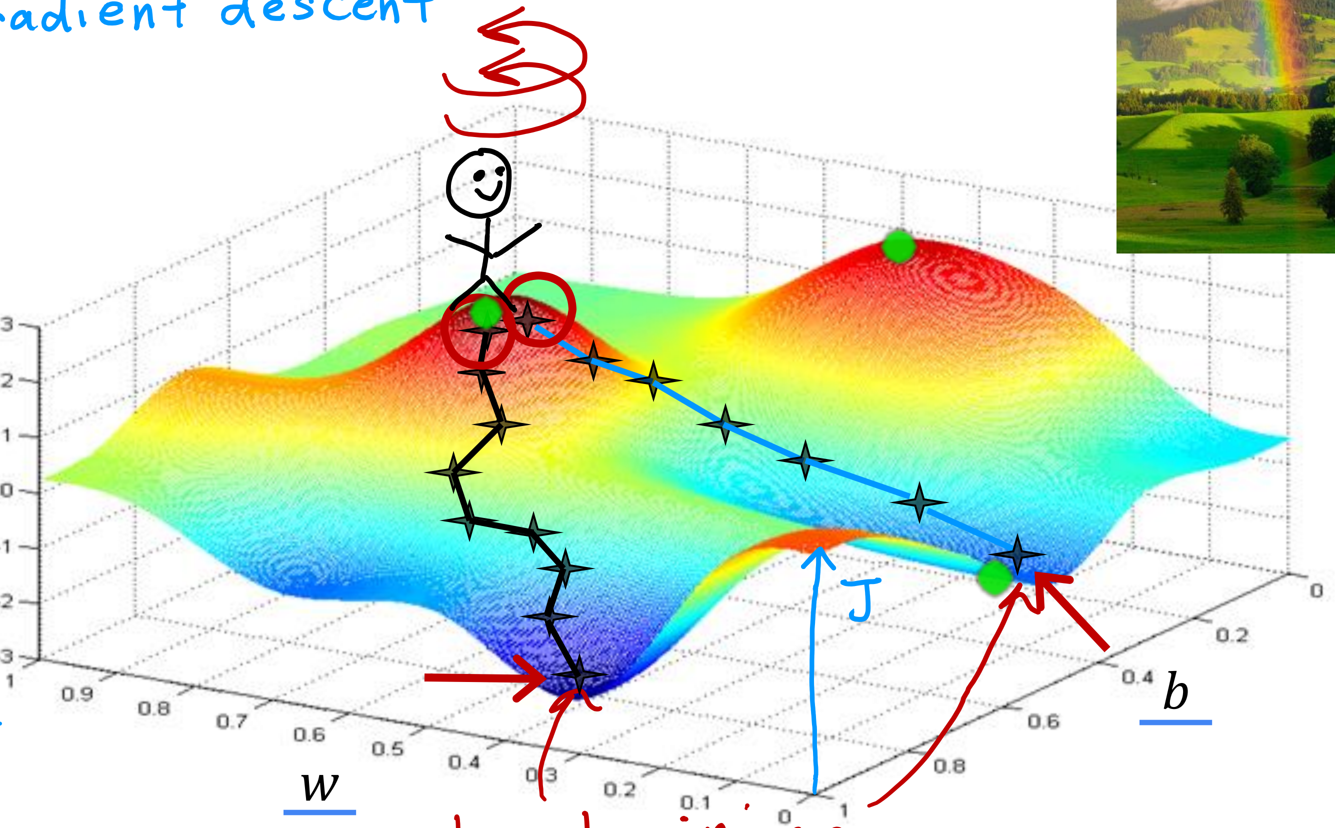


gradient descent

$J(w,b)$

not squared error cost

not linear regression



local minima

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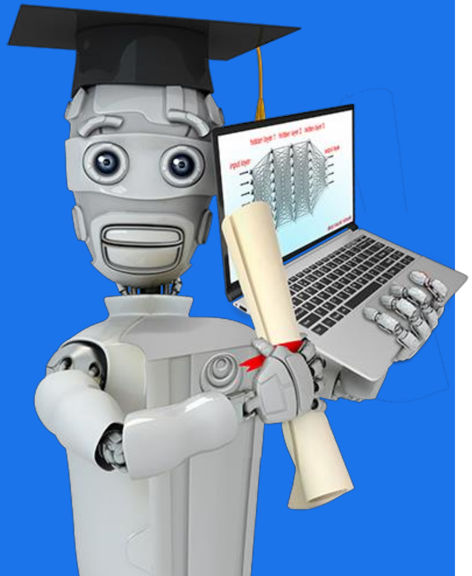


Training Linear Regression

Gradient Descent Intuition

Gradient descent algorithm

repeat until convergence {

learning rate

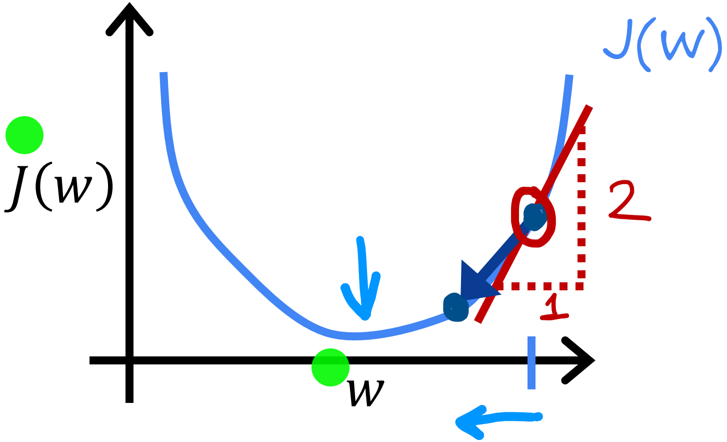
$$\begin{cases} \underline{w} = w - \alpha \boxed{\frac{\partial}{\partial w} J(w,b)} \\ \underline{b} = b - \alpha \frac{\partial}{\partial b} J(w,b) \end{cases}$$

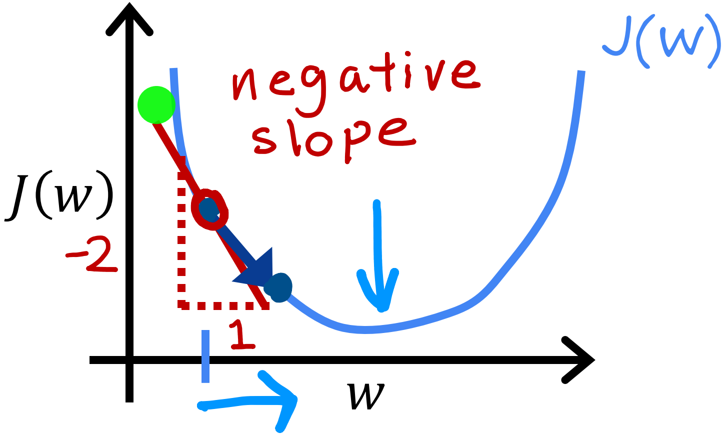
derivative

$J(w)$

$$w = w - \alpha \frac{\partial}{\partial w} J(w)$$

$$\underline{\min_{w}} J(w)$$





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

>0

$$w = w - \alpha \cdot (positive\ number)$$

$$\frac{d}{dw}J(w) \quad < 0$$

$$w = w - \alpha \cdot (negative\ number)$$

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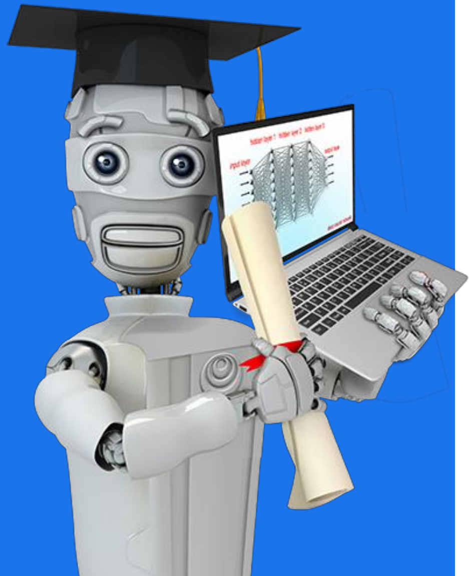


Training Linear Regression

Learning Rate

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

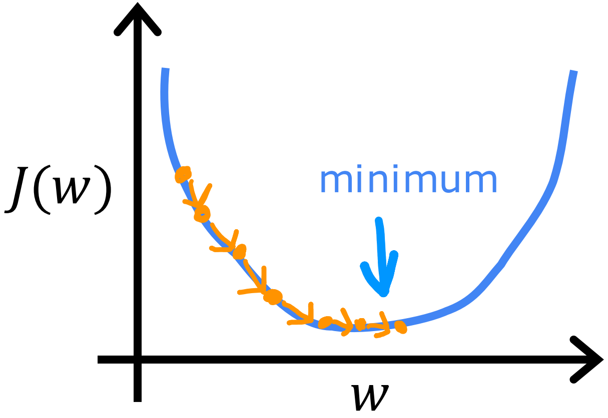
If α is too small...

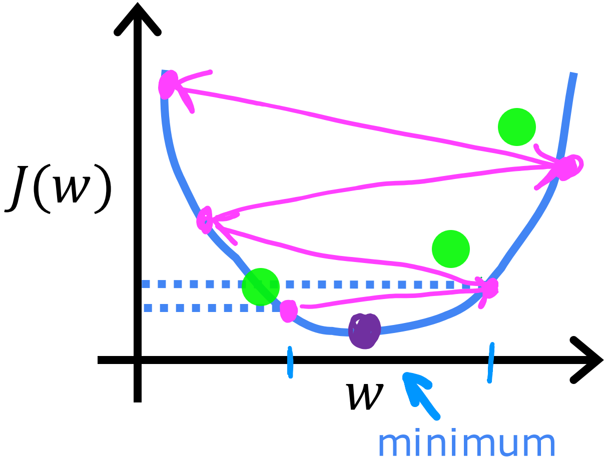
Gradient descent may be slow.

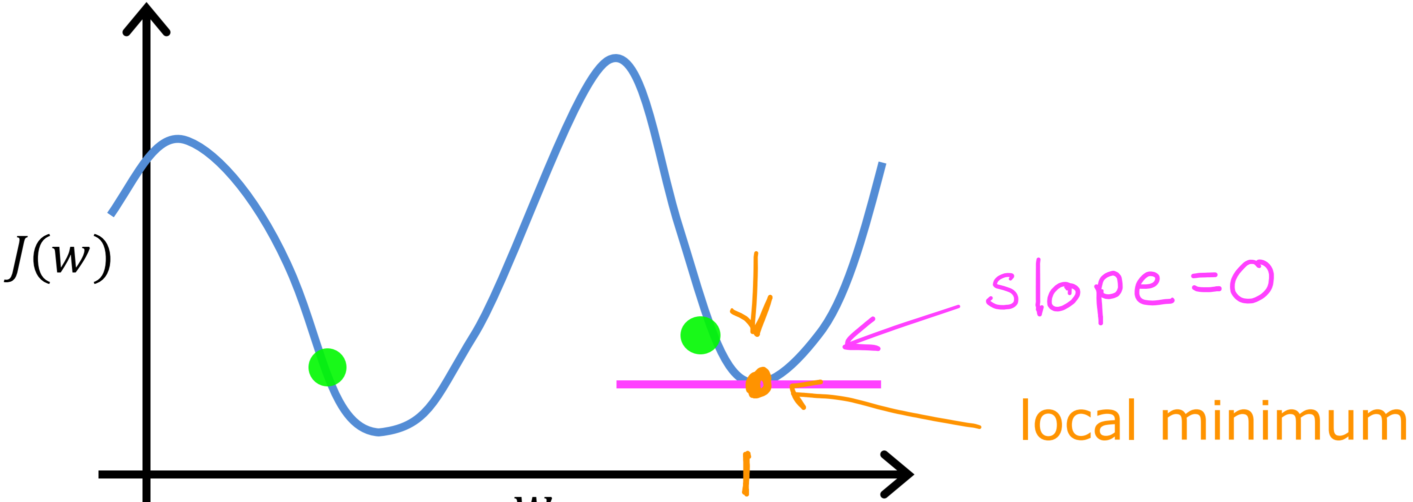
If α is too large...

