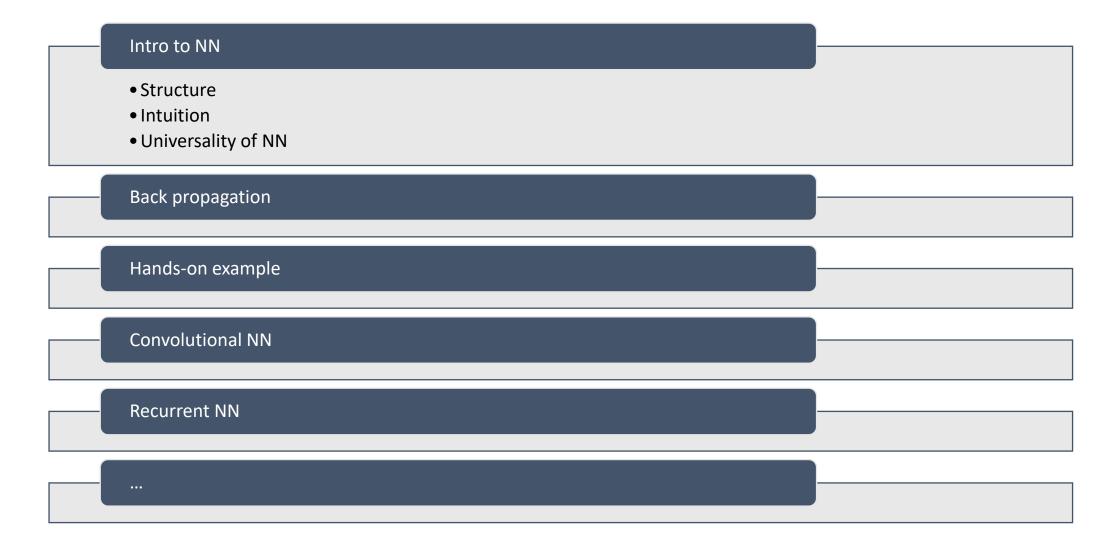
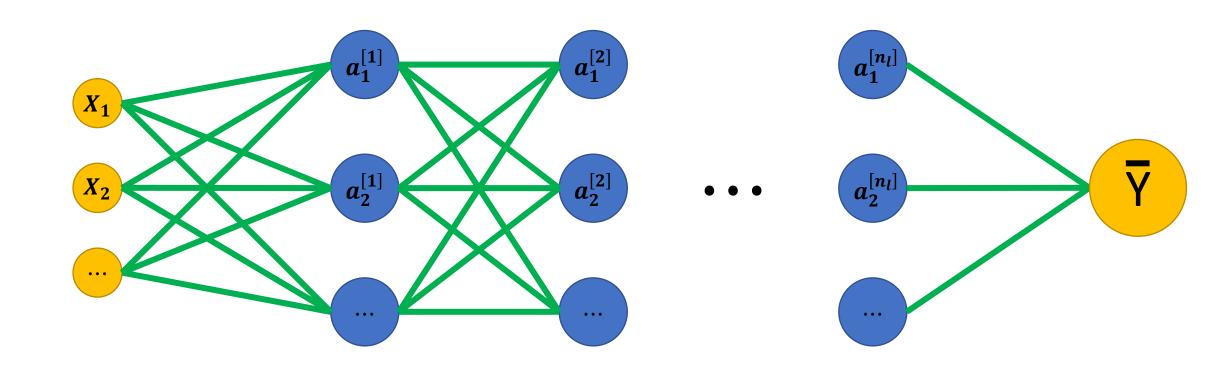
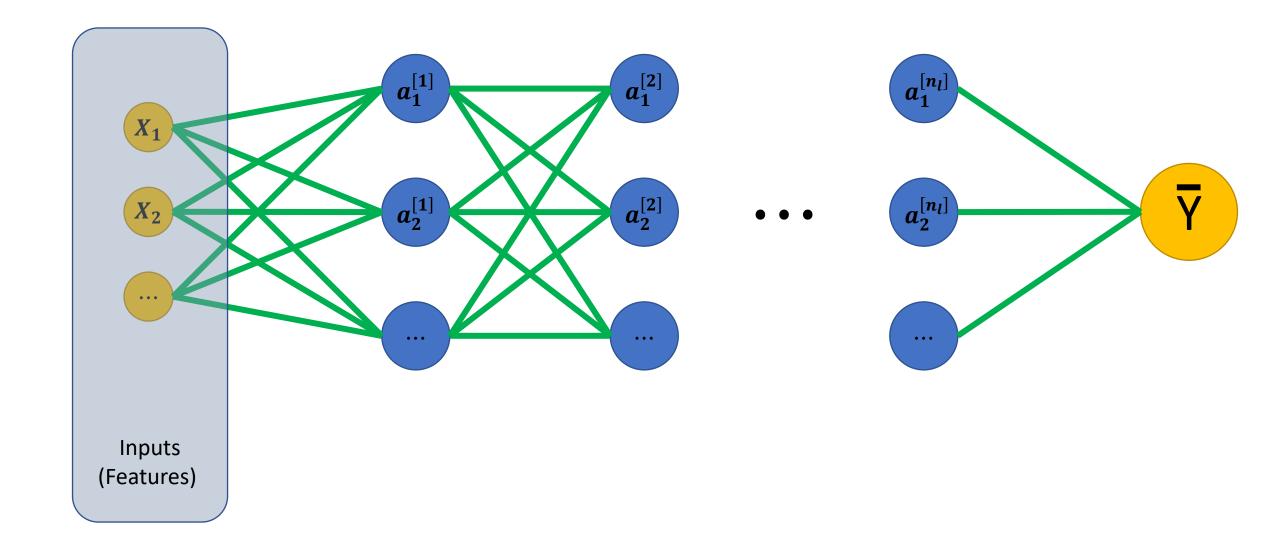


