From linear and logistic regression to neural networks

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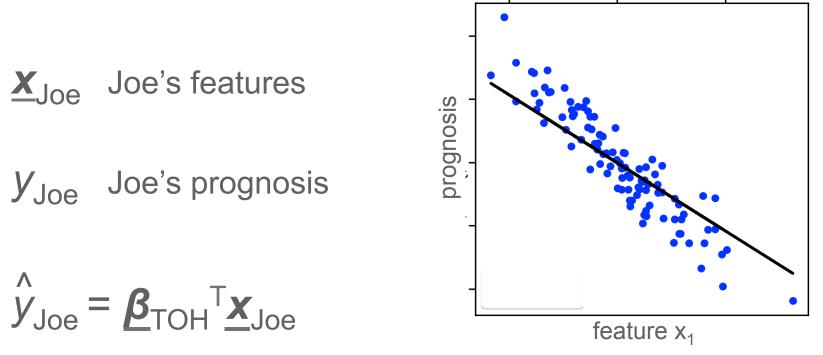
We denote one patients features by $\underline{\mathbf{x}} = [\mathbf{x}_1 \ \mathbf{x}_2 \ ...]^T$ and the targets for all patients by $\underline{\mathbf{y}} = [\mathbf{y}_1 \ \mathbf{y}_2 \ ...]^T$

	features: <u>x</u>							target		
	wgt	height	pulse	age	sex	acr	gfr		ckd	
	X 1	X 2	X 3	X 4	X 5	X 6	X 7		У	
patient 1	170	68	80	65	0	30	60		1	y 1
patient 2	150	65	60	46	1	5	30		1	y 2
patient 3	155	66	65	22	0	2	95		-1	Уз
patient 4	160	68	60	37	1	2	100		-1	y 4



A chronic kidney disease (ckd) example.

Linear regression (multiple linear regression)



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Joe's estimated prognosis



Logistic regression (a generalized linear model)

• From
$$\hat{y} = \underline{\beta}^{\mathsf{T}} \underline{x}$$
 to $\hat{y} = \sigma(\underline{\beta}_{\mathsf{TOH}}^{\mathsf{T}} \underline{x}_{\mathsf{Joe}})$

• A non-linear link function σ is applied to the linear model, which allows for a non-linear fit.