Gradient descent may:

- Overshoot, never reach minimum
- Fail to converge, diverge







current value of w → 5

$$w = w - \underset{0.1}{\alpha} \underbrace{\boxed{\frac{d}{dw}J(w)}}_{=0}$$

5 − 0.1 · 0

$$w = w - \alpha \cdot 0$$

5 5

$$w = w$$

Can reach local minimum with fixed learning rate

α

$$w = w - \underbrace{\boxed{\alpha \frac{d}{dw} J(w)}}$$

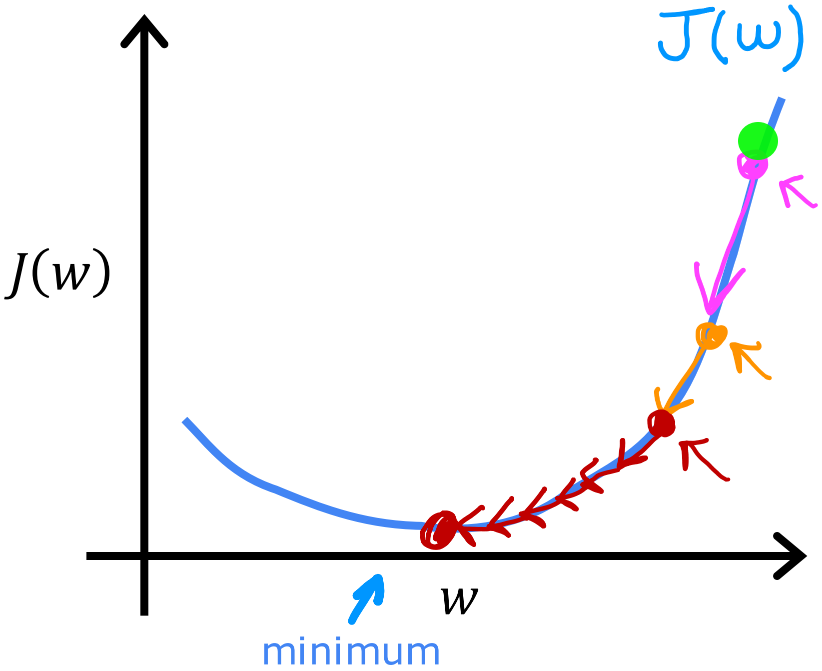
smaller

not as large

large

Near a local minimum,
- Derivative becomes smaller
- Update steps become smaller

Can reach minimum without decreasing learning rate α



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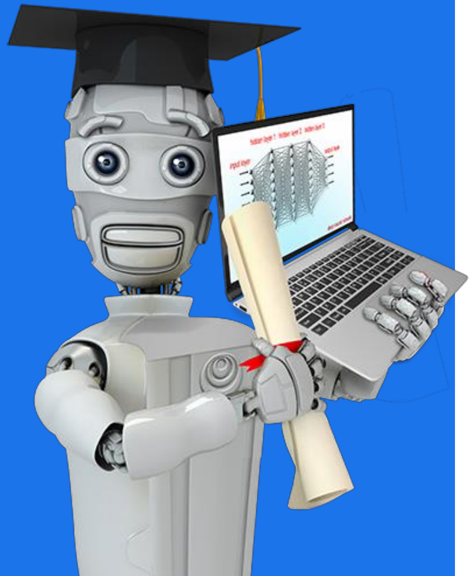
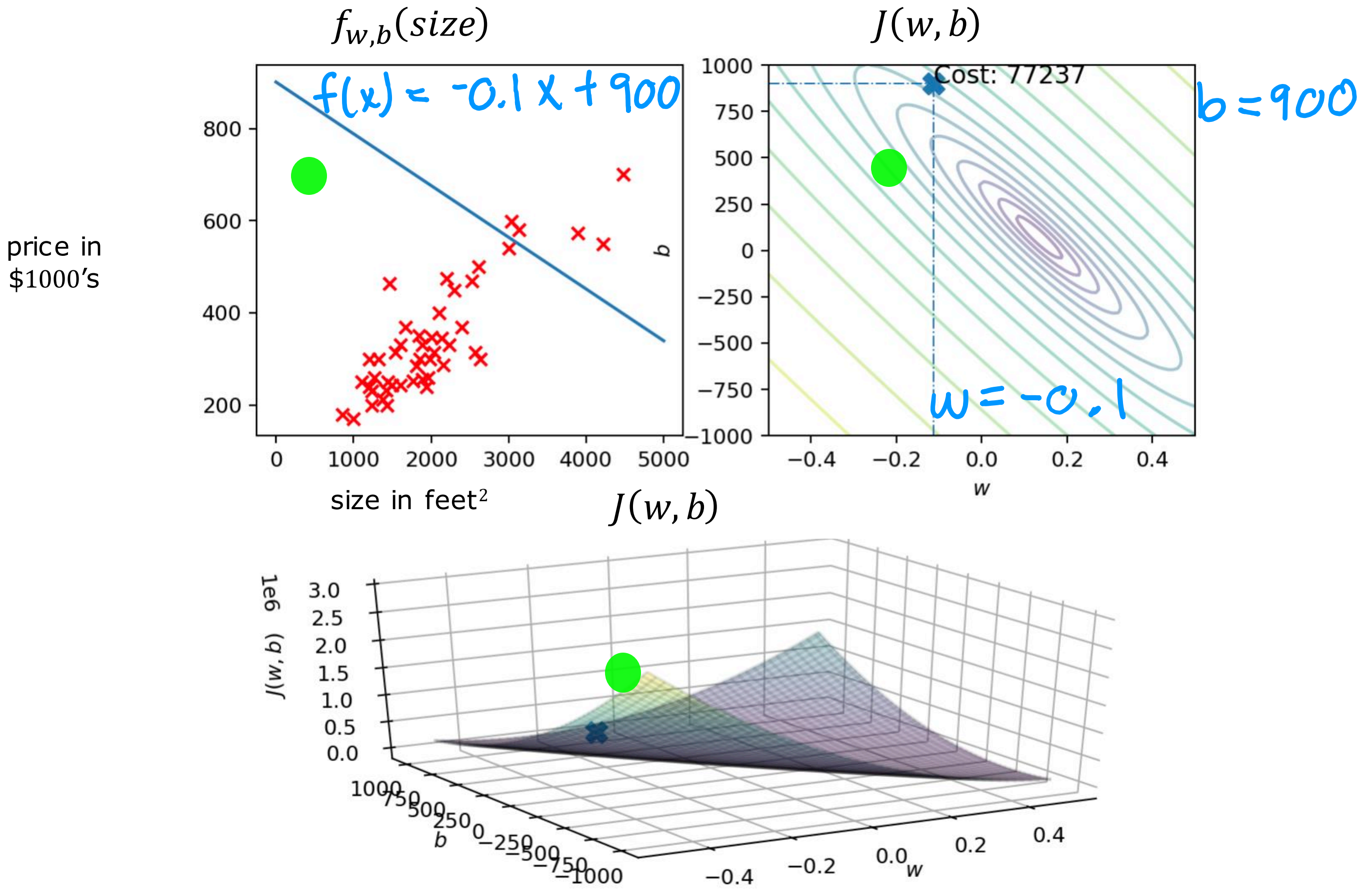


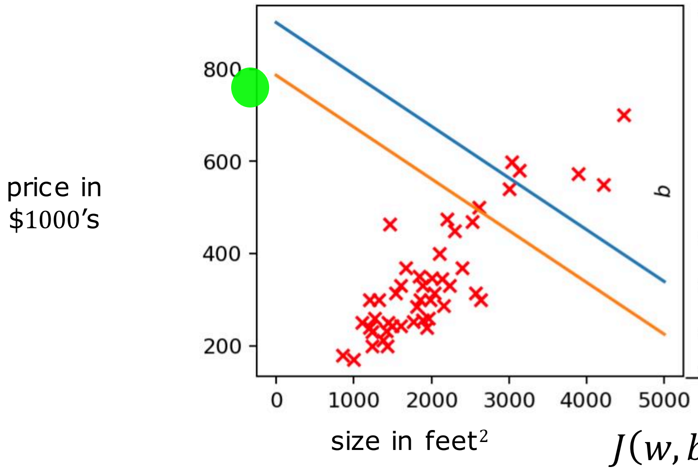
Training Linear Regression

Running Gradient Descent

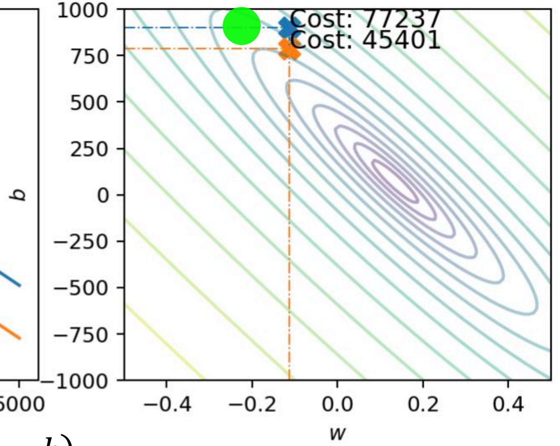


$f_{w,b}(size)$
$J(w,b)$
$f(x) = -0.1x + 900$
Cost: 77237
$b = 900$
$w = -0.1$
price in $1000's
size in feet^2
b
w
$J(w,b)$
1e6
$J(w,b)$