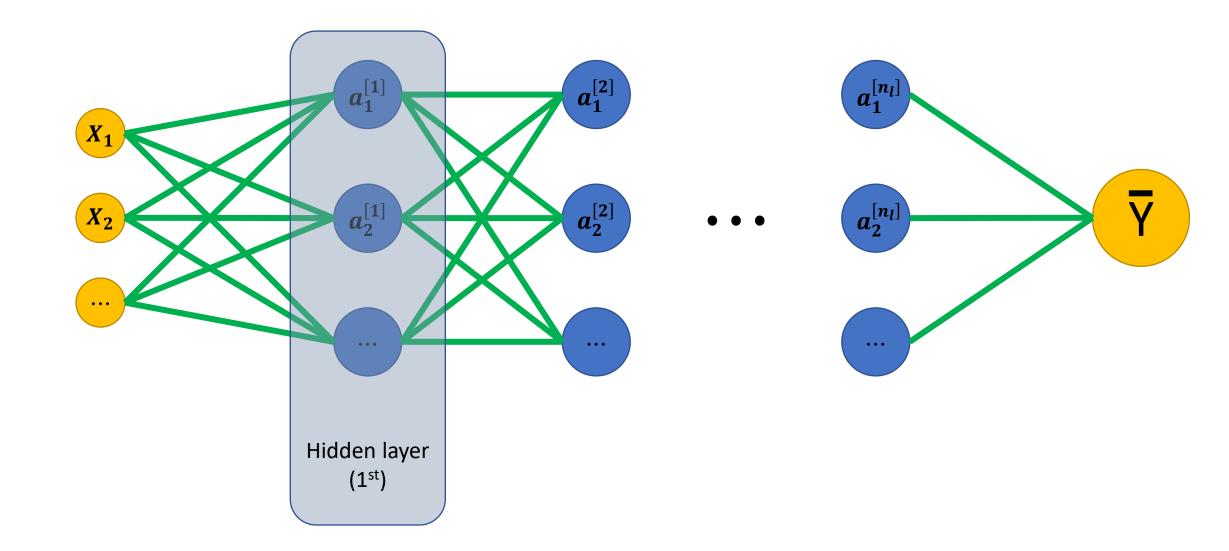
Plan for the next part