•
$$\sigma(\beta^{\tau}x) = e^{\beta^{\tau}x}$$

 $1 - e^{\beta^{\tau}x}$

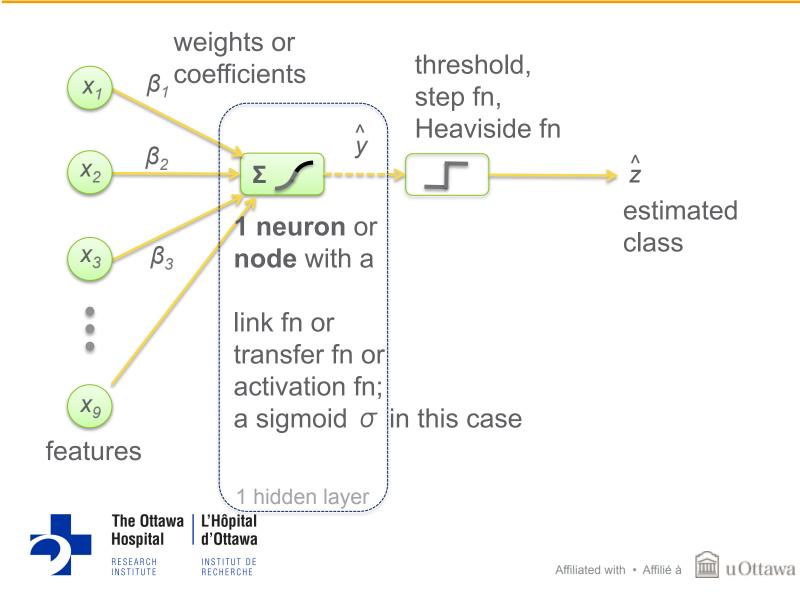


Neural networks

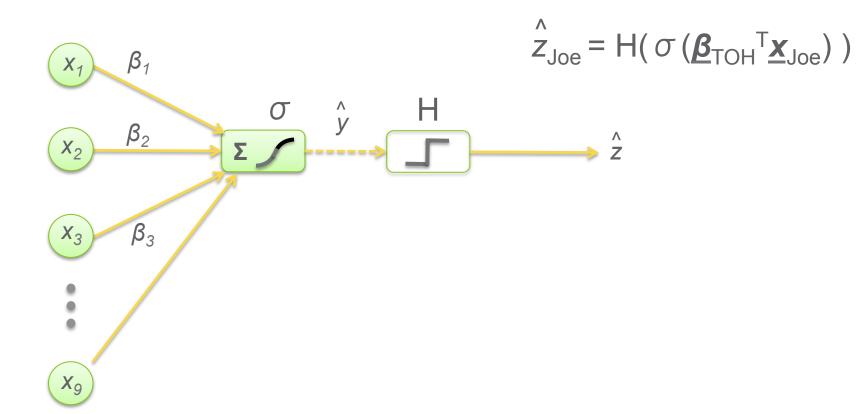
- You already know one!
- Logistic regression is a neural network with:
 - one hidden layer & one neuron!