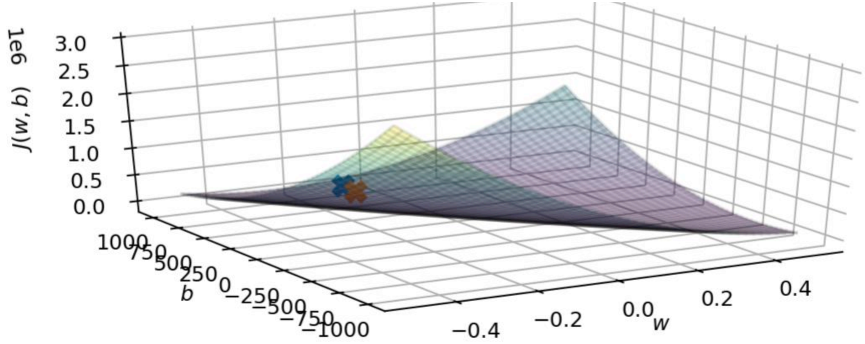
$f_{w,b}(size)$

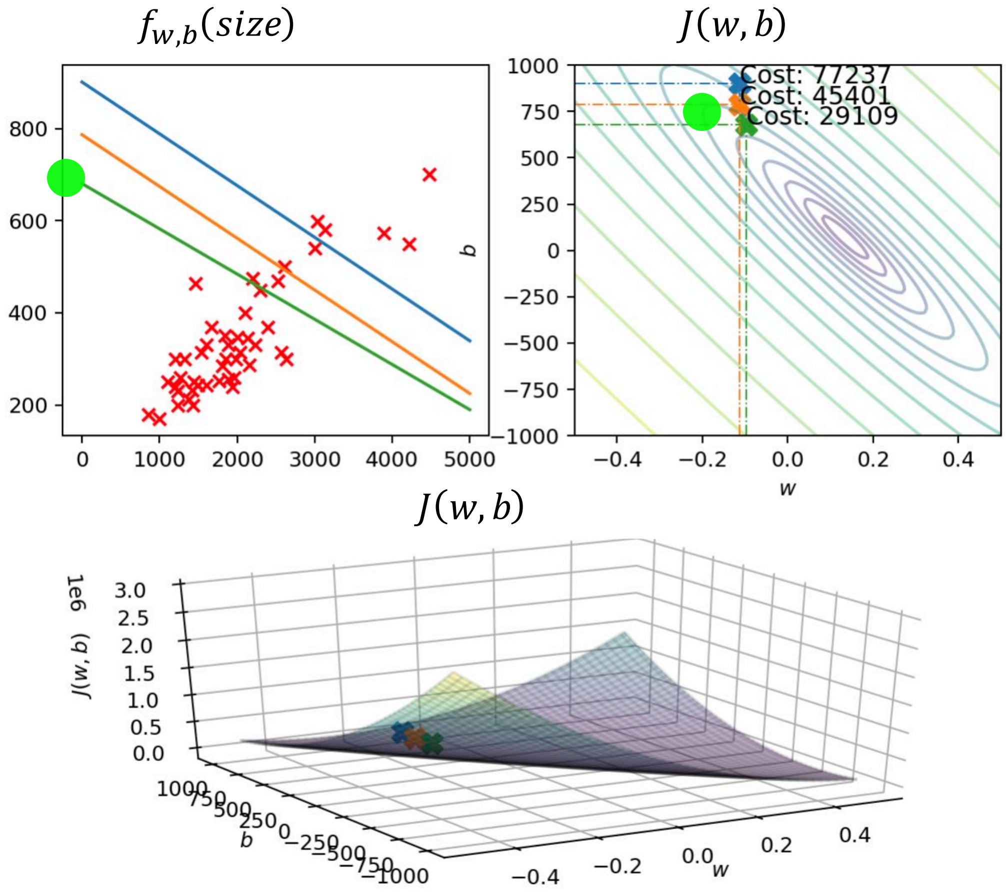


$J(w,b)$

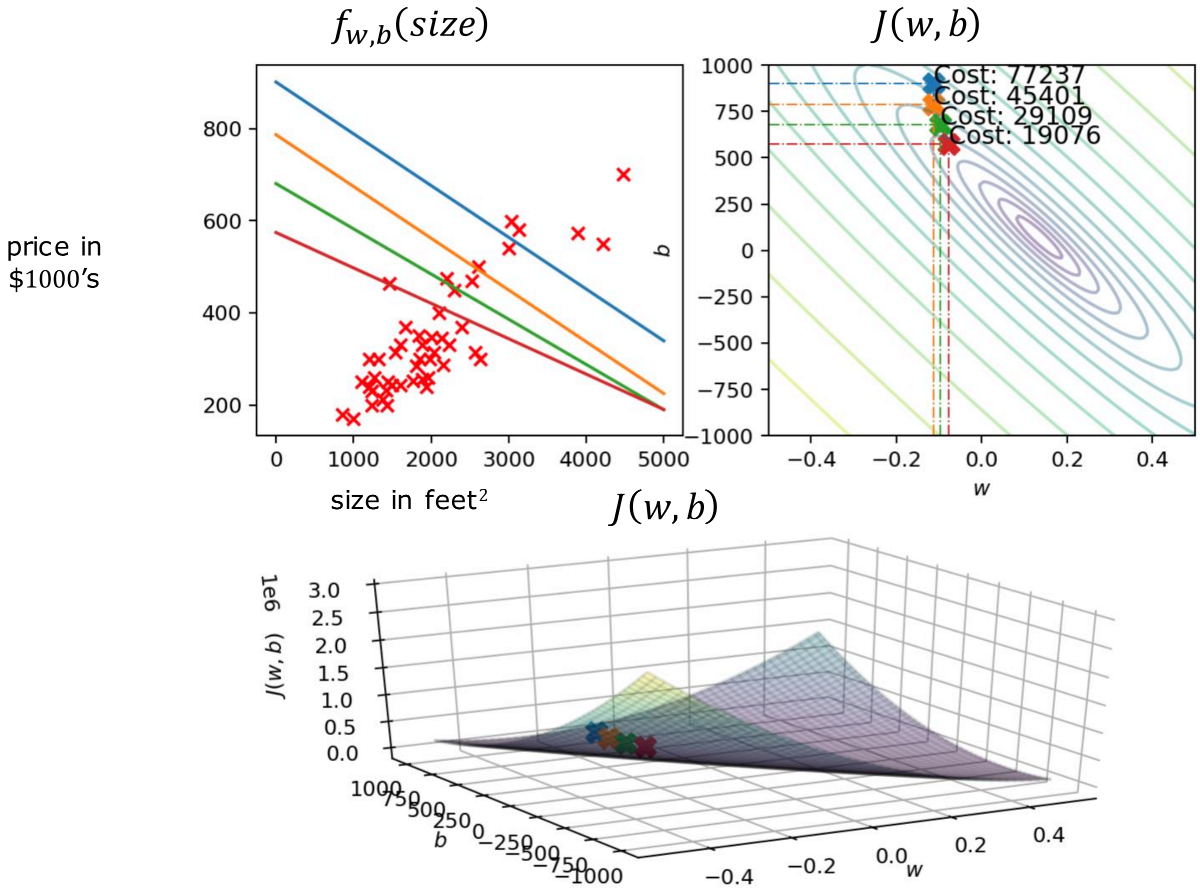


$J(w,b)$

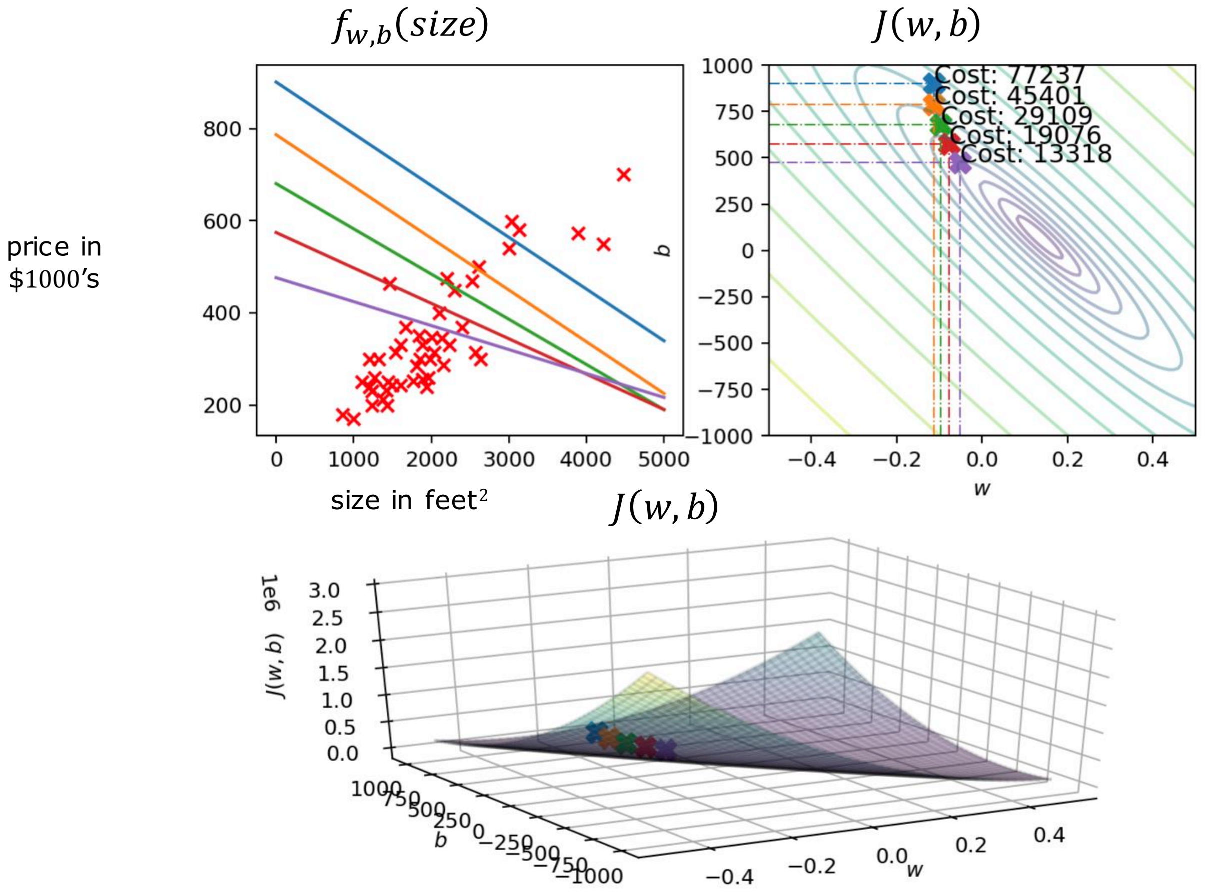




$f_{w,b}(size)$
$J(w,b)$
Cost: 77237
Cost: 45401
Cost: 29109
b
w
$J(w,b)$
1e6
J(w, b)
b
w

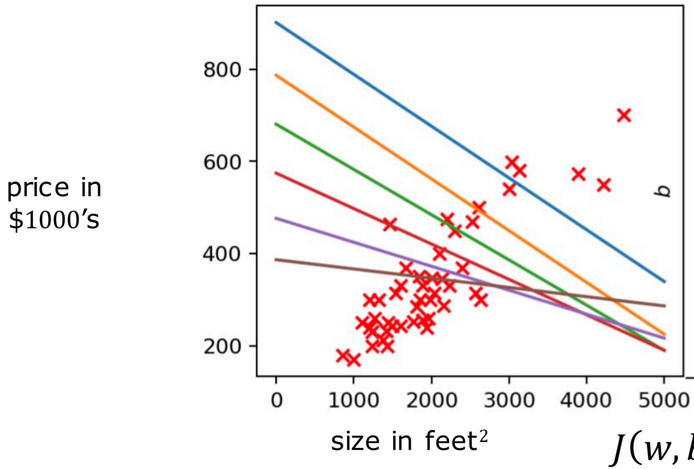


$f_{w,b}(size)$
$J(w,b)$
price in
$1000's
size in feet^2
Cost: 77237
Cost: 45401
Cost: 29109
Cost: 19076
b
w
$J(w,b)$
1e6
J(w, b)

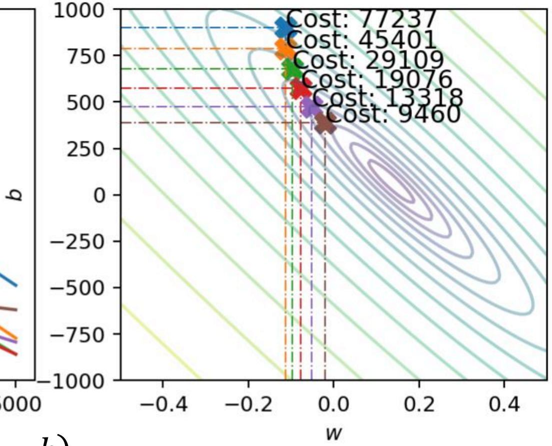


$f_{w,b}(size)$
price in $1000's
size in feet^2
$J(w,b)$
Cost: 77237
Cost: 45401
Cost: 29109
Cost: 19076
Cost: 13318
b
w
$J(w,b)$
1e6
J(w, b)

