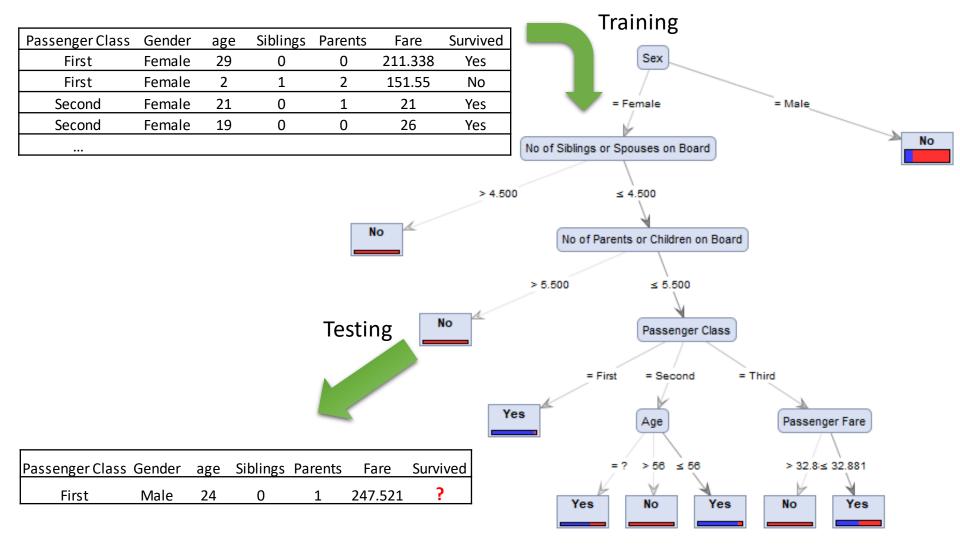
An Introduction to Deep Learning with TensorFlow

Steven H. H. Ding

School of Information Studies

Last Workshop - Classification with Decision Tree















































Non-linearity













Non-linearity













Non-linearity













Non-linearity





Recursive Network T≡5L⊓









Non-linearity





Recursive Network T≡5L⊓

Deep Brief Network







Non-linearity

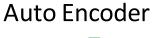




Recursive Network T≡5L⊓

Deep Brief Network

Stochastic Gradient Descend











Non-linearity





Recursive Network T≡5L7

Deep Brief Network

Stochastic Gradient Descend

Convolutionary Neural Network

Auto Encoder









Non-linearity

Deep Brief Network





Recursive Network T≡5L□

Back Propagation

Stochastic Gradient Descend

Convolutionary Neural Network

Auto Encoder









Non-linearity





Recursive Network T≡5L□

Deep Brief Network

Recurrent Network

Back Propagation

Stochastic Gradient Descend

Convolutionary Neural Network

Auto Encoder













Non-linearity

'Deep Learning' means using a *neural network* with several layers of nodes between input and output.

It's deep if it has more than one stage of non-linear feature transformation.







Agenda

- Logistic Regression
- Neural Network
- Convolutional Neural Network
- Why deep learning works
- Hands-on example using TensorFlow
- Q&A

Agenda

• Logistic Regression

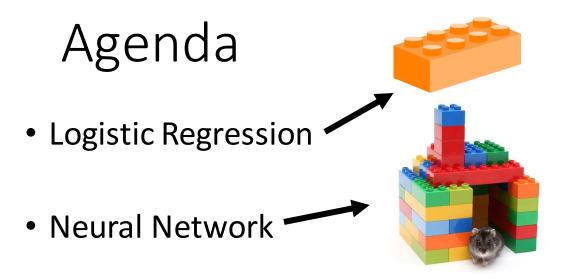
Neural Network

Convolutional Neural Network

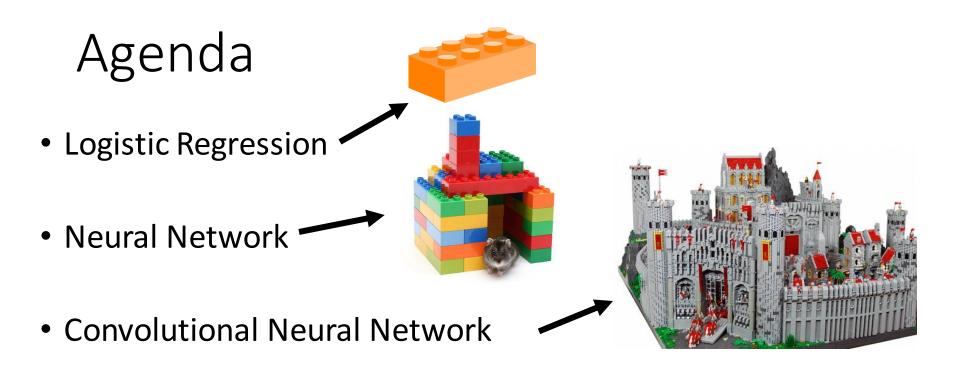
Why deep learning works

Hands-on example using TensorFlow

Q&A



- Convolutional Neural Network
- Why deep learning works
- Hands-on example using TensorFlow
- Q&A



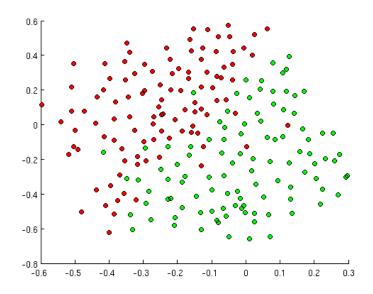
- Why deep learning works
- Hands-on example using TensorFlow
- Q&A



Passenger Class	Age	Survived
1	29	1
1	2	0
2	21	1
2	19	1

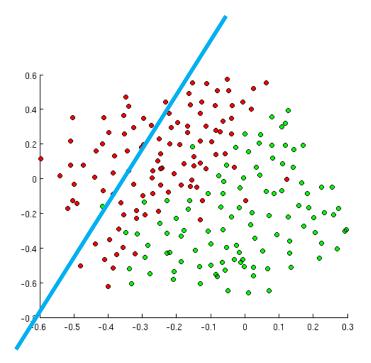


Passenger Class	Age	Survived
1	29	1
1	2	0
2	21	1
2	19	1





Passenger Class	Age	Survived
1	29	1
1	2	0
2	21	1
2	19	1





w1

w2

Logistic Regression

0.2

Passenger Class	Age	Survived
1	29	1
1	2	0
2	21	1
2	19	1

0.6

0.4

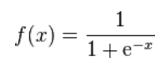
0.2

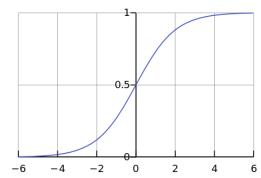
-0.2

-0.4

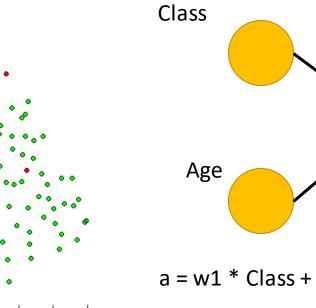
-0.6







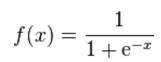
f(x)

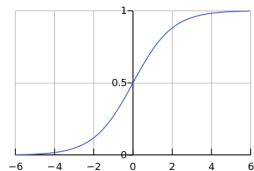


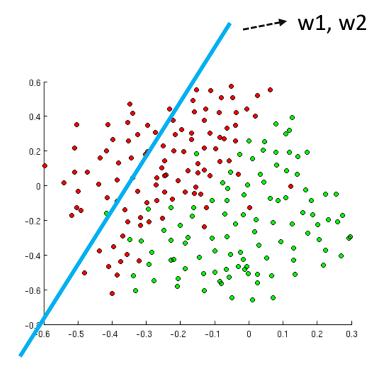
$$y = f(a)$$

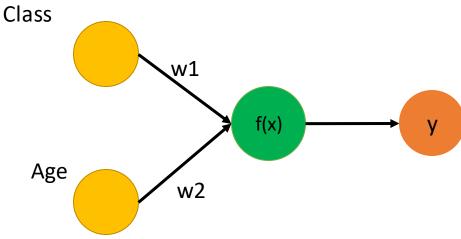


Passenger Class	Age	Survived
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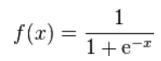