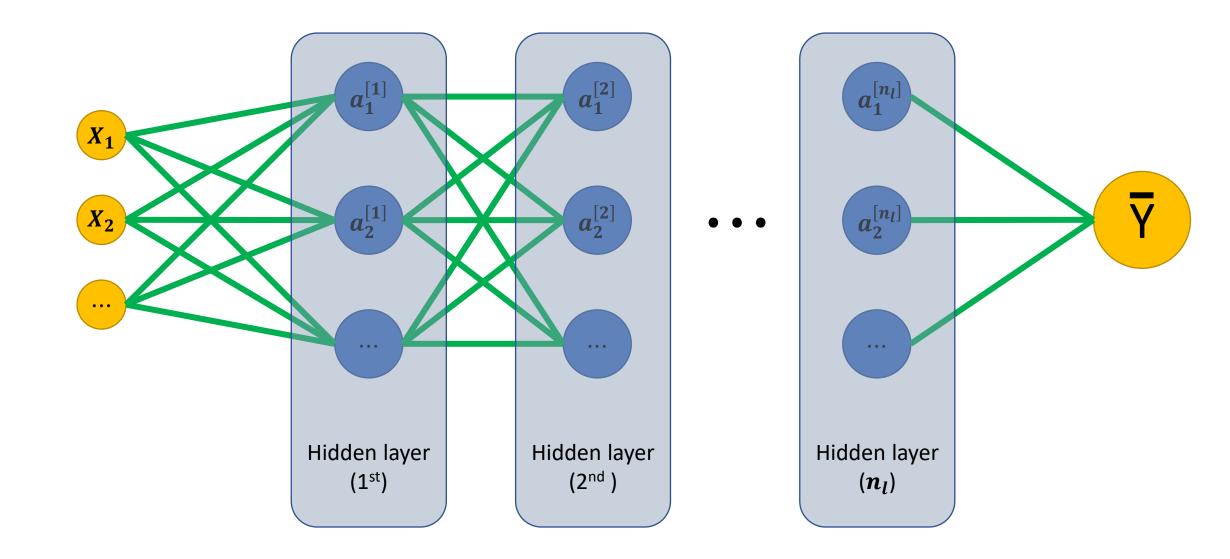


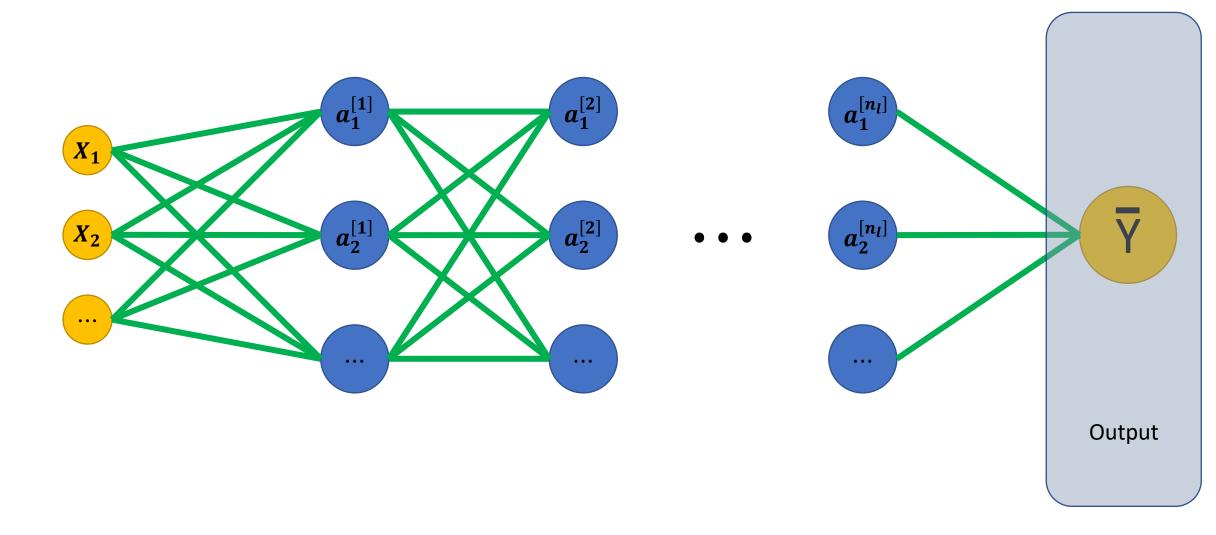
What is a NN?