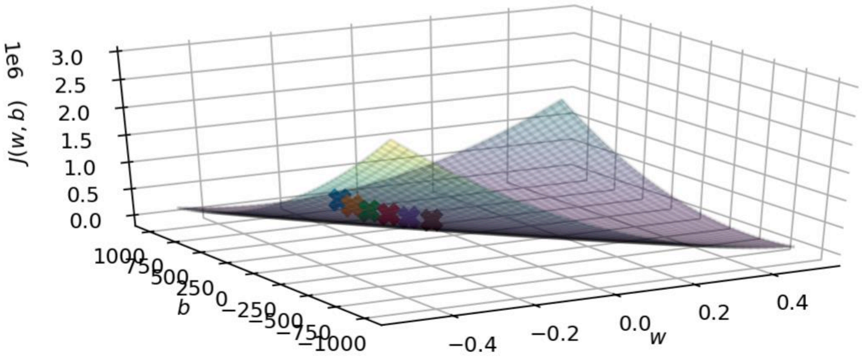
$f_{w,b}(size)$

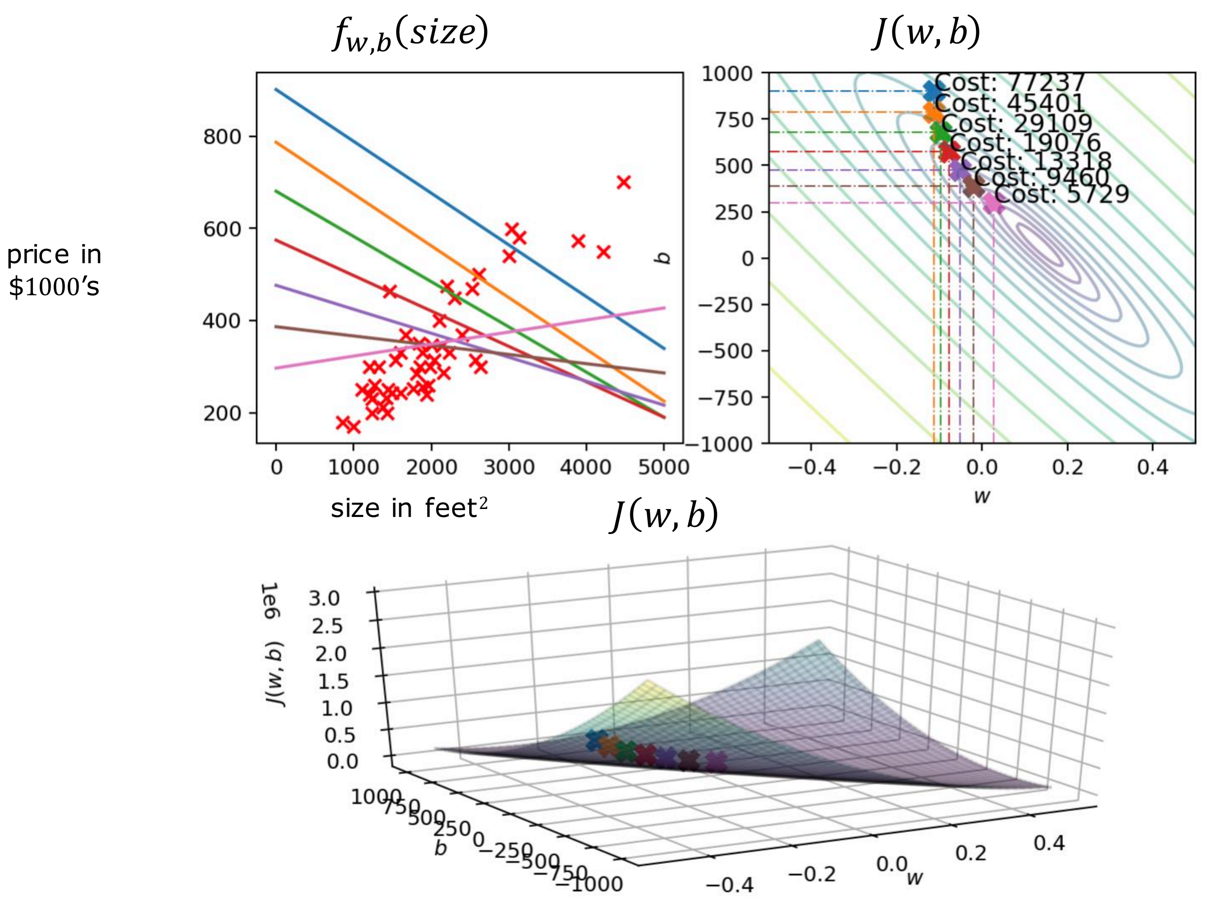


$J(w,b)$

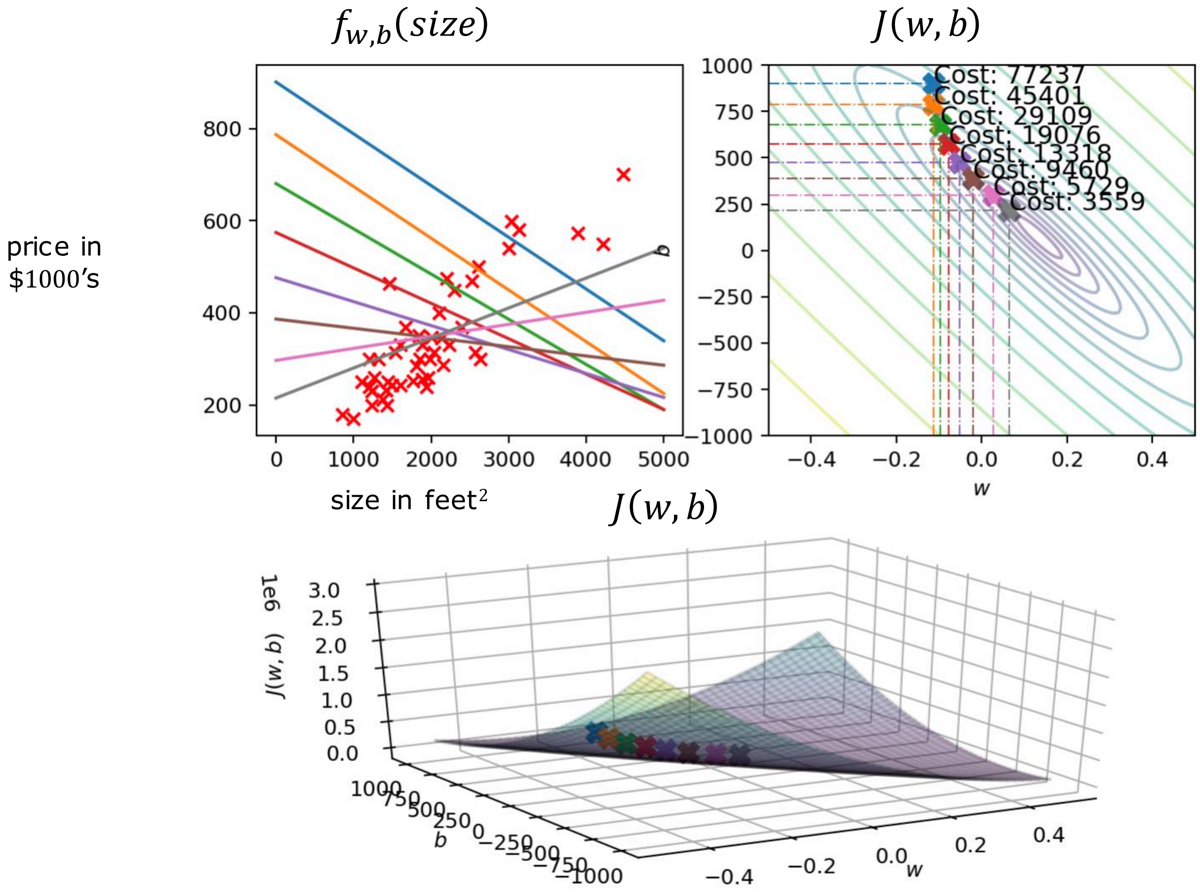


$J(w,b)$

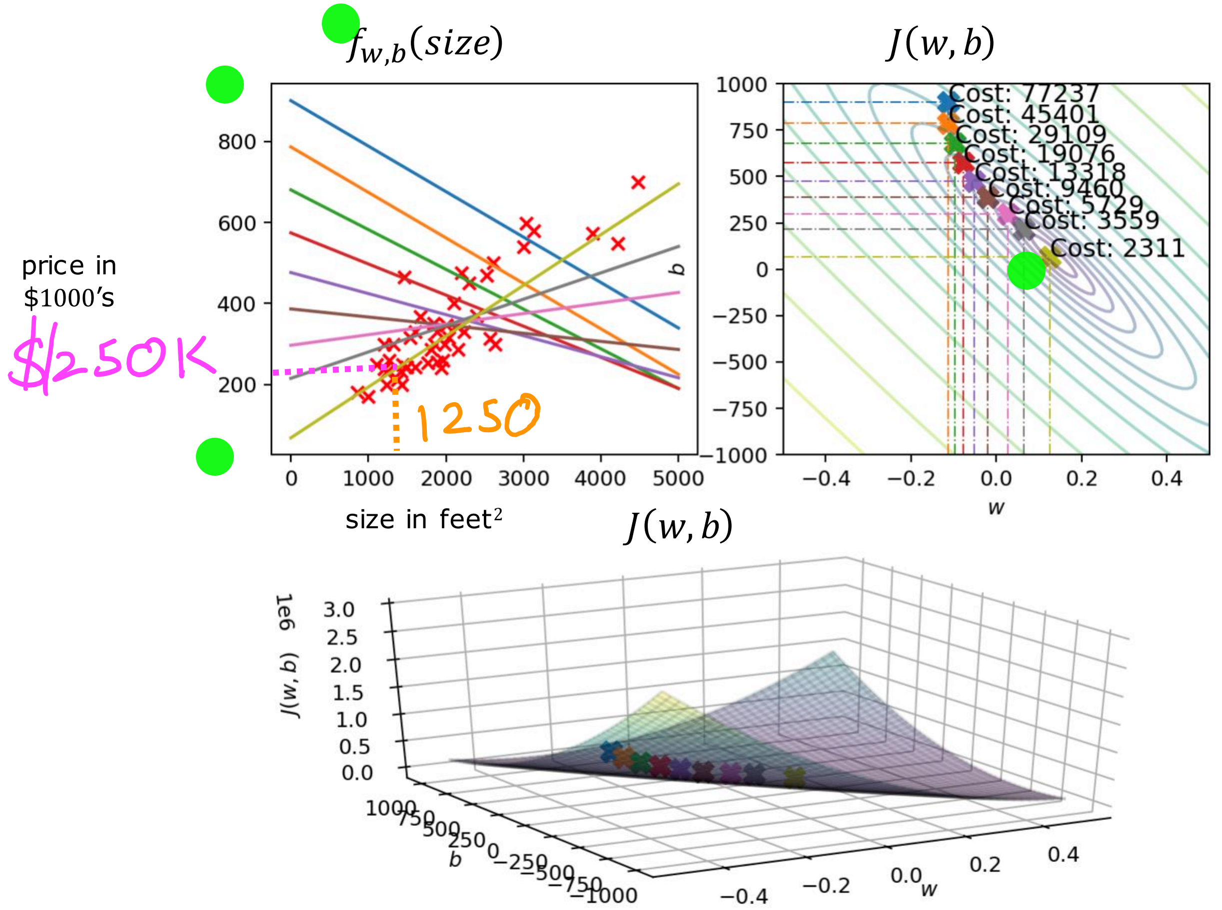




$f_{w,b}(size)$
price in
$1000's
size in feet^2
$J(w,b)$
Cost: 77237
Cost: 45401
Cost: 29109
Cost: 19076
Cost: 13318
Cost: 9460
Cost: 5729
$J(w,b)$



$f_{w,b}(size)$
$J(w,b)$
price in
$1000's
size in feet^2
Cost: 77237
Cost: 45401
Cost: 29109
Cost: 19076
Cost: 13318
Cost: 9460
Cost: 5729
Cost: 3559
w
$J(w,b)$
1e6
$J(w,b)$
b
w



$f_{w,b}(size)$
$J(w,b)$
price in
$1000's
$250K
1250
size in feet^2
Cost: 77237
Cost: 45401
Cost: 29109
Cost: 19076
Cost: 13318
Cost: 9460
Cost: 5729
Cost: 3559
Cost: 2311
b
w
$J(w,b)$
1e6
$J(w,b)$

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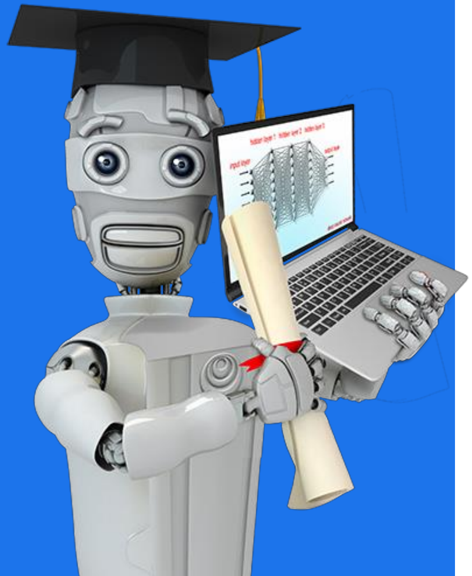

Linear Regression with Multiple Variables

Multiple Features

Multiple features (variables)

one feature

Size in feet^2 (x)	Price (\$) in 1000's (y)
2104	400
1416	232
1534	315
852	178
…	…

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

Multiple features (variables)

Size in feet² x_1	Number of bedrooms x_2	Number of floors x_3	Age of home in years x_4	Price ($) in $1000's
2104	5	1	45	460
1416	3	2	40	232
1534	3	2	30	315
852	2	1	36	178
…	…	…	…	…

$j = 1 \ldots 4$

$n = 4$

$i = 2$

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

$\vec{x}^{(2)} = [1416 \ 3 \ 2 \ 40]$

$x_3^{(2)} = 2$

Model:

Previously: $f_{w,b}(x) = wx + b$

$f_{w,b}(X) = w_1 X_1 + w_2 X_2 + w_3 X_3 + w_4 X_4 + b$

example

$f_{w,b}(X) = 0.1 X_1 + 4 X_2 + 10 X_3 + -2 X_4 + 80$

size #bedrooms #floors years base price

$f_{w,b}(\mathrm{x}) = w_1 x_1 + w_2 x_2 + \cdots + w_n x_n + b$

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

$\vec{w} = [w_1 \ w_2 \ w_3 \ \ldots \ w_n]$ parameters of the model

b is a number

vector $\vec{x} = [x_1 \ x_2 \ x_3 \ \ldots \ x_n]$

$$f_{\vec{w},b}(\vec{x}) = \vec{w} \cdot \vec{x} + b = w_1x_1 + w_2x_2 + w_3x_3 + \cdots + w_nx_n + b$$

dot product

multiple linear regression

(not multivariate regression)