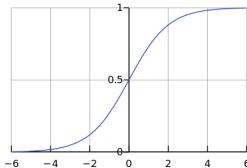


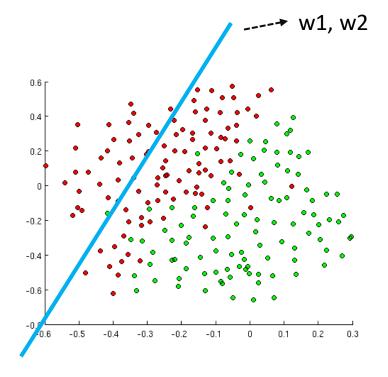
$$y = f(a)$$

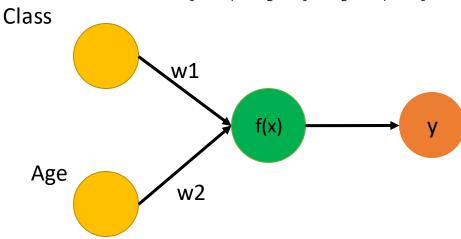


Pa	assenger Class	Age	Survived
	1	29	1
	1	2	0
	2	21	1
	2	19	1





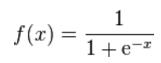


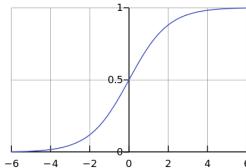


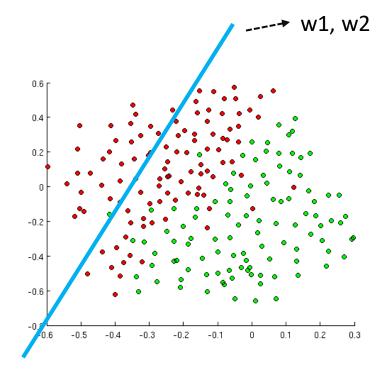
$$y = f(a)$$

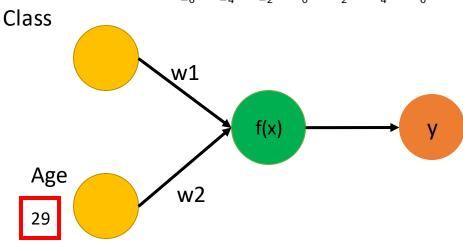


Pa	assenger Class	Age	Survived
	1	29	1
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	2	21	1
	2	19	1





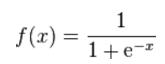


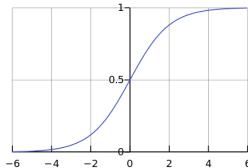


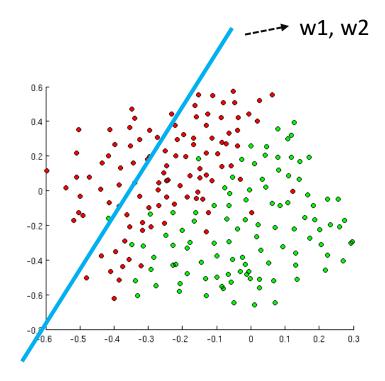
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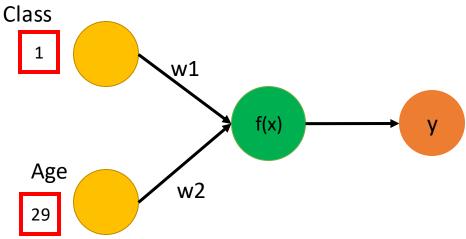


Pa	assenger Class	Age	Survived
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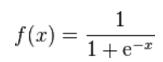


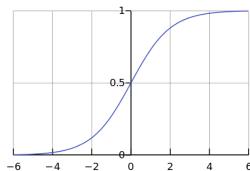


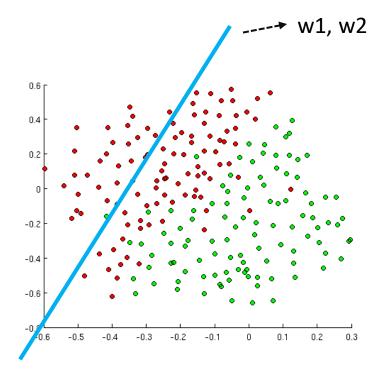
$$y = f(a)$$

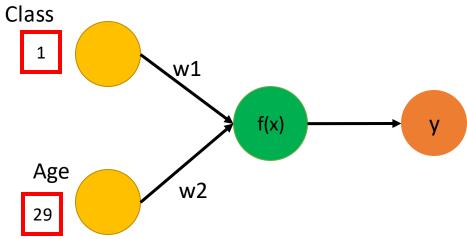


Pa	assenger Class	Age	Survived
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	2	21	1
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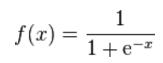


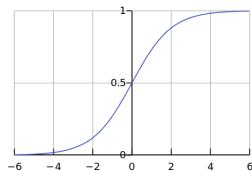


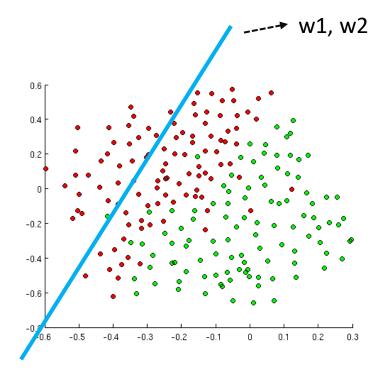


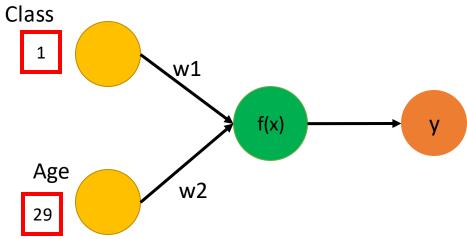


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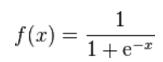


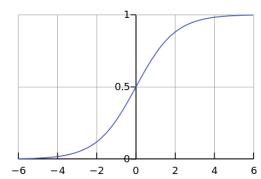


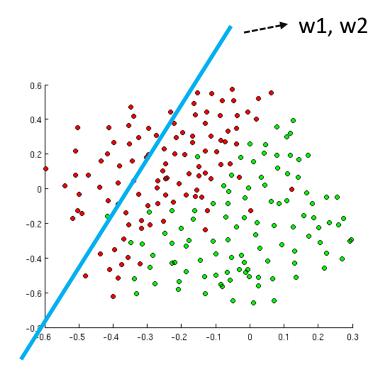


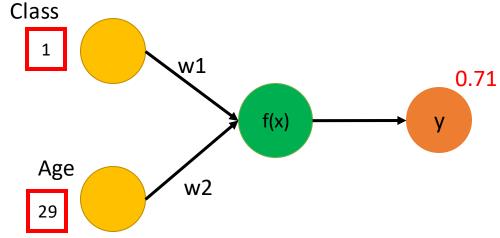


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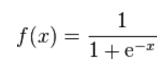


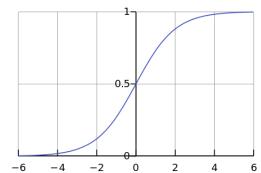


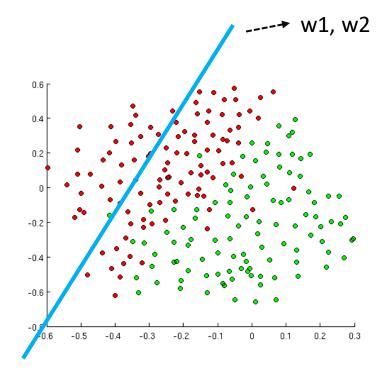


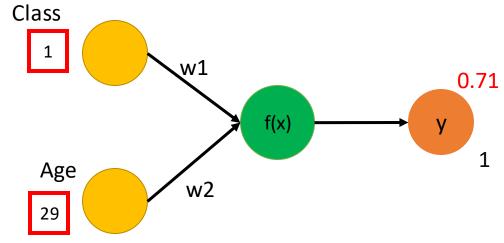


Pá	assenger Class	Age	Survived
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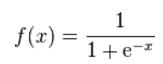