Logistic regression in network form

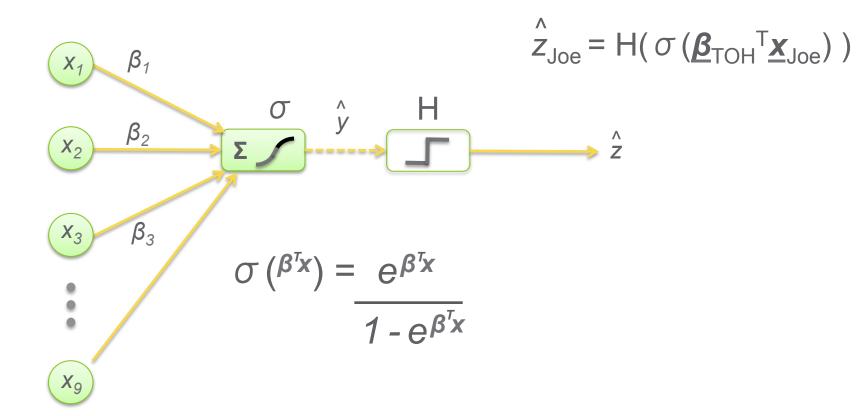


Logistic regression in network form



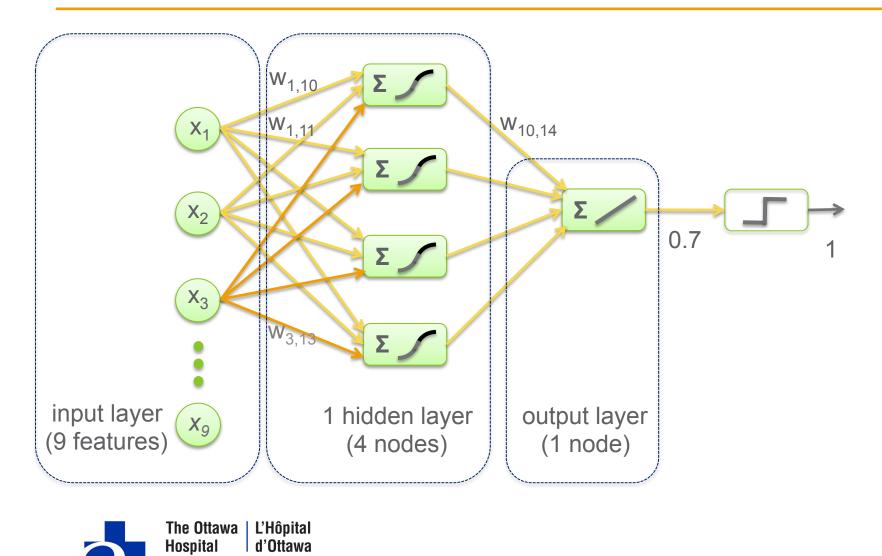


Logistic regression in network form





A standard neural network example



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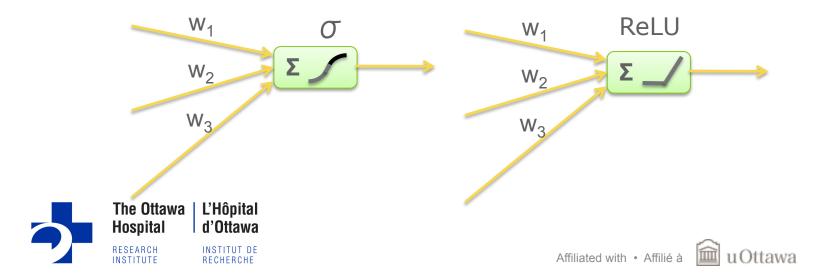
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Typical transfer/activation functions in neurons

- Activation (output high) occurs when the inputs are sufficiently high collectively. Activation functions are:
 - Sigmoids σ , i.e., S-curves
 - Rectified linear units (ReLU), i.e. filter out negatives
 - Step functions



Universal approximators

- Learning theory says the following can approximate any function given *sufficient* (infinite?) data
 - a neural network with a single hidden layer and a *sufficient* number of nodes
 - a support vector machines with a *sufficient* number of support vectors
 - a polynomial kernel
 - > a sigmoid kernel
 - > a Gaussian (radial basis function, RBF) kernel



But that theory does not help practice

- We have finite data, finite computing power/time, and we want finite understandable models.
- In the theoretical case of infinite data there is no "generalization" necessary from training to testing, they are the same.
- Theory tells us nothing about training fit with finite data, nor how well a model generalizes to new data



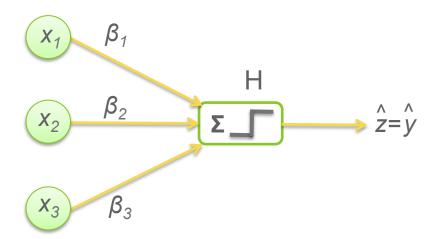
In conclusion

- We have seen a neural network for binary classification, as a natural extension of logistic regression.
- We introduced types of activation (transfer) functions.
- We introduced the theory and limits of universal approximators.



Extras: a perceptron in network form

- A single node using a step function instead of a sigmoid
- A classifier that finds a line of separation given a separable data set. Fails for non-separable data



Neural networks are called multilayer perceptrons (MLP)



A support vector machine in network form

The network form for SVM differs from neural networks.

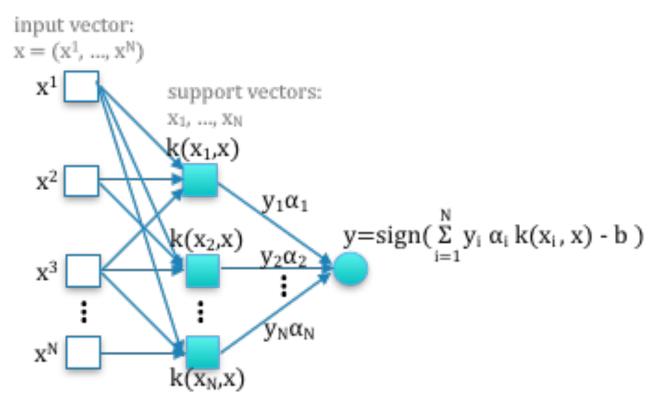




Figure adapted from Vapnik.

Future topics

- Back-propagation
- Multiclass classification with the softmax transfer function.
- Sequences or time series with recurrent neural networks (RNNs) and long-short term memory (LSTM) transfer functions.
- Deep learning with convolutional neural networks (CNNs).



Questions?

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