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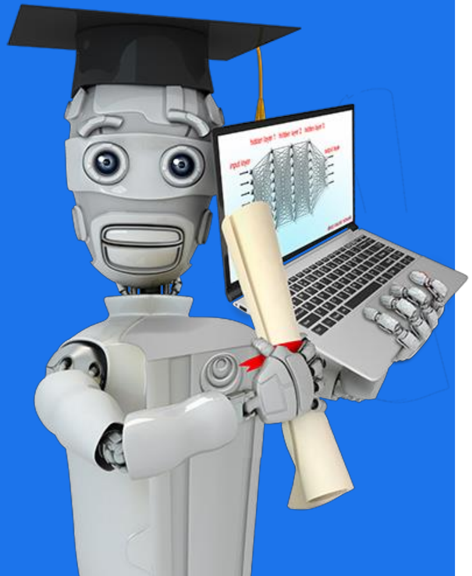


Classification

Motivations

Classification

Question	Answer "y"	
Is this email spam?	no	yes
Is the transaction fraudulent?	no	yes
Is the tumor malignant?	no	yes

y can only be one of two values

"binary classification"

class = category

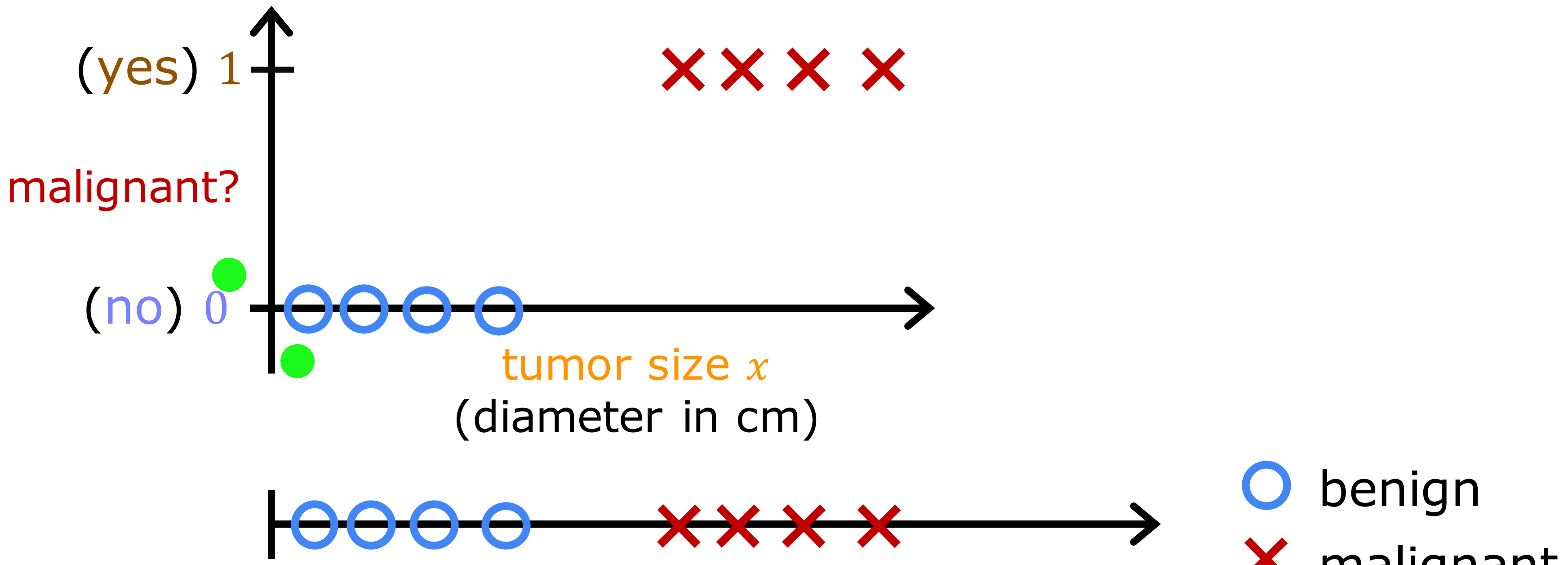
false true

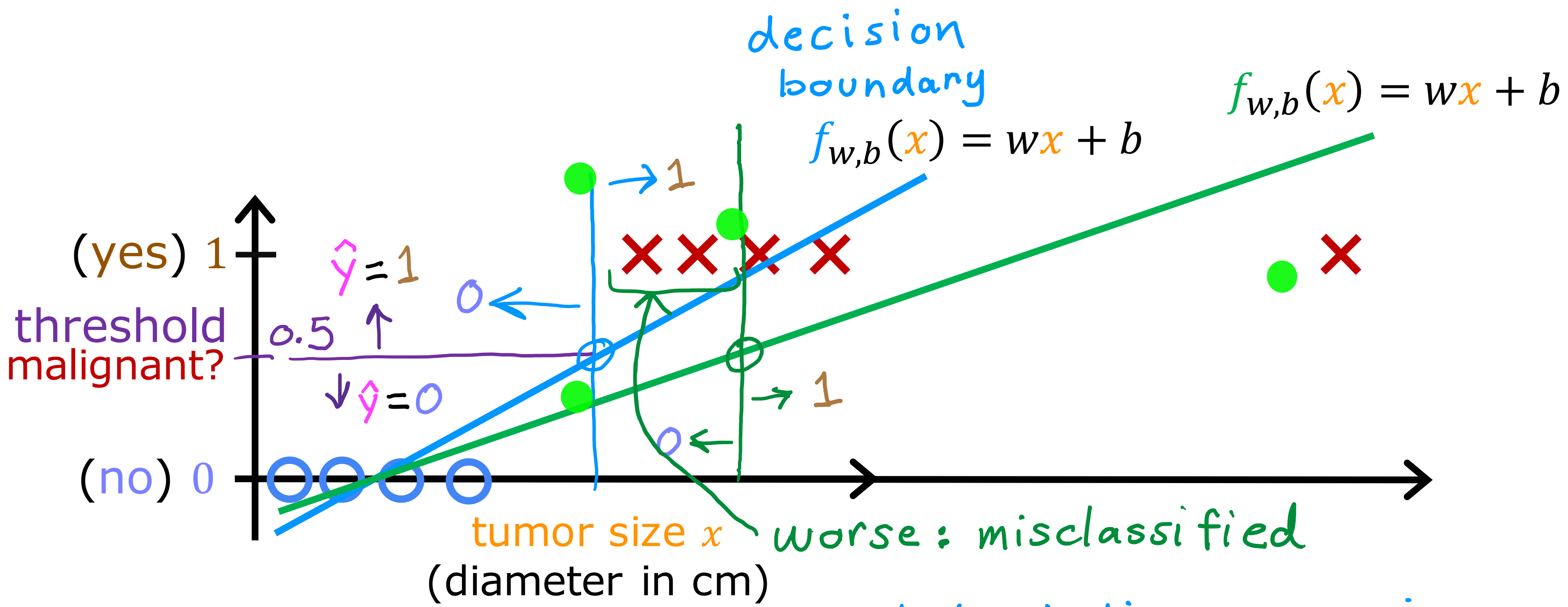
0 1

useful for classification

"negative class" ≠ "bad" absence

"positive class" ≠ "good" presence


(yes) 1
malignant?
(no) 0
tumor size x
(diameter in cm)
benign
malignant



if $f_{w,b}(x) < 0.5 \rightarrow \hat{y} = 0$

if $f_{w,b}(x) \geq 0.5 \rightarrow \hat{y} = 1$

next: $\underbrace{\text{logistic regression}}_{\text{classification}}$

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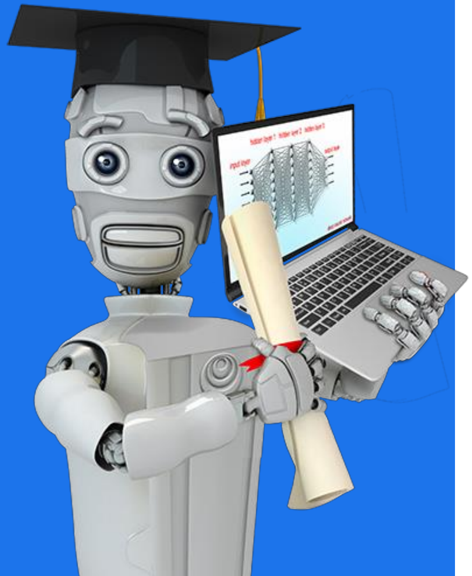
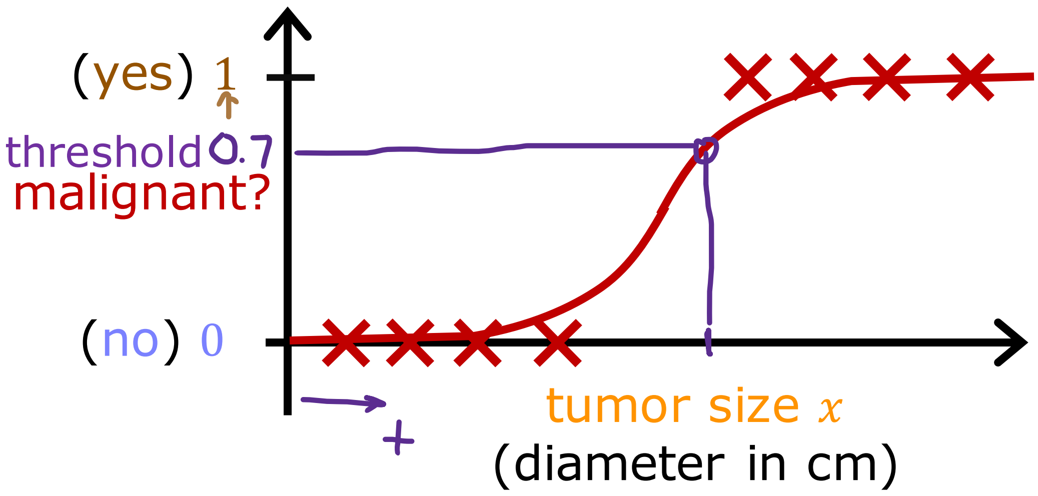
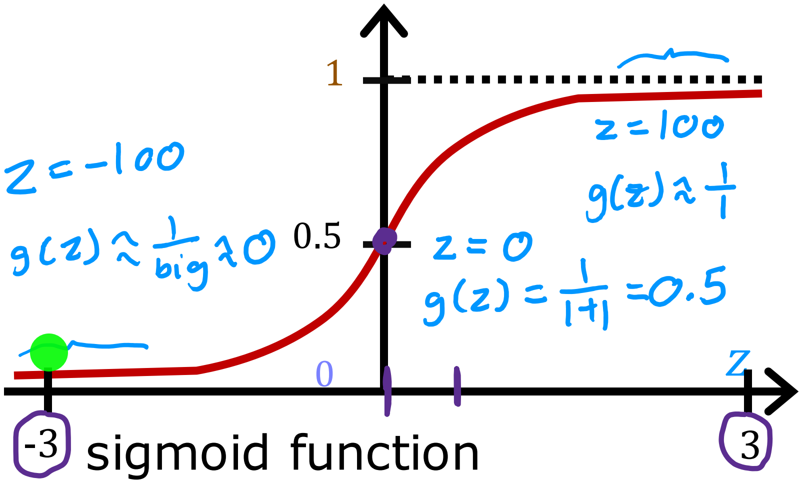


Classification

Logistic Regression

Want outputs between 0 and 1





sigmoid function

logistic function

outputs between 0 and 1

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

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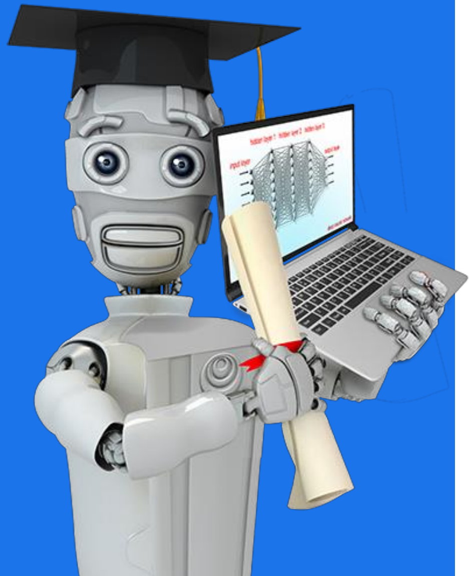

Cost Function

Simplified Cost Function for Logistic Regression

Simplified cost function

loss

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

cost

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

convex
(single global minimum)

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

maximum likelihood
(don't worry about it!)