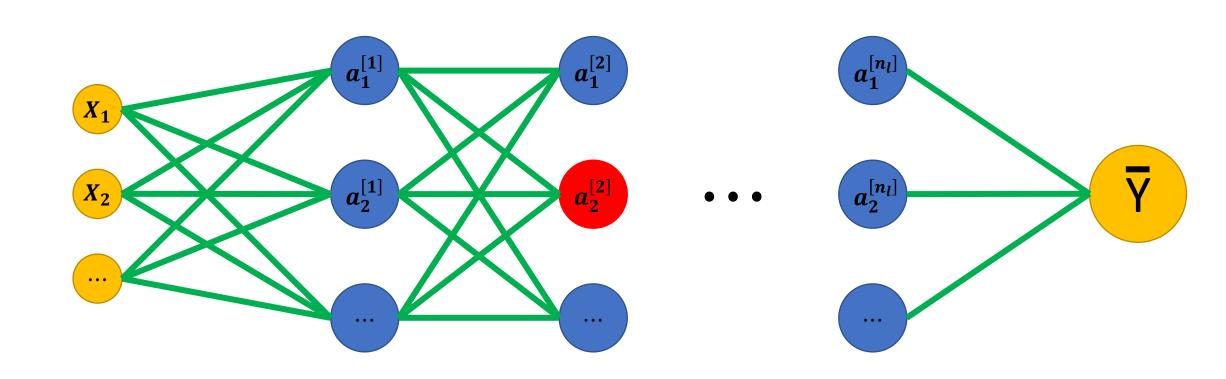


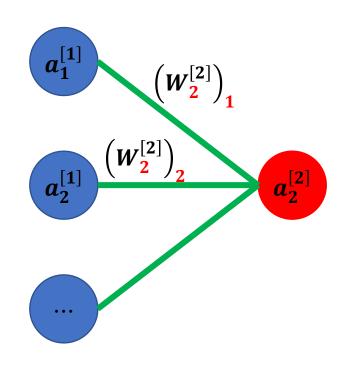






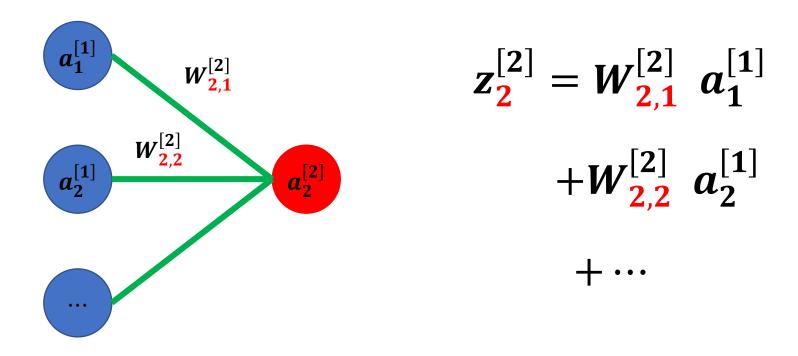




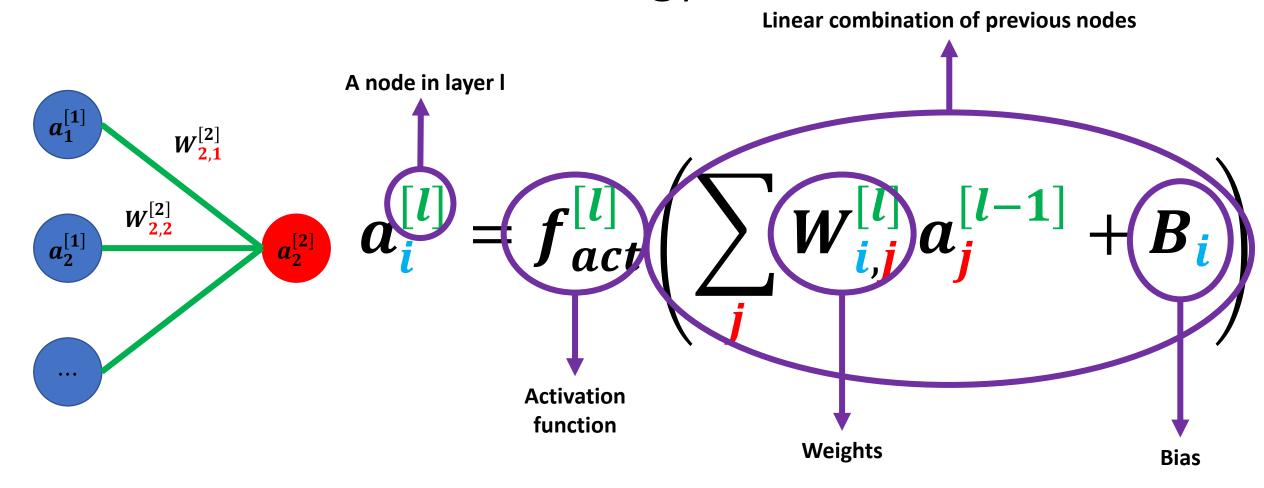


$$z_{2}^{[2]} = \left(W_{2}^{[2]}\right)_{1} a_{1}^{[1]} + \left(W_{2}^{[2]}\right)_{2} a_{2}^{[1]} + \cdots$$