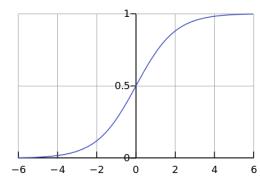


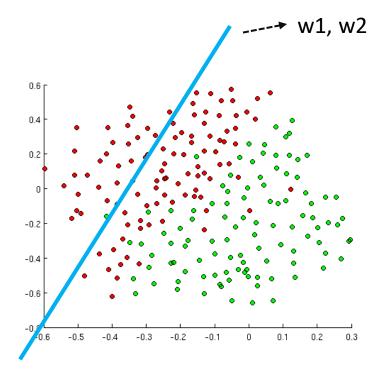


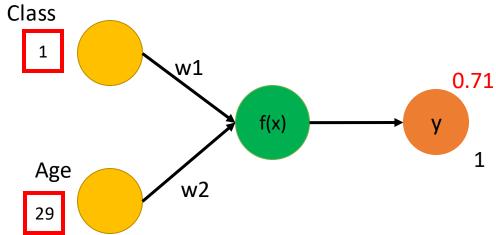


Passenger Class		Age	Survived
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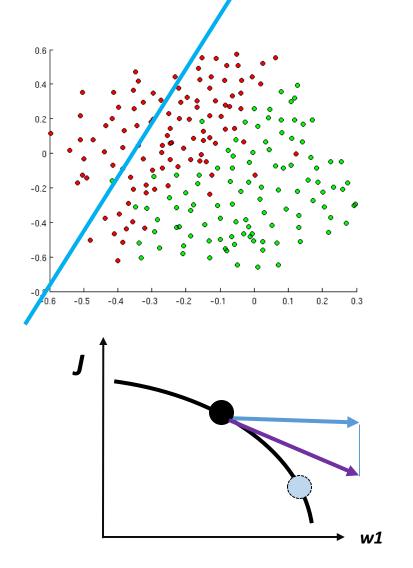


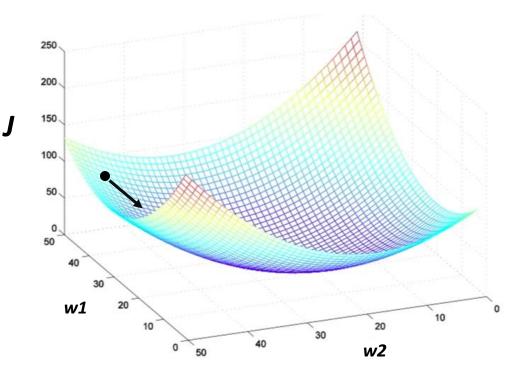


a = w1 * Class + w2 * Age
a' = -2 * 1 + 0.1 * 29 = 0.9
$$J(w) = \Sigma (y' - y)^2$$

y = f(a)
y' = f(0.9) = 0.71

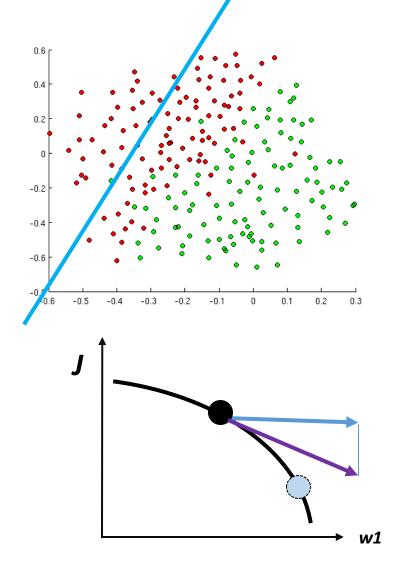


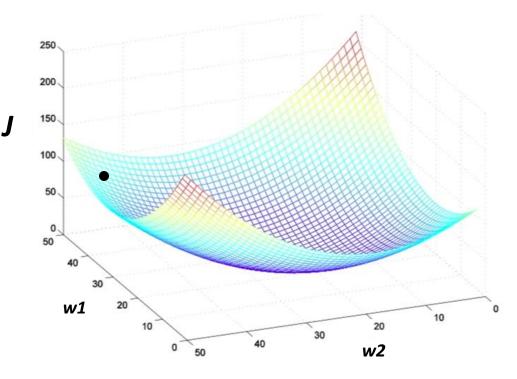




$$J(w) = \Sigma (y' - y)^2$$

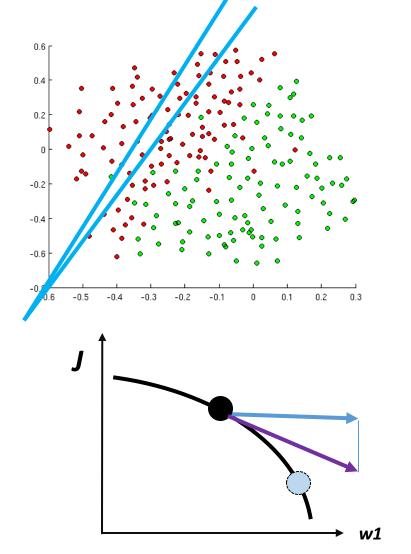


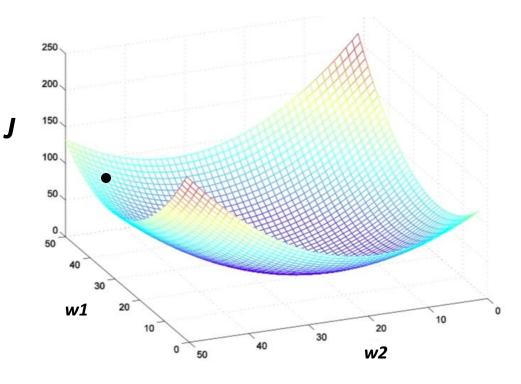




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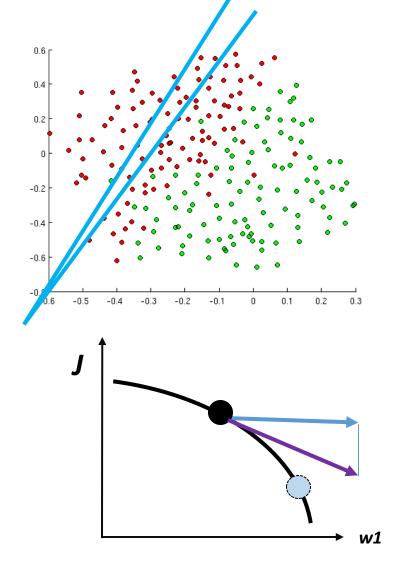


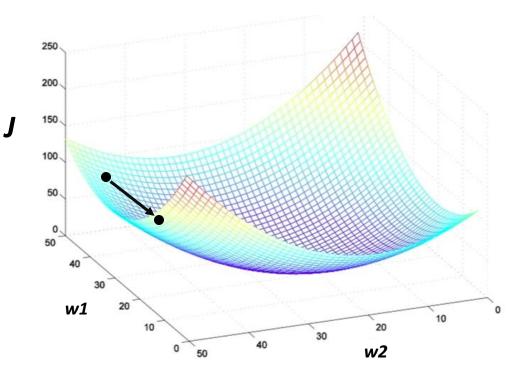




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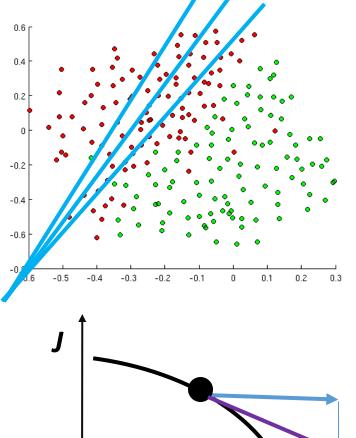