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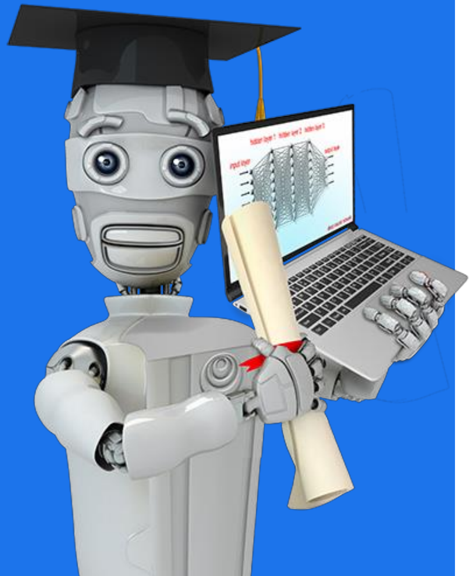
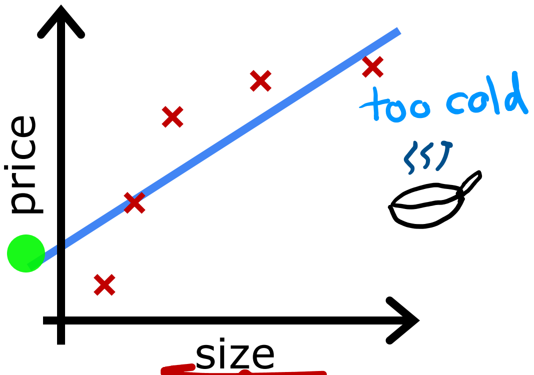


Regularization to Reduce Overfitting

The Problem of Overfitting

Regression example

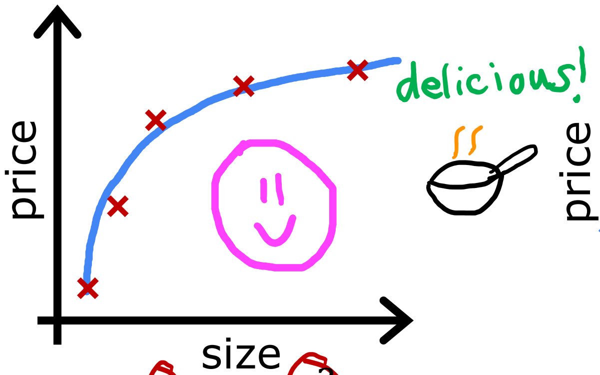


$$w_1 x + b$$

underfit

- Does not fit the training set well

high bias

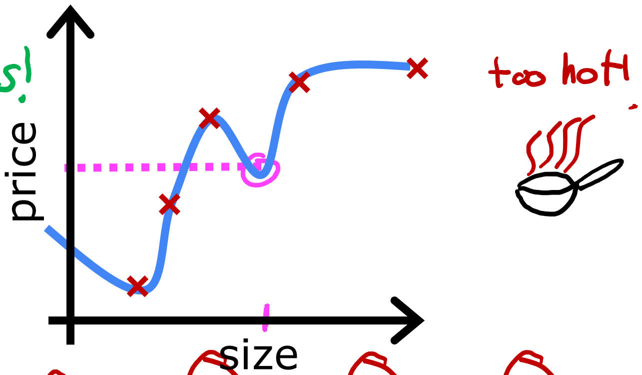


$$w_1 x + w_2 x^2 + b$$

just right

- Fits training set pretty well

generalization



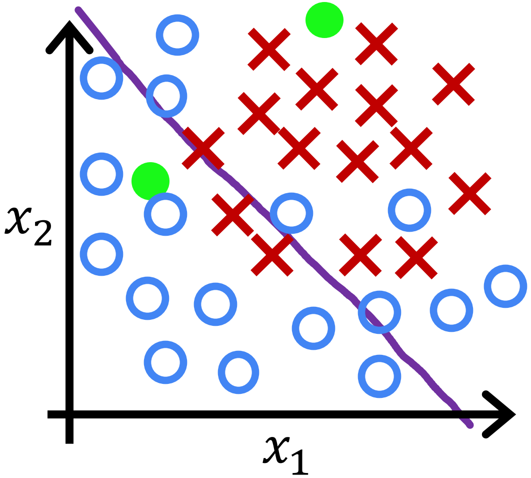
$$w_1 x + w_2 x^2 + w_3 x^3 + w_4 x^4 + b$$

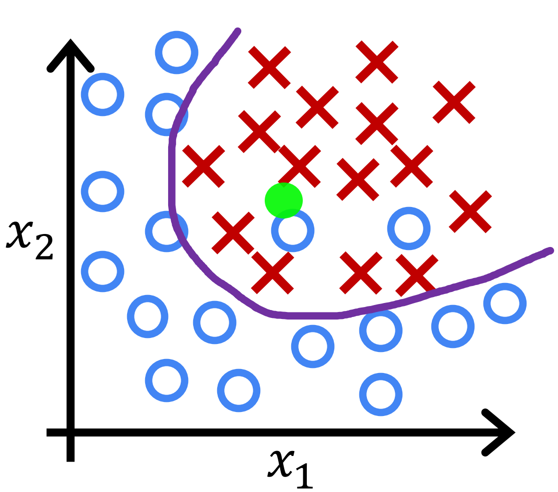
overfit

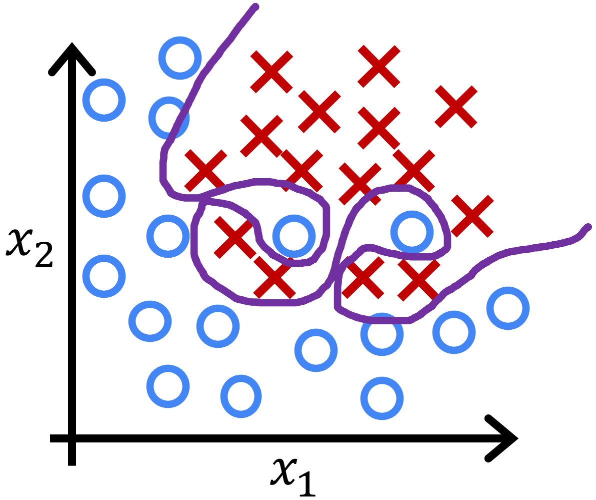
- Fits the training set extremely well

high variance

Classification







$$z = w_1 x_1 + w_2 x_2 + b$$

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

g is the sigmoid function

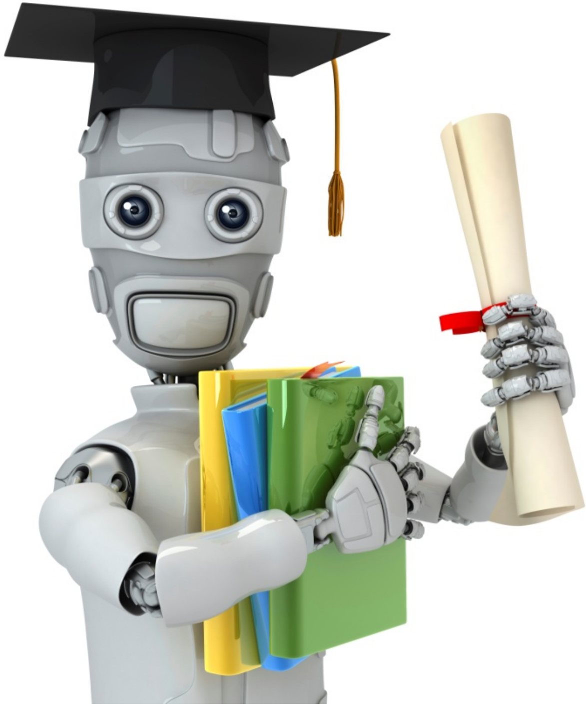
underfit high bias

$$z = w_1 x_1 + w_2 x_2 + w_3 x_1^2 + w_4 x_2^2 + w_5 x_1 x_2 + b$$

just right

$$z = w_1 x_1 + w_2 x_2 + w_3 x_1^2 x_2 + w_4 x_1^2 x_2^2 + w_5 x_1^2 x_2^3 + w_6 x_1^3 x_2 + \cdots + b$$

overfit

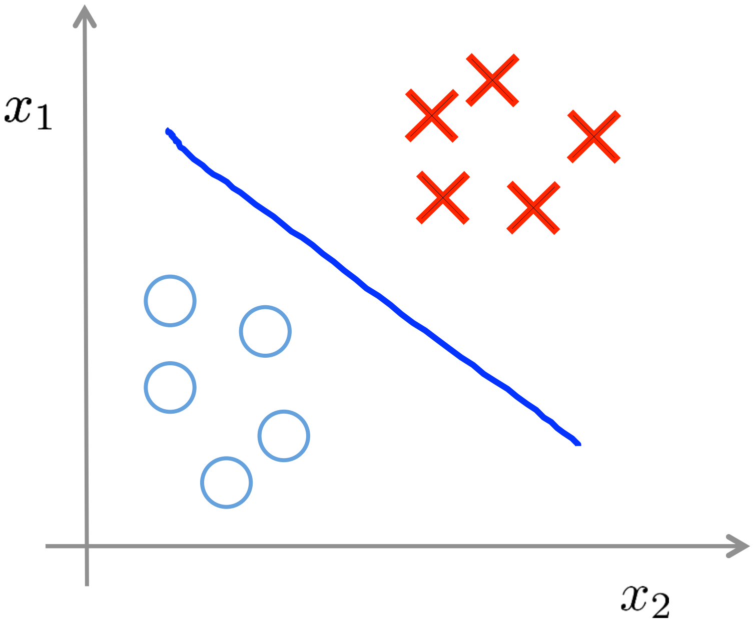


Machine Learning

Clustering

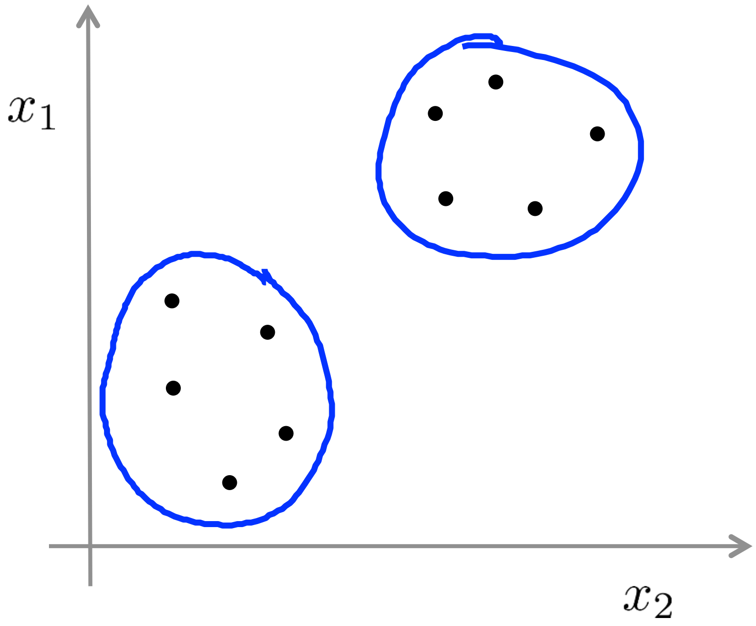
Unsupervised learning introduction

Supervised learning



Training set: $\{(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), (x^{(3)}, y^{(3)}), \ldots, (x^{(m)}, y^{(m)})\}$