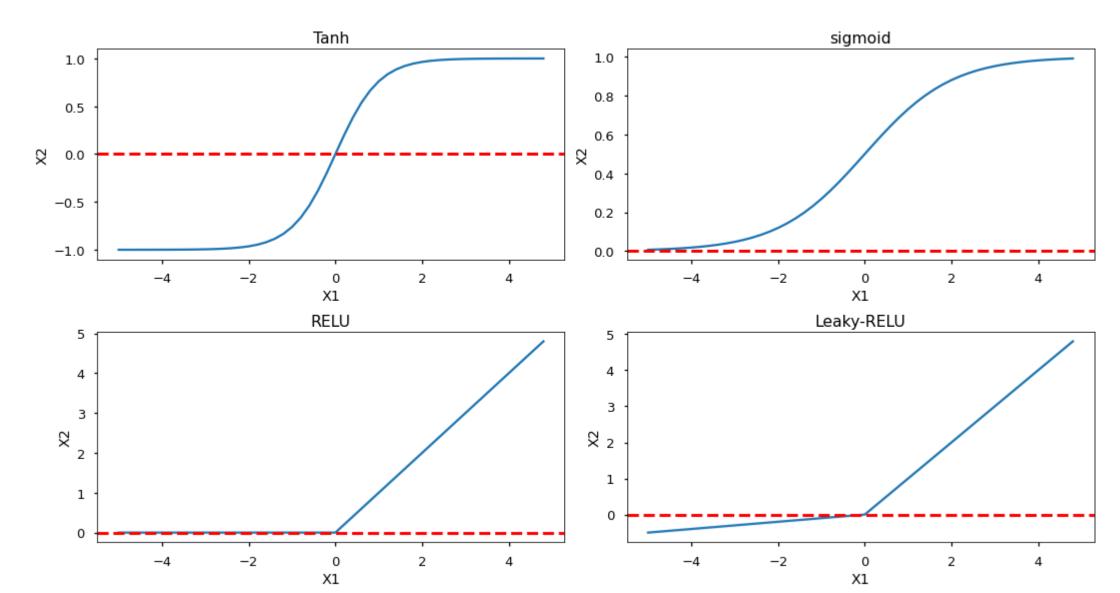
$$a_{\mathbf{2}}^{[2]} = f_{act}\left(\mathbf{z}_{\mathbf{2}}^{[2]}\right)$$



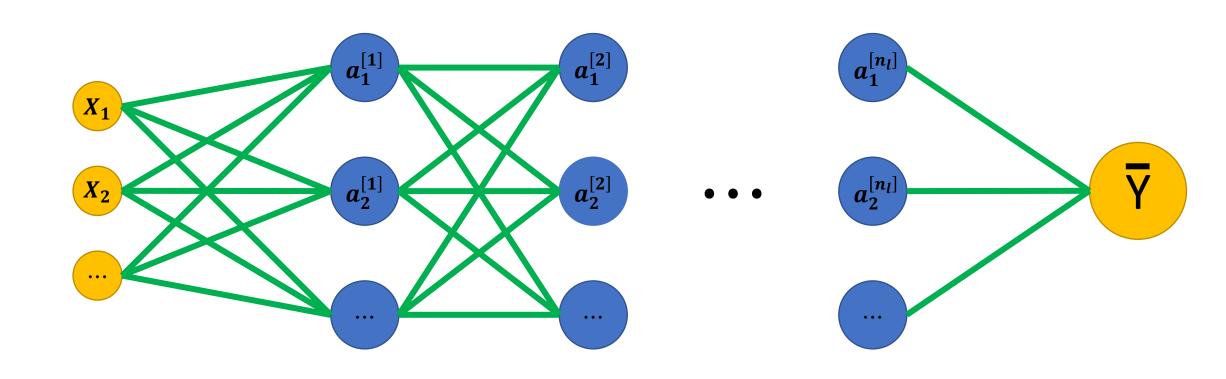
$$a_{\mathbf{2}}^{[2]} = f_{act}\left(\mathbf{z}_{\mathbf{2}}^{[2]}\right)$$