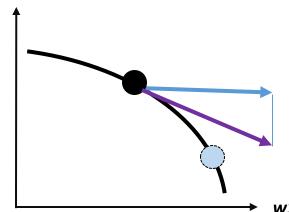


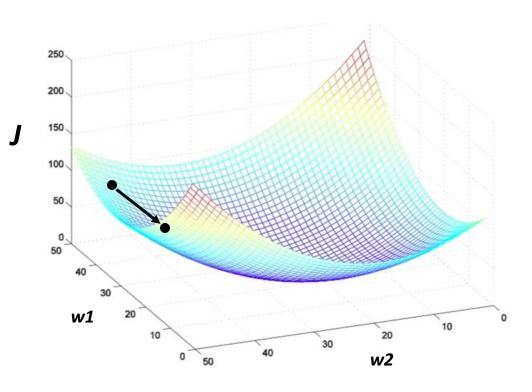


$$J(w) = \Sigma (y' - y)^2$$



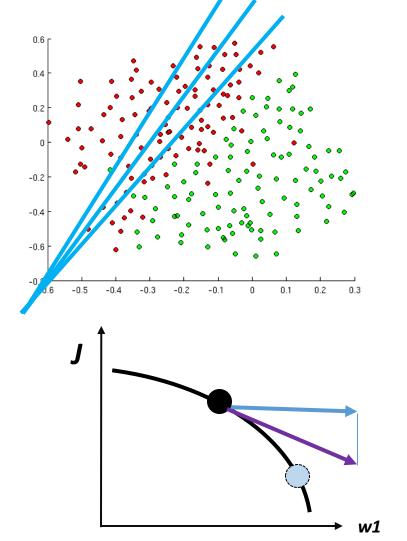


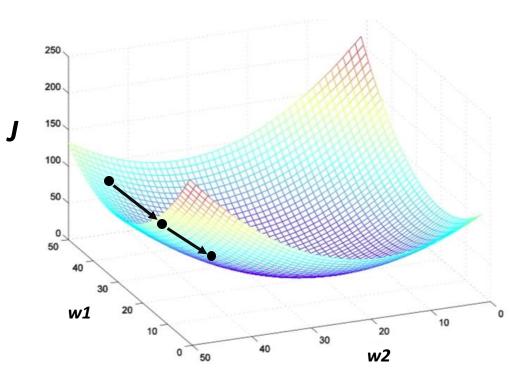




$$J(w) = \Sigma (y' - y)^2$$

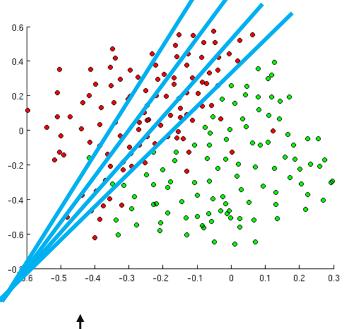


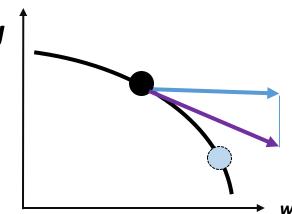


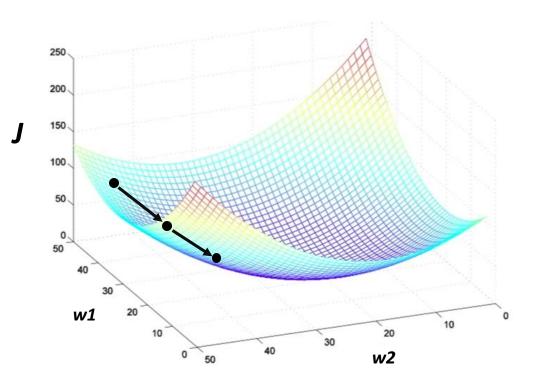


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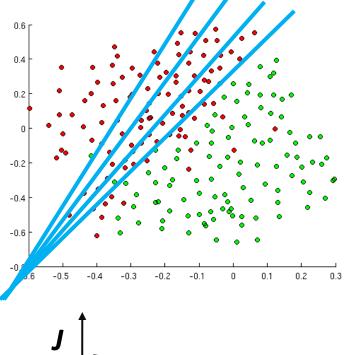


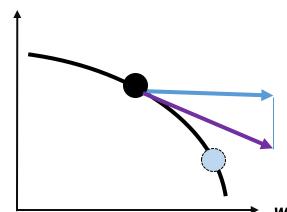


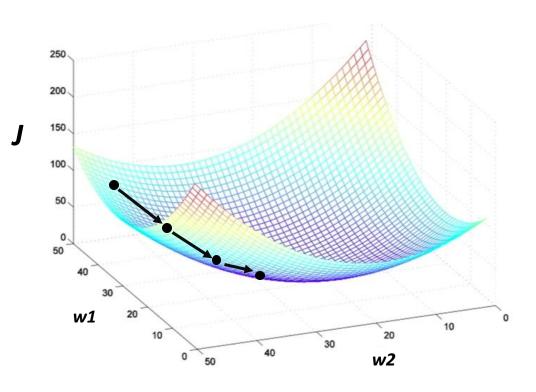


$$J(w) = \Sigma (y' - y)^2$$



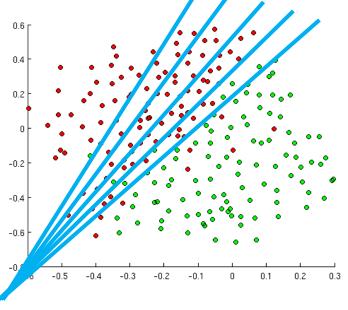


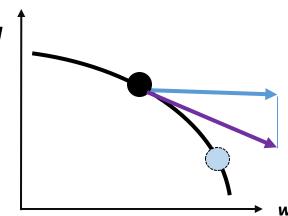


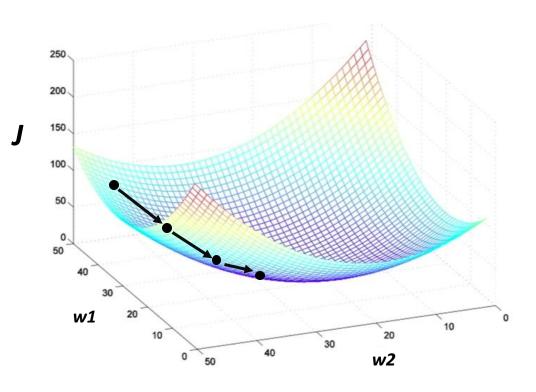


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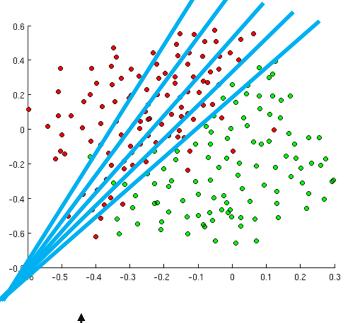


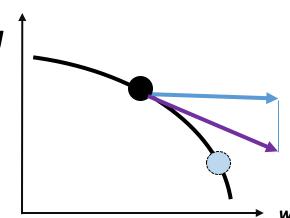


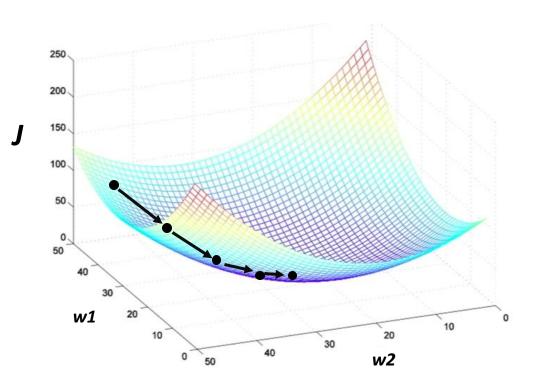


$$J(w) = \Sigma (y' - y)^2$$



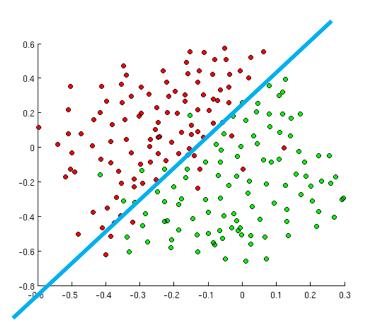




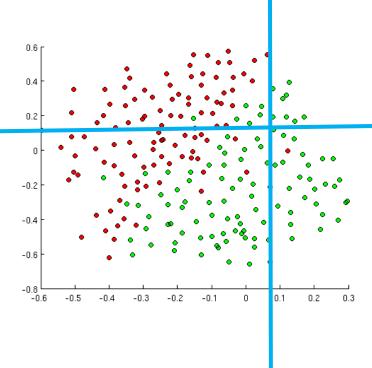


$$J(w) = \Sigma (y' - y)^2$$





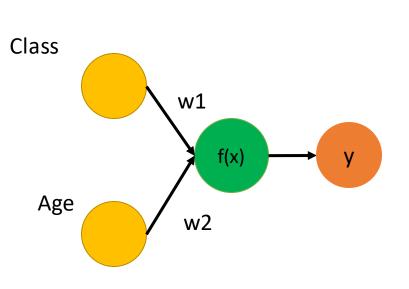
Decision boundary made by a linear model (logistic regression)



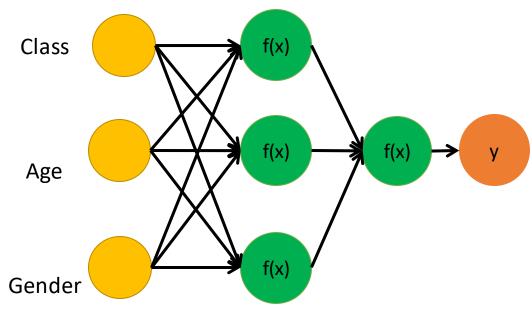
Decision boundary made by a decision tree.



- Adds multiple layer of interconnected regression node.
- Following the same way of training.



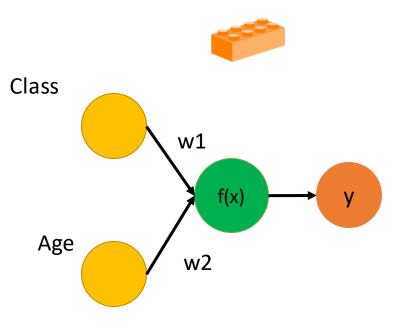
A logistic regression model.