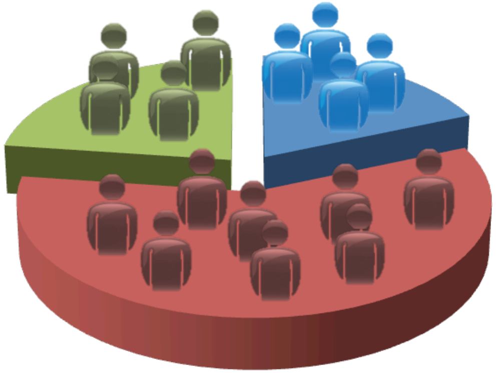
Unsupervised learning



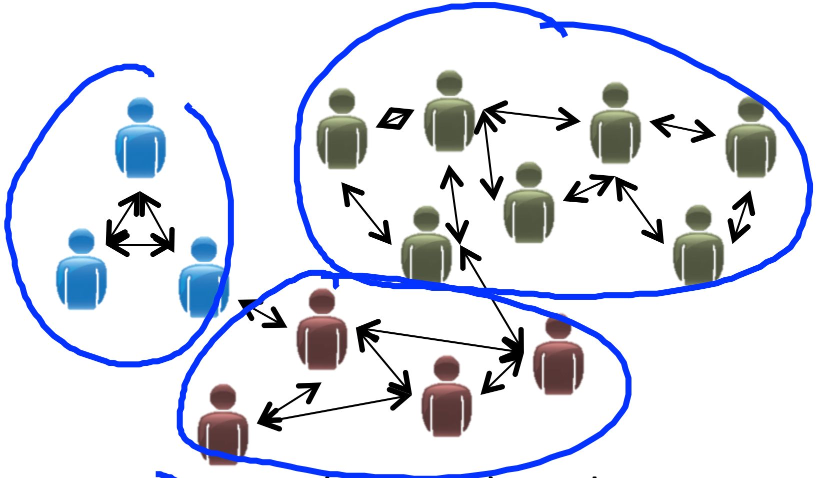
Clustering algorithm

Training set: $\{x^{(1)}, x^{(2)}, x^{(3)}, \ldots, x^{(m)}\}$ ←

Applications of clustering

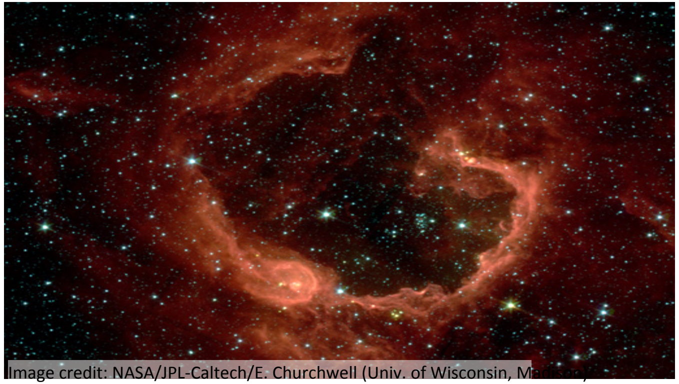


Market segmentation



Social network analysis

Organize computing clusters



Astronomical data analysis

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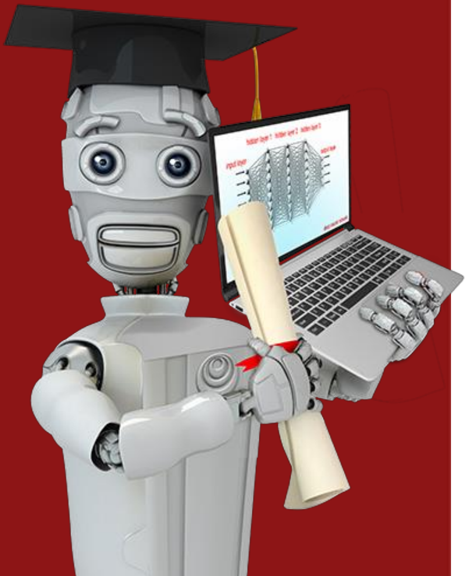


Neural Networks Intuition

Neurons and the brain

Neural networks

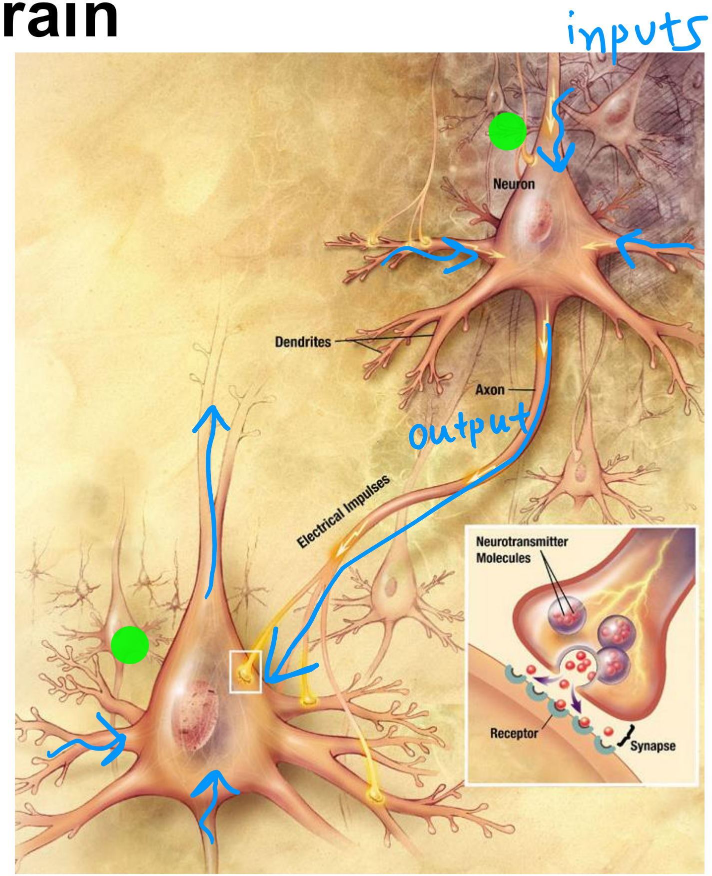
Origins: Algorithms that try to mimic the brain.

Used in the 1980's and early 1990's.
Fell out of favor in the late 1990's.

Resurgence from around 2005.

speech → images → text (NLP) → ...

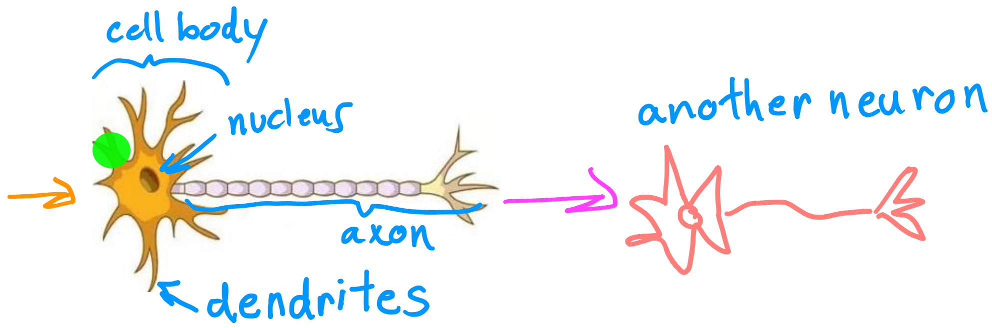
Neurons in the brain



[Credit: US National Institutes of Health, National Institute on Aging]

Biological neuron

inputs outputs



Simplified mathematical model of a neuron

inputs outputs

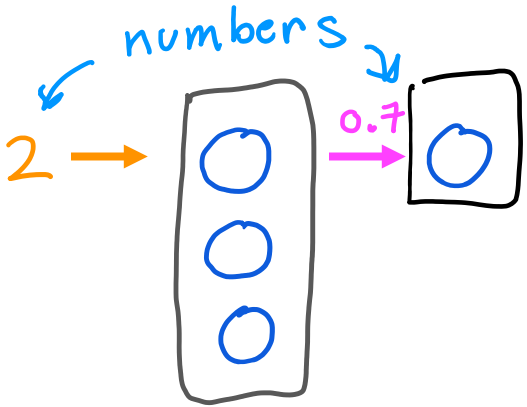


image source: https://biologydictionary.net/sensory-neuron/

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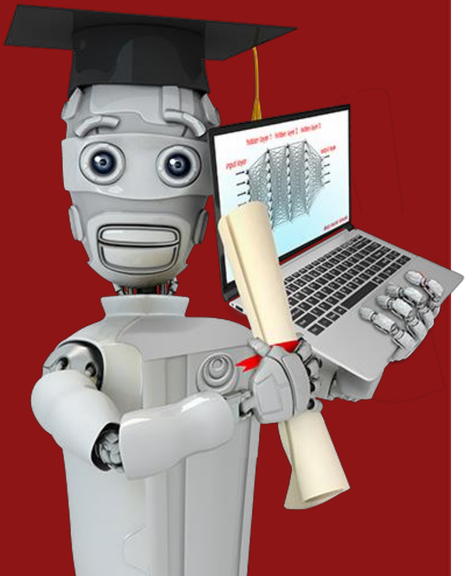
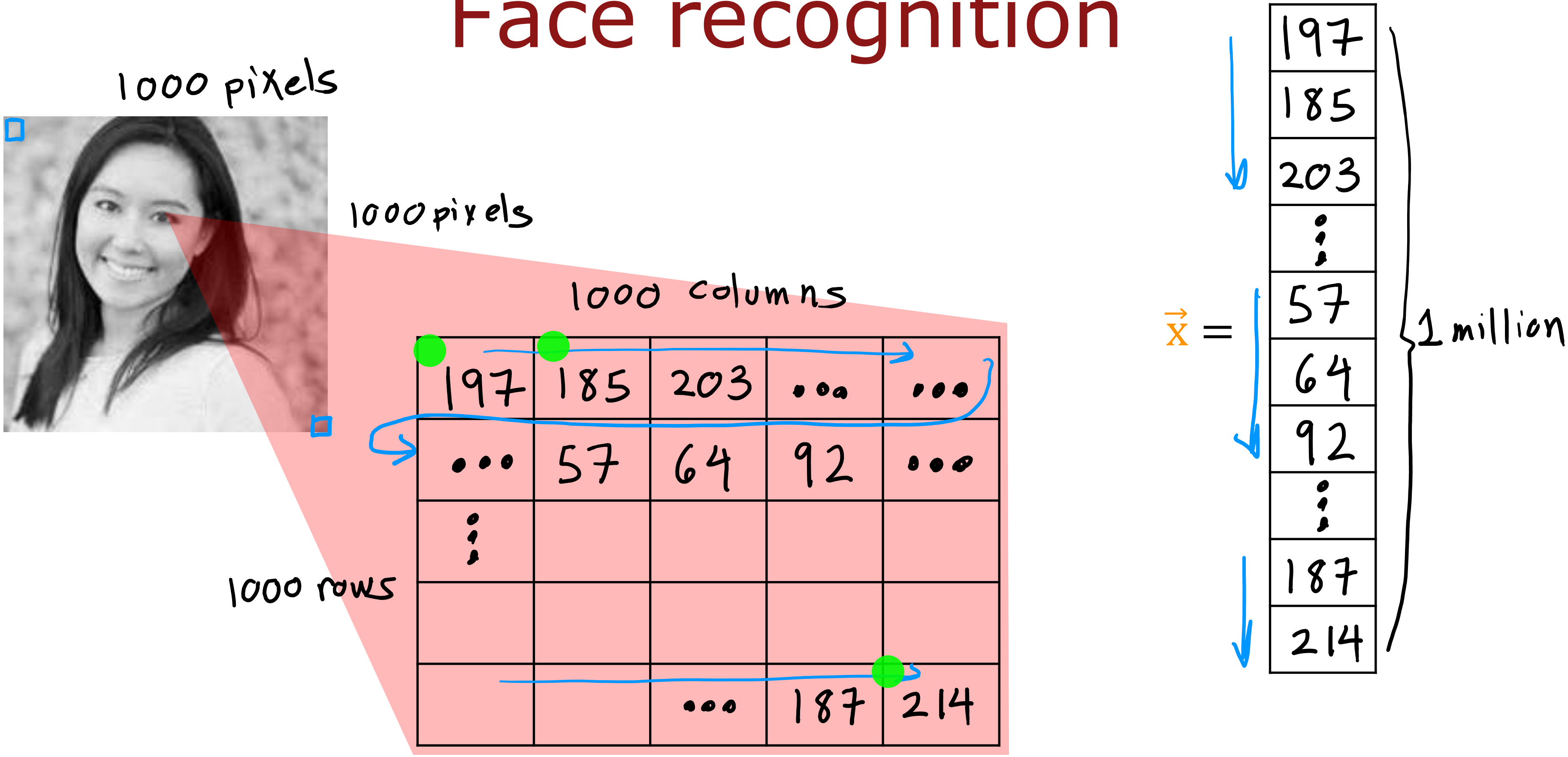
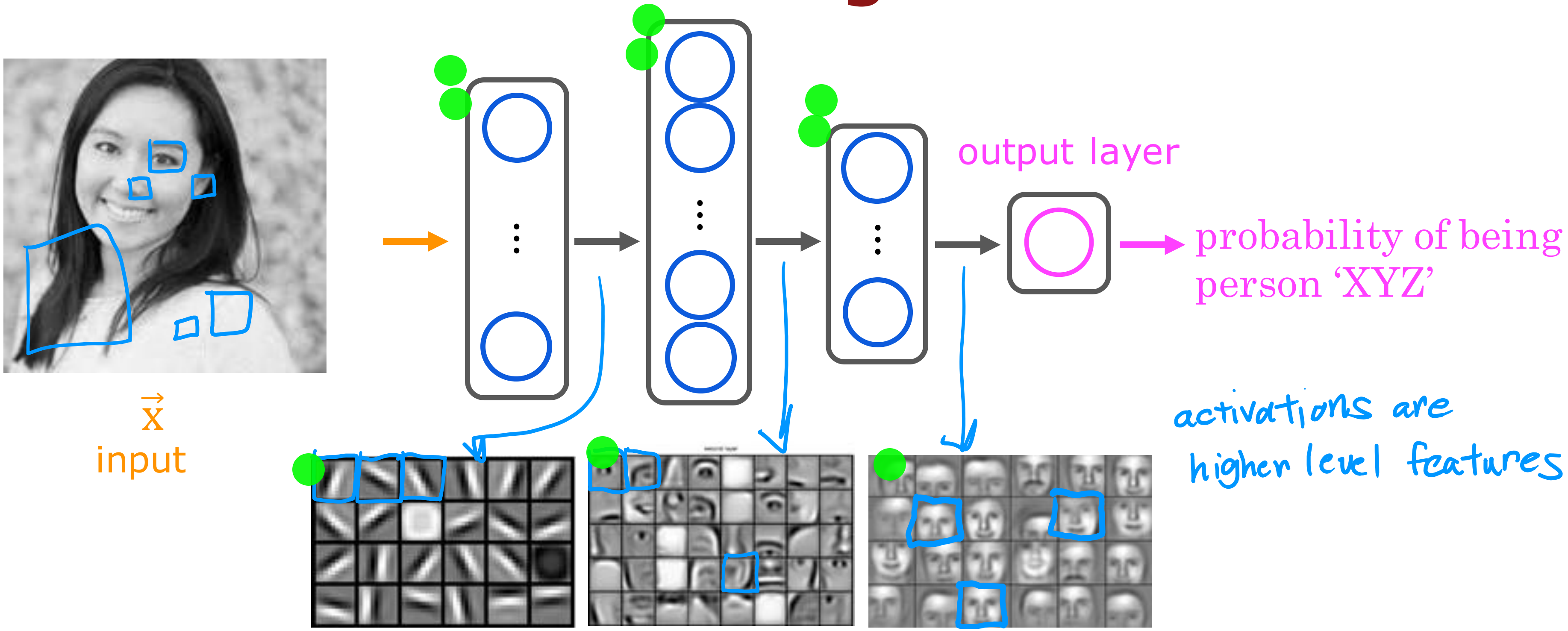