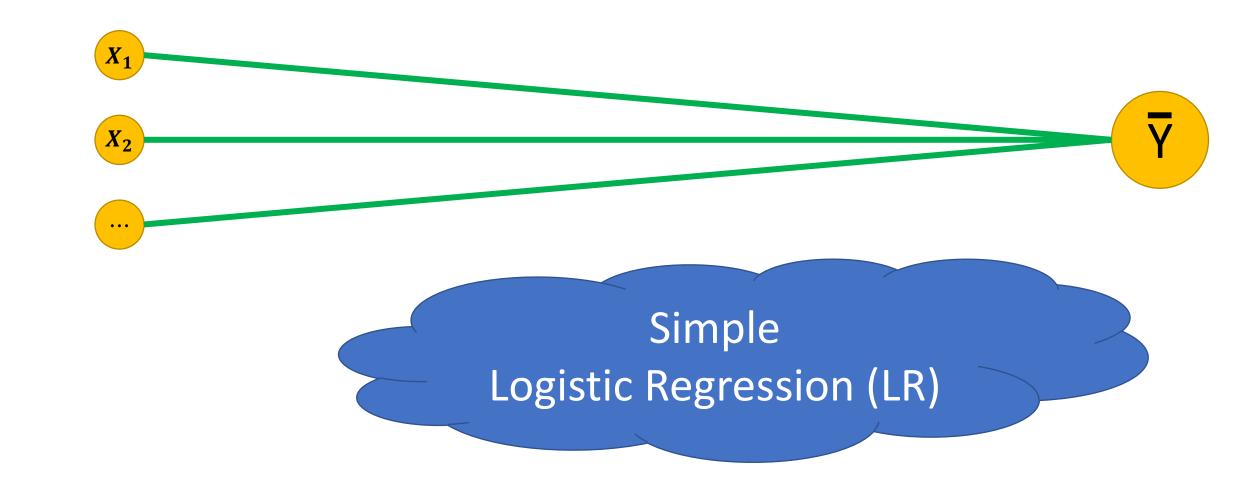
Activation Functions



What would happen without activation func?



What would happen without activation func?



What are the parameters?

What are the hyper-parameters?

$$z_{i}^{[l]} = \sum_{j} W_{i,j}^{[l]} a_{j}^{[l-1]} + B_{i}^{[l]}$$

$$a_{i}^{[l]} = f_{act}^{[l]} \left(z_{i}^{[l]} \right)$$

 $\boldsymbol{W}^{[l]}$: Weights in layer I

 $B^{[l]}$: Bias in layer I

 $oldsymbol{Z}^{[oldsymbol{l}]}$: Linear outcome in layer I

 $f_{act}^{[l]}$: Activation func. in layer I

 $A^{[l]}$: Full outcome in layer I

$$Z^{[l]} = W^{[l]}.A^{[l-1]} + B^{[l]}$$

$$A^{[l]} = f_{act}^{[l]}(Z^{[l]})$$

$$Z^{[l]} = W^{[l]}.A^{[l-1]} + B^{[l]}$$
 $A^{[l]} = f^{[l]}_{act}(Z^{[l]})$

$$n^{[l]}$$
: #nodes in layer I

$$\boldsymbol{W}^{[l]}$$
: Weights in layer l

$$B^{[l]}$$
: Bias in layer I

$$\boldsymbol{Z}^{[l]}$$
: Linear outcome in layer l

$$f_{act}^{[l]}$$
: Activation func. in layer l

$$A^{[l]}$$
: Full outcome in layer I

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

$$\boldsymbol{B}^{[l]}:(n^{[l]})$$

$$\boldsymbol{Z}^{[l]}:(n^{[l]},n_s)$$

$$A^{[l]}$$
: $(n^{[l]}, n_s)$

$$Z^{[l]} = W^{[l]} \cdot A^{[l-1]} + B^{[l]}$$
 $A^{[l]} = f^{[l]}_{act}(Z^{[l]})$

$$egin{aligned} W^{[l]} &: (n^{[l]}, n^{[l-1]}) \ & B^{[l]} &: (n^{[l]}) \ & Z^{[l]} &: (n^{[l]}, n_s) \ & A^{[l]} &: (n^{[l]}, n_s) \end{aligned}$$

MIN3 The Logic of using a layered model

Why do we need to do layers?