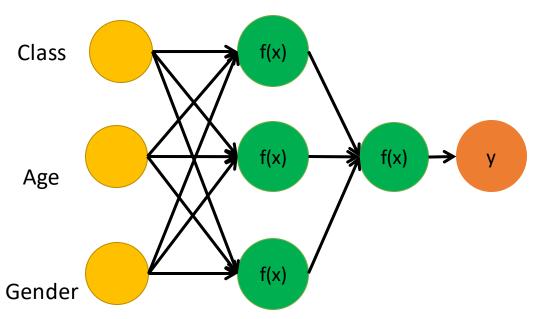
A neural network model.



- Adds multiple layer of interconnected regression node.
- Following the same way of training.



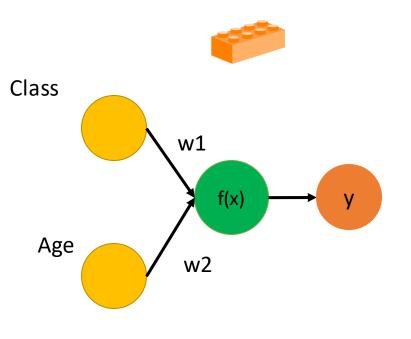
A logistic regression model.



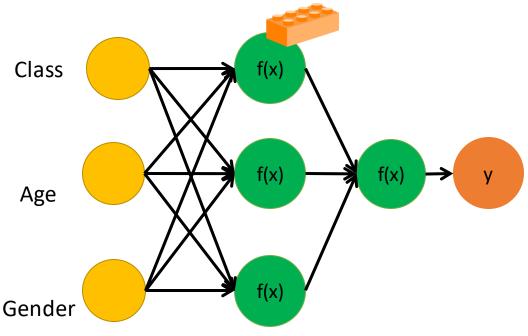
A neural network model.



- Adds multiple layer of interconnected regression node.
- Following the same way of training.



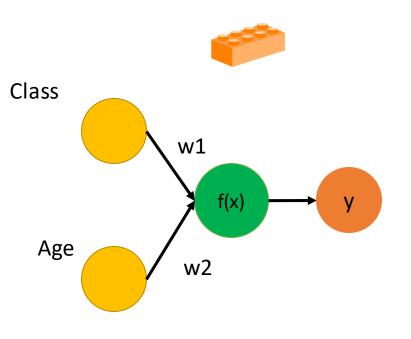
A logistic regression model.



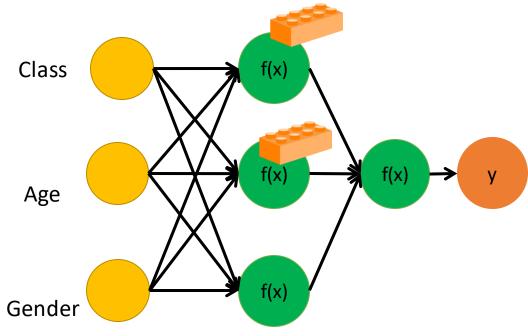
A neural network model.



- Adds multiple layer of interconnected regression node.
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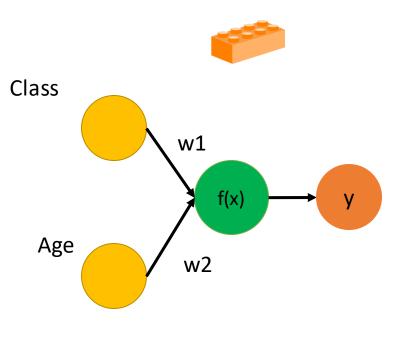
A logistic regression model.



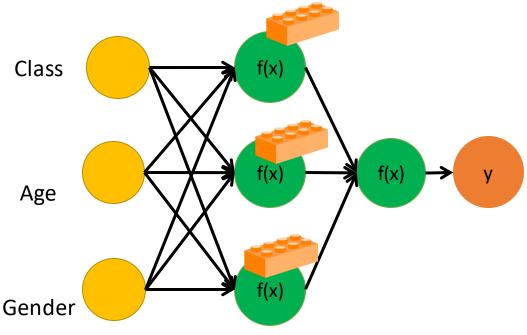
A neural network model.



- Adds multiple layer of interconnected regression node.
- Following the same way of training.



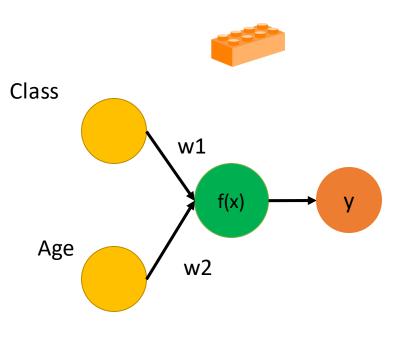
A logistic regression model.



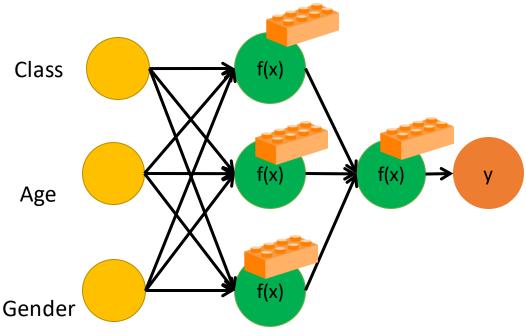
A neural network model.



- Adds multiple layer of interconnected regression node.
- Following the same way of training.



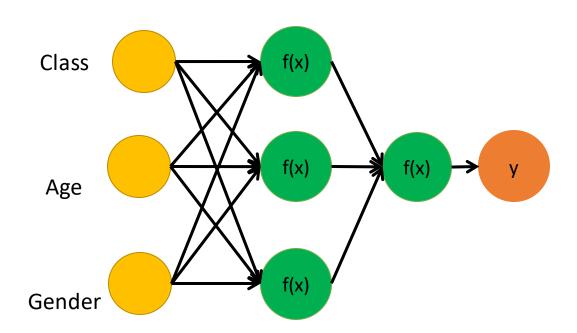
A logistic regression model.



A neural network model.

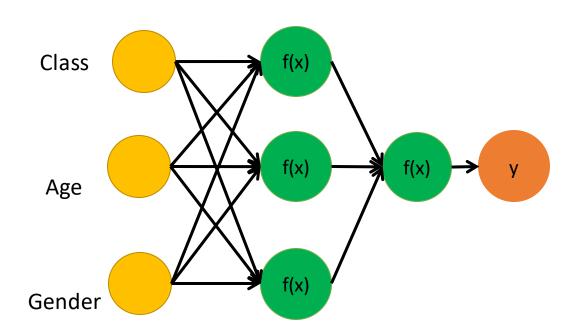


Passenger Class	Gender	age	Survived
1	1	29	1
1	2	2	0
2	2	21	1
2	1	19	1



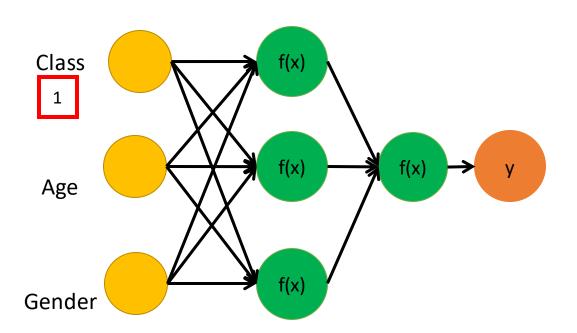


P	assenger Class	Gender	age	Survived
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Г	2	1	19	1