Example:
Recognizing Images

Face recognition

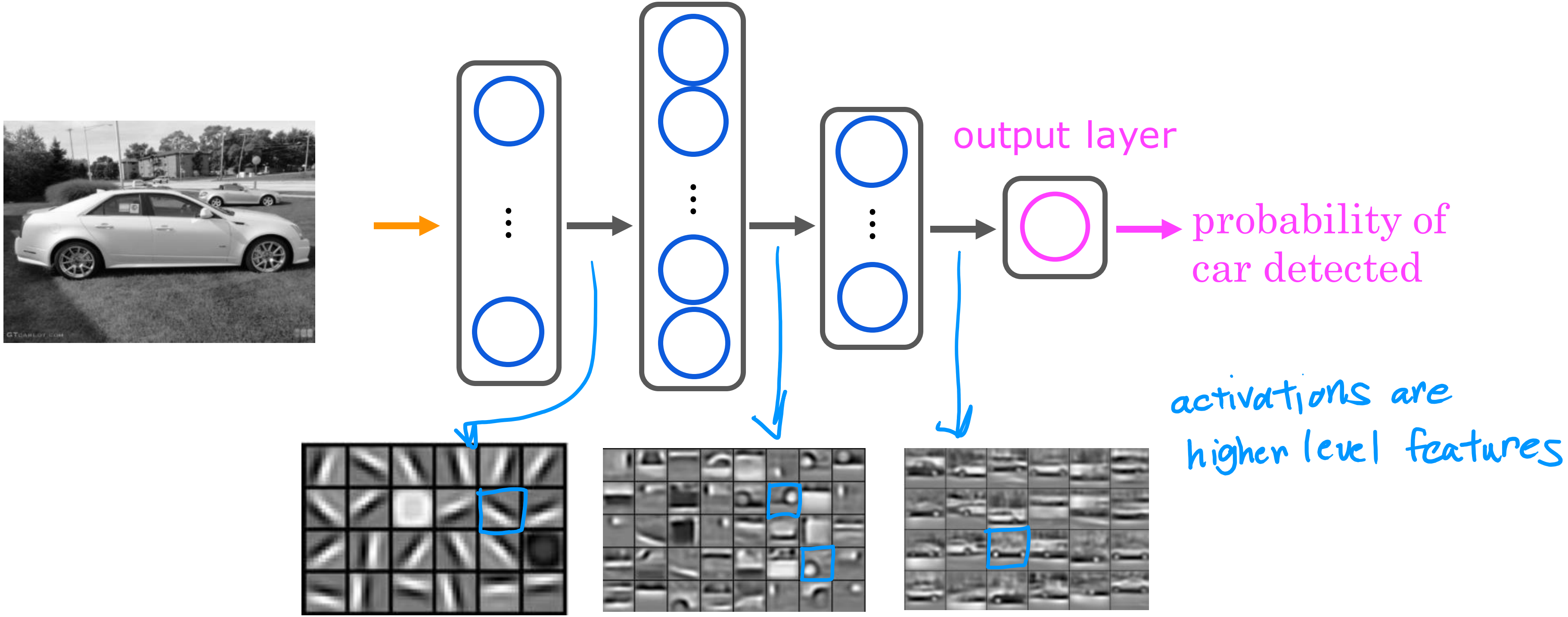


Face recognition



source: Convolutional Deep Belief Networks for Scalable Unsupervised Learning of Hierarchical Representations by Honglak Lee, Roger Grosse, Ranganath Andrew Y. Ng

Car classification



source: Convolutional Deep Belief Networks for Scalable Unsupervised Learning of Hierarchical Representations by Honglak Lee, Roger Grosse, Ranganath Andrew Y. Ng

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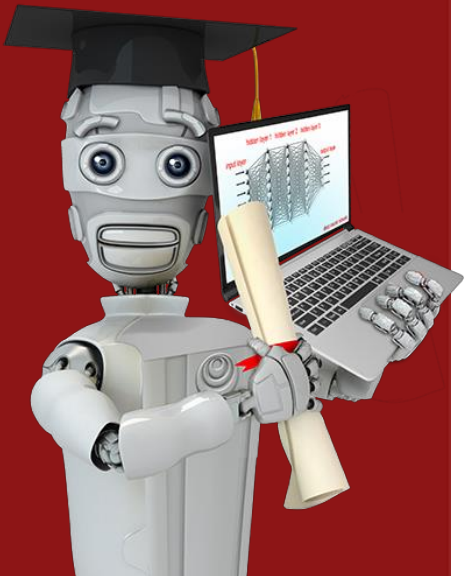
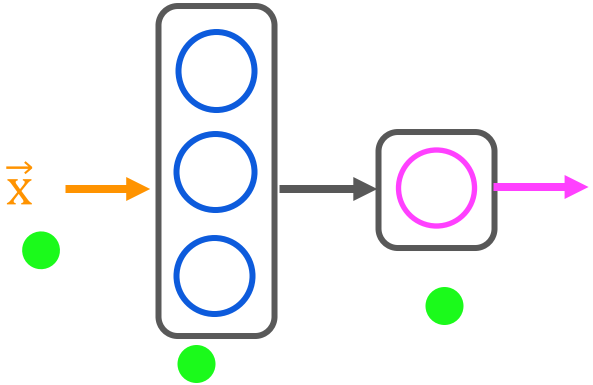


Neural network model

Neural network layer

Neural network layer



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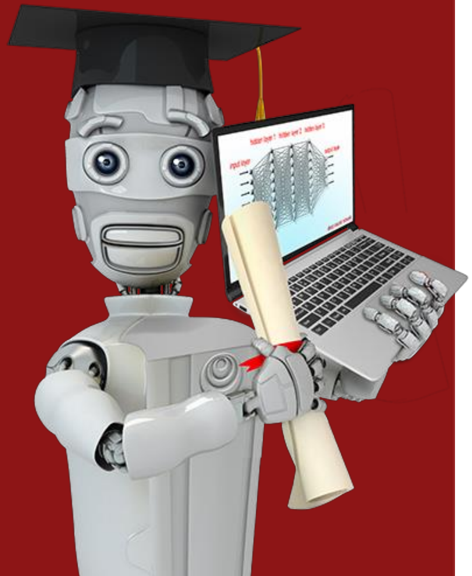
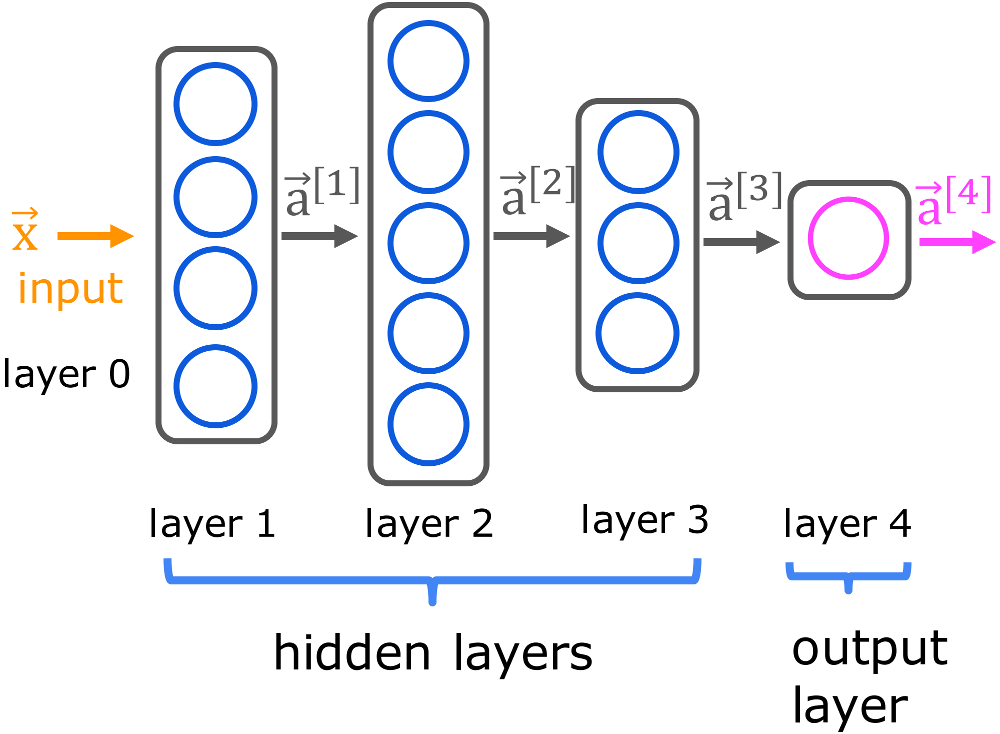


Neural Network Model

More complex neural networks

More complex neural network



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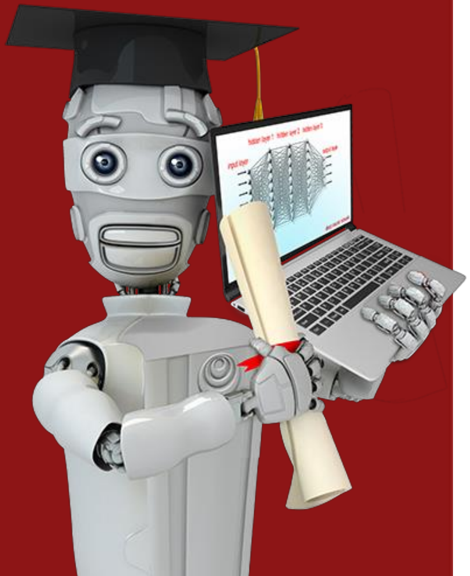

Speculations on artificial general intelligence (AGI)

Is there a path to AGI?

AI

ANI
(artificial narrow intelligence)

E.g., smart speaker,
self-driving car, web search,
AI in farming and factories

AGI
(artificial general intelligence)

Do anything a human can do