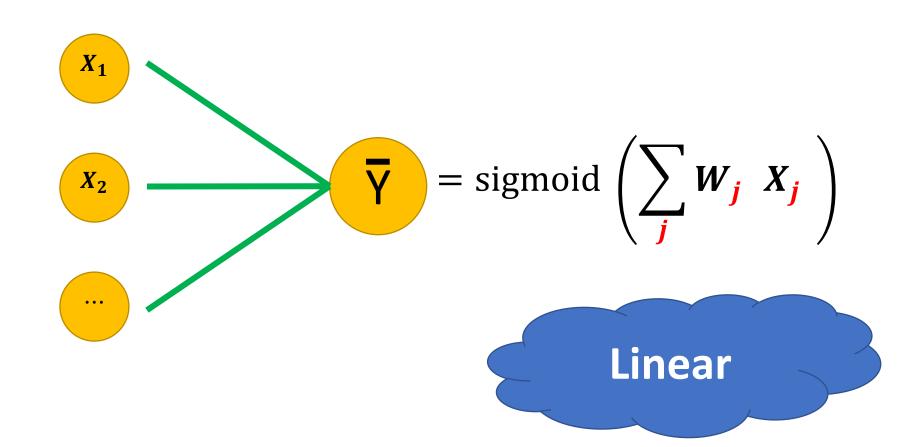
Reductionism: how we solve problems ...

Complex Problem



Simple Problem Simple Problem

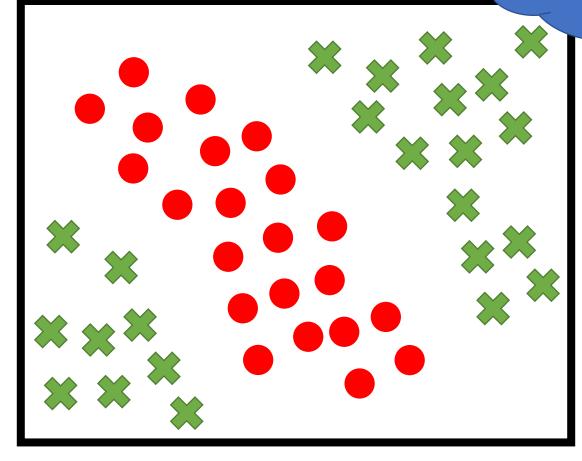
Simple Problem Simple Problem Let's take a step back and take a look at Logistic Regression.



Consider the following classification

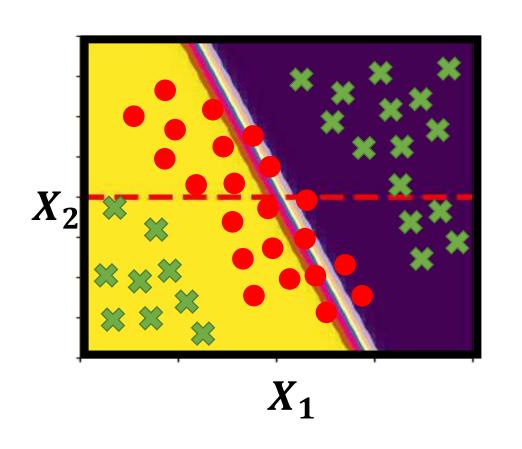
Example

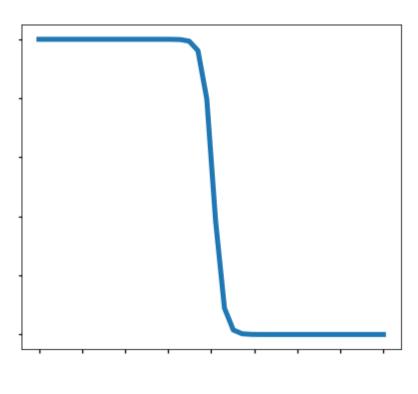
How well would LR do on this?