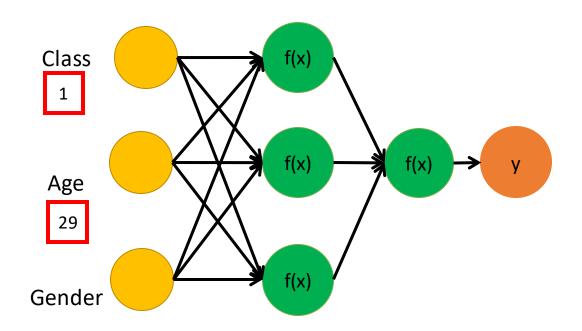


F	assenger Class	Gender	age	Survived
	1	1	29	1
	1	2	2	0
	2	2	21	1
Γ	2	1	19	1



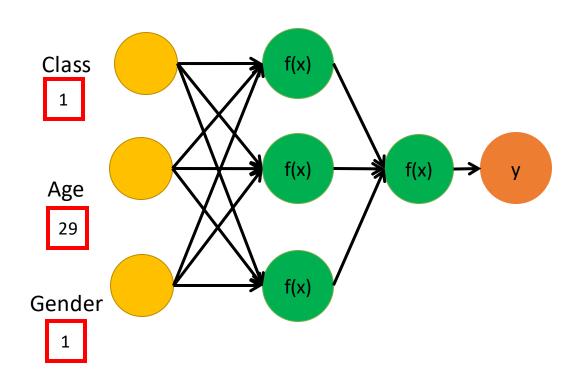


Р	assenger Class	Gender	age	Survived
	1	1	29	1
	1	2	2	0
	2	2	21	1
Г	2	1	19	1



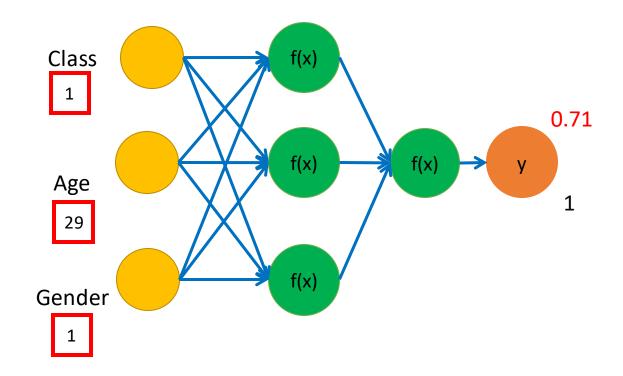


E	assenger Class	Gender	age	Survived
	1	1	29	1
	1	2	2	0
	2	2	21	1
	2	1	19	1



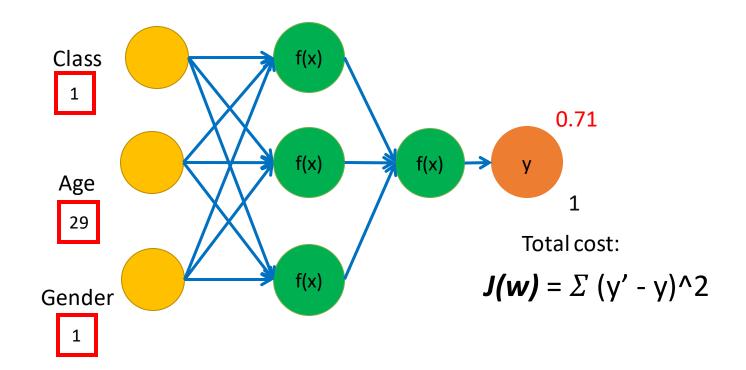


Р	assenger Class	Gender	age	Survived
	1	1	29	1
	1	2	2	0
	2	2	21	1
	2	1	19	1



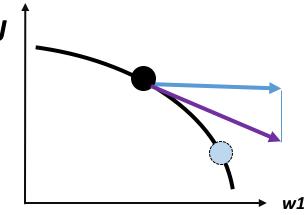


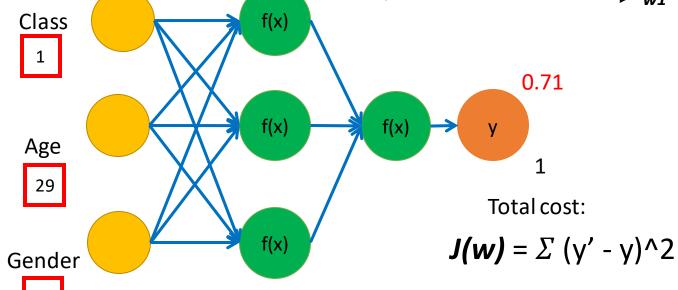
F	assenger Class	Gender	age	Survived
	1	1	29	1
	1	2	2	0
	2	2	21	1
Γ	2	1	19	1





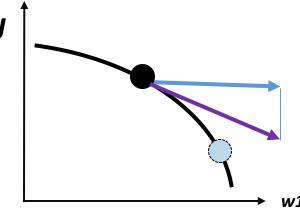
P	assenger Class	Gender	age	Survived
	1	1	29	1
	1	2	2	0
	2	2	21	1
Γ	2	1	19	1

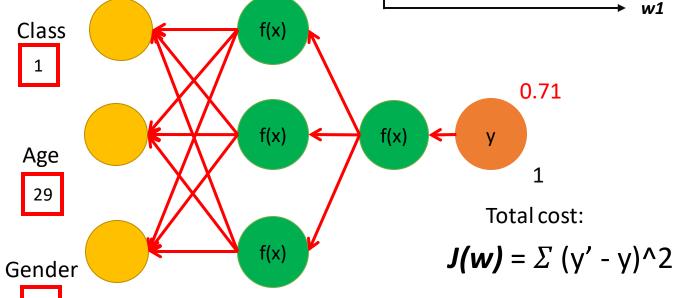






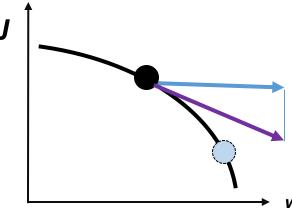
P	assenger Class	Gender	age	Survived
	1	1	29	1
	1	2	2	0
	2	2	21	1
Γ	2	1	19	1

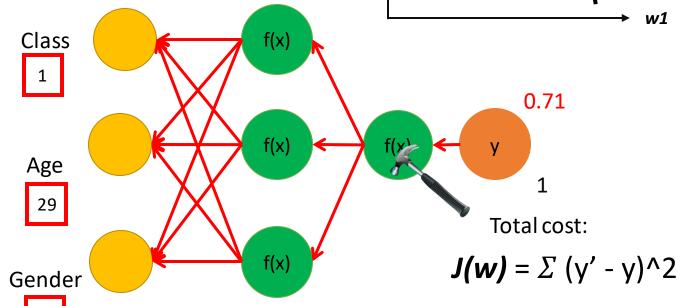






P	assenger Class	Gender	age	Survived
	1	1	29	1
	1	2	2	0
	2	2	21	1
Γ	2	1	19	1







				A
Passenger Class	Gender	age	Survived	J 1
1	1	29	1	
1	2	2	0	
2	2	21	1	
2	1	19	1	
		[Class 1	0.71
			Age 29	$f(x) \qquad f(y) \qquad 1$ $Total cost:$ $J(w) = \sum_{i=1}^{n} (v' - v)^{2}$
		Ge	ender 🖯	$J(w) = \Sigma (y' - y)^2$
			4	



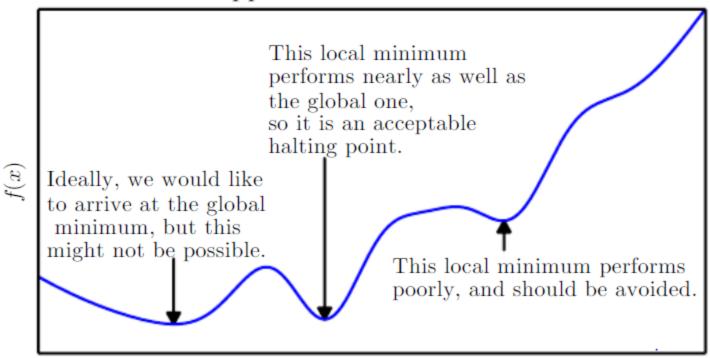
Passenger Class Gender age Survived 1					▲
1 2 2 0 2 2 21 1 2 1 19 1 Class 1 Age 29	Passenger Class	Gender	age	Survived	, T
2 2 21 1 2 1 19 1 Class 1 Age 29	1	1		1	
2 1 19 1 Class 1 Age 29				0	
Class 1 O.71 Age 29				1	
Class 1 Age 29	2	1	19	1	
Age 29 1			c [— `	
					f(x) f(x) Total cost:
Gender $J(w) = \Sigma (y' - y)^2$			Ge	nder	$J(w) = \sum_{i=1}^{n} (y' - y)^2$
Centre!				11461	

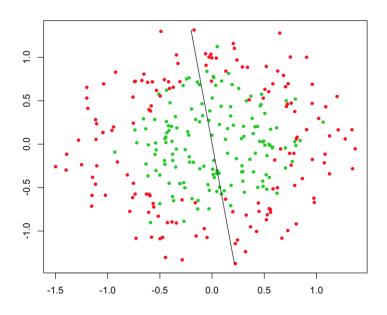


Passenger Class			Survived	J T
1	1	29	1	
1	2	2	0	
2	2	21	1	
2	1	19	1	
		Cli	ass 1	f(x) w1
		2	ge 29 nder	f(x) $f(y)$ $Total cost:$ $J(w) = \Sigma (y' - y)^2$

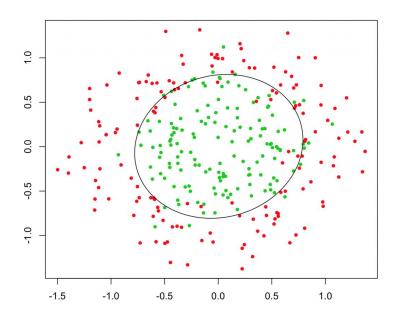


Approximate minimization

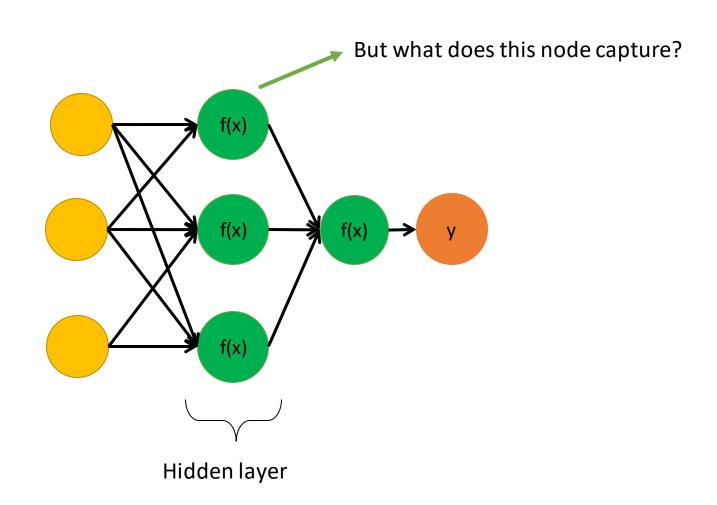




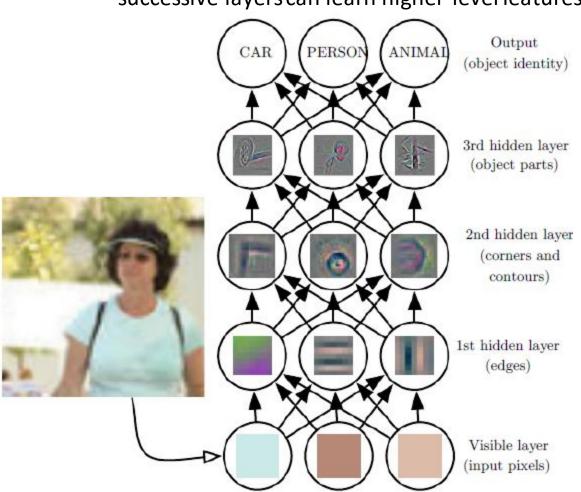
Decision boundary made by a linear model (logistic regression)

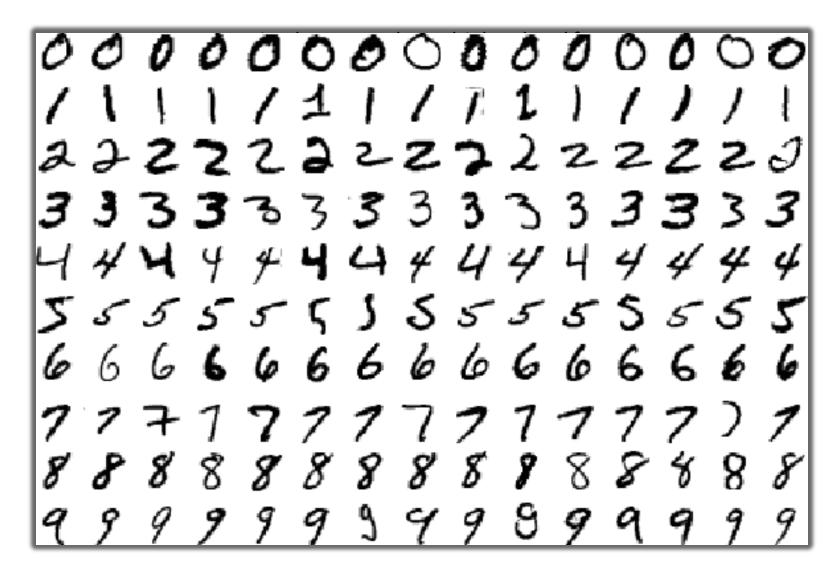


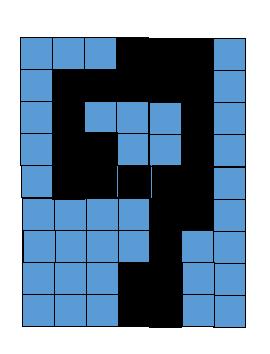
Decision boundary made by a neural network

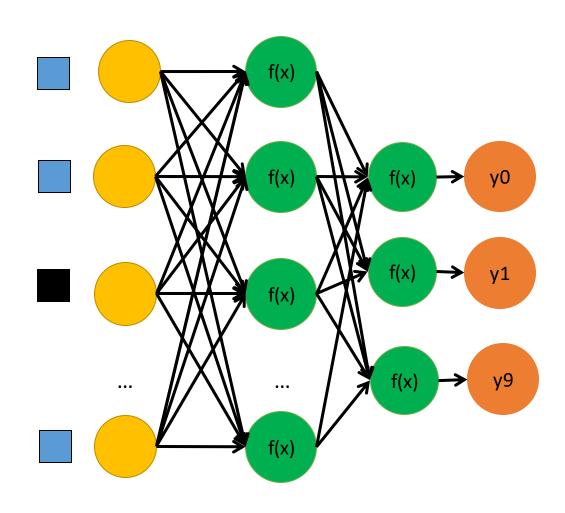


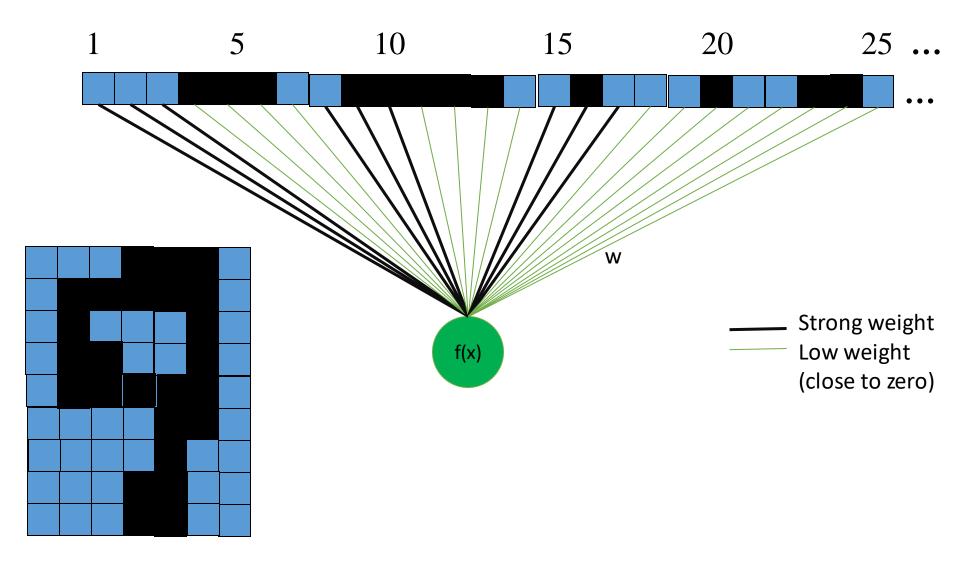
successive layers can learn higher-level features

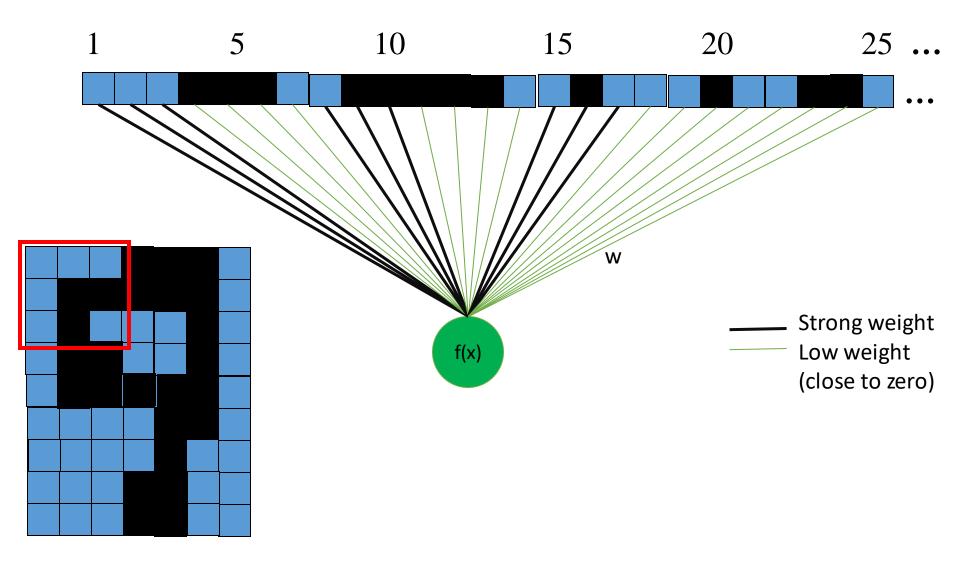


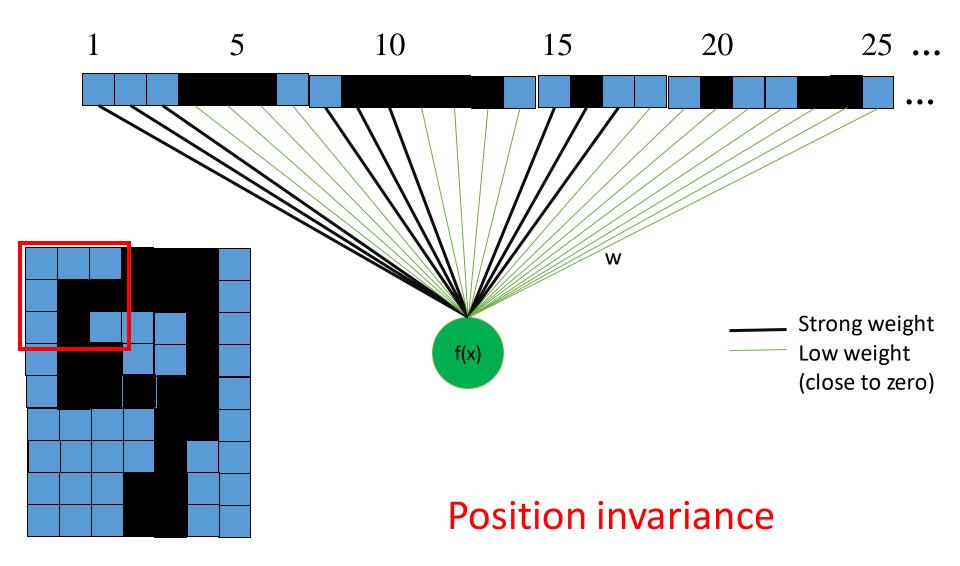


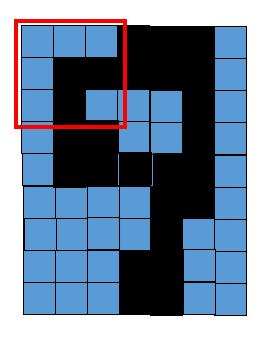




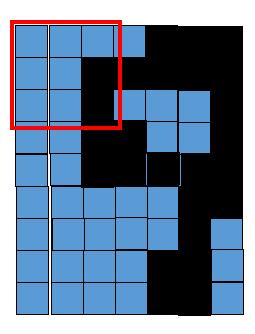






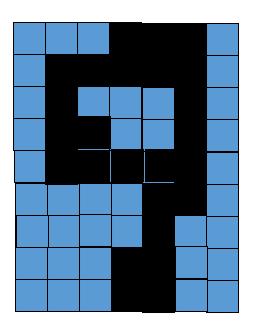


A training sample.

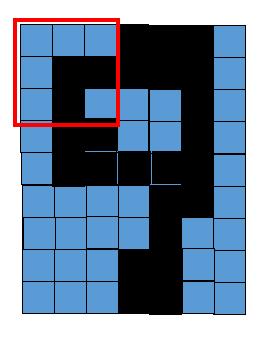


A testing sample. The old hidden unit failed to find the curve.

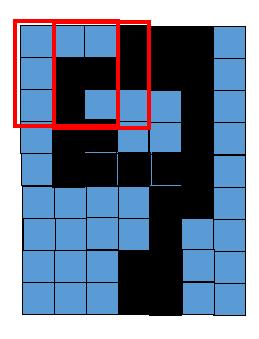
Position invariance



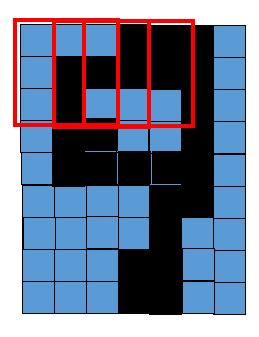
A training sample.



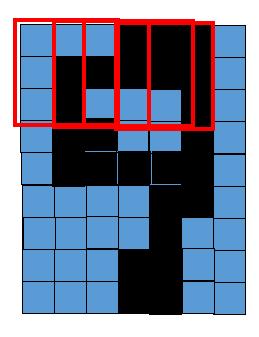
A training sample.



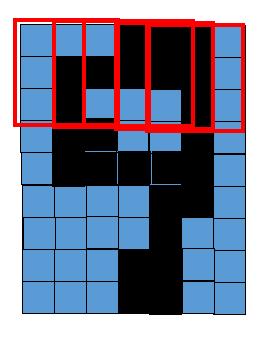
A training sample.



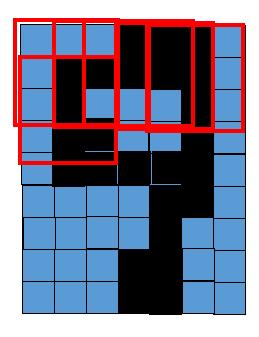
A training sample.



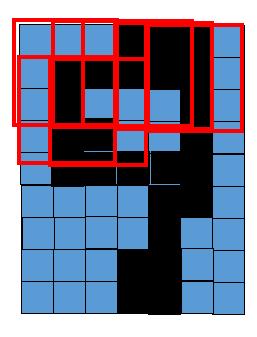
A training sample.



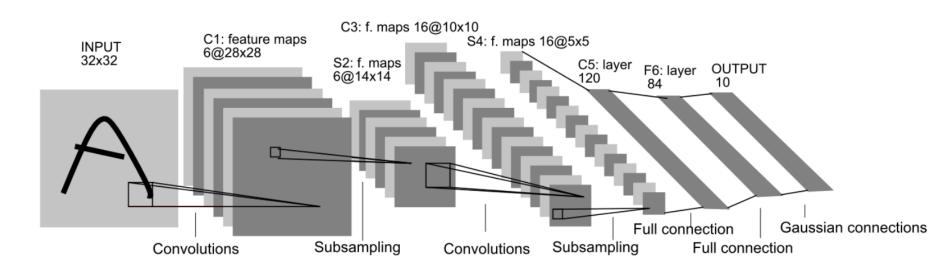
A training sample.



A training sample.



A training sample.

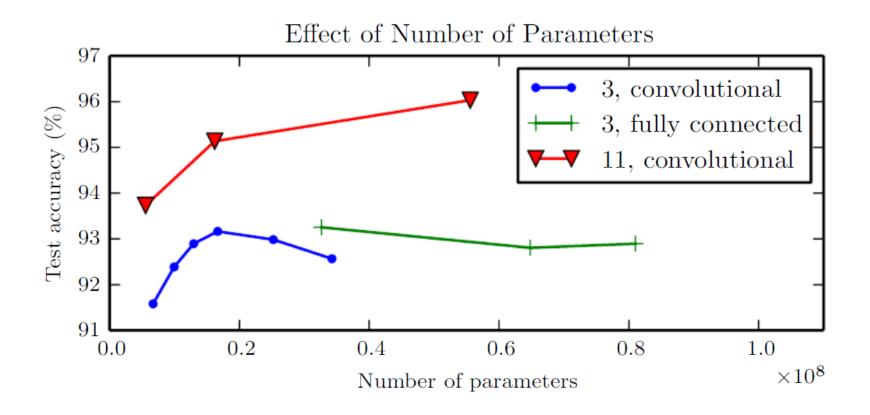


LeNet 5, Layer C5

Why going deep?

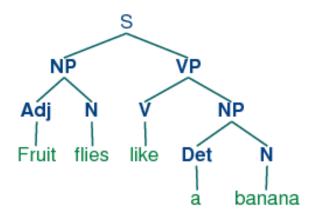
- Most deep learning models have been around for more than 25 years.
 - Theoretically even a NN with a single hidden layer can fit any function.
 - Gradient vanishing problem solved by new set of training algorithms and models.
- Deep structure:
 - Successive layers can learn higher-level features (latent factors)
 - Replace manual feature engineering.
 - Better generalizability. Can represent more complex functions with less parameters.

Why going deep?



What else?

- Classification
- Regression
- Sequential output
- Structured output





Thank you!