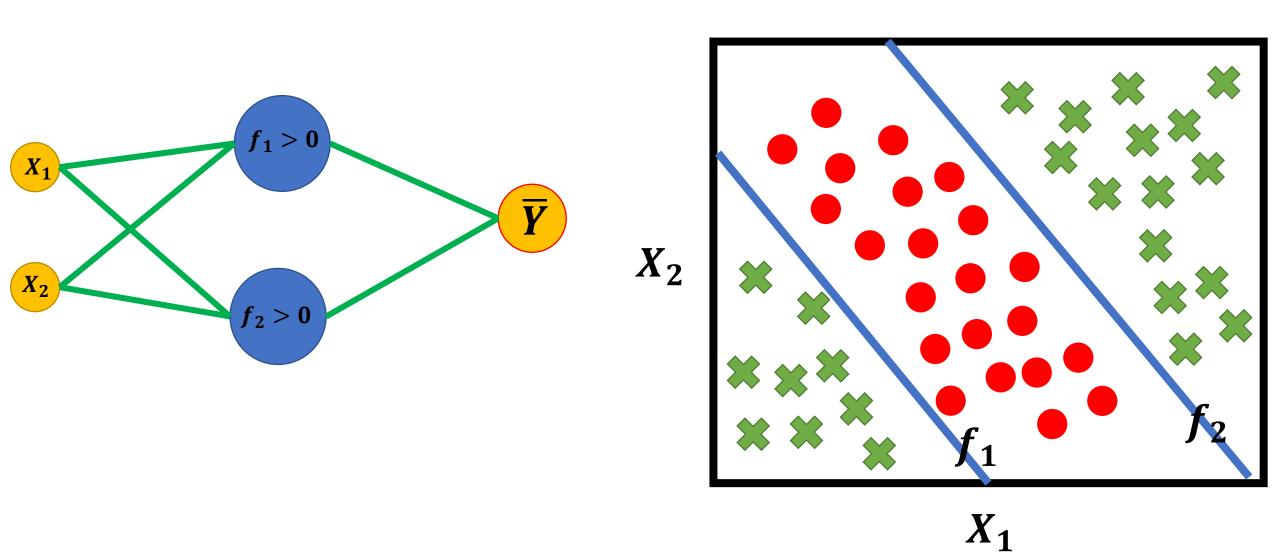
 $\boldsymbol{X_1}$

Example





Example: what is the solution



Example: NMR spectrum

Universality of NN:

Universal approximation theorem

 Hornik, Kurt; Tinchcombe, Maxwell; White, Halbert (1989). <u>Multilayer Feedforward Networks are Universal</u> <u>Approximators</u>. Neural Networks. 2. Pergamon Press. pp. 359–366.

Universality of NN:

Arbitrary width and Sigmoid, George Cybenko 89

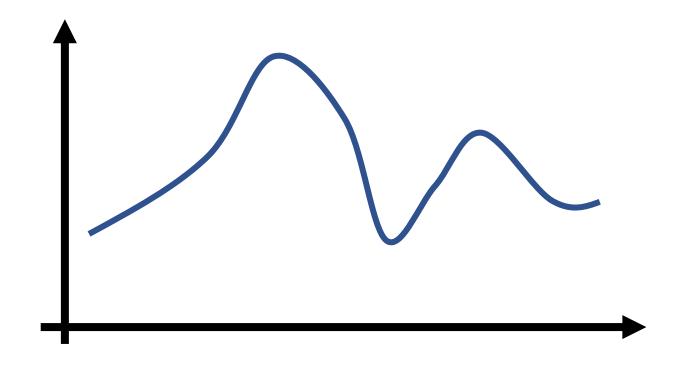
Depth

Enough depth, can reduce the width to n+c

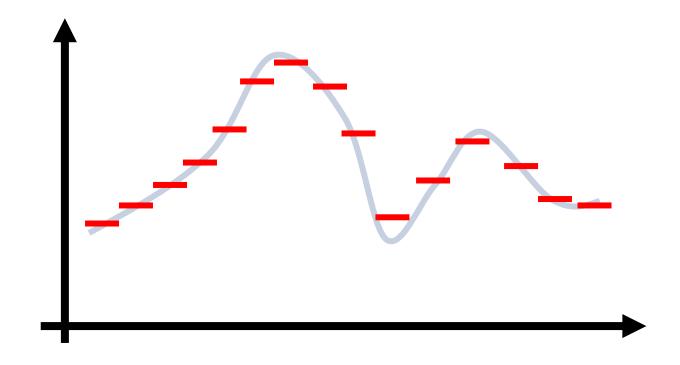
Activation Funciton

- Any activation function, Kurt Hornik 91
- Non-polynomial activation func are universal, Moshe Leshno et al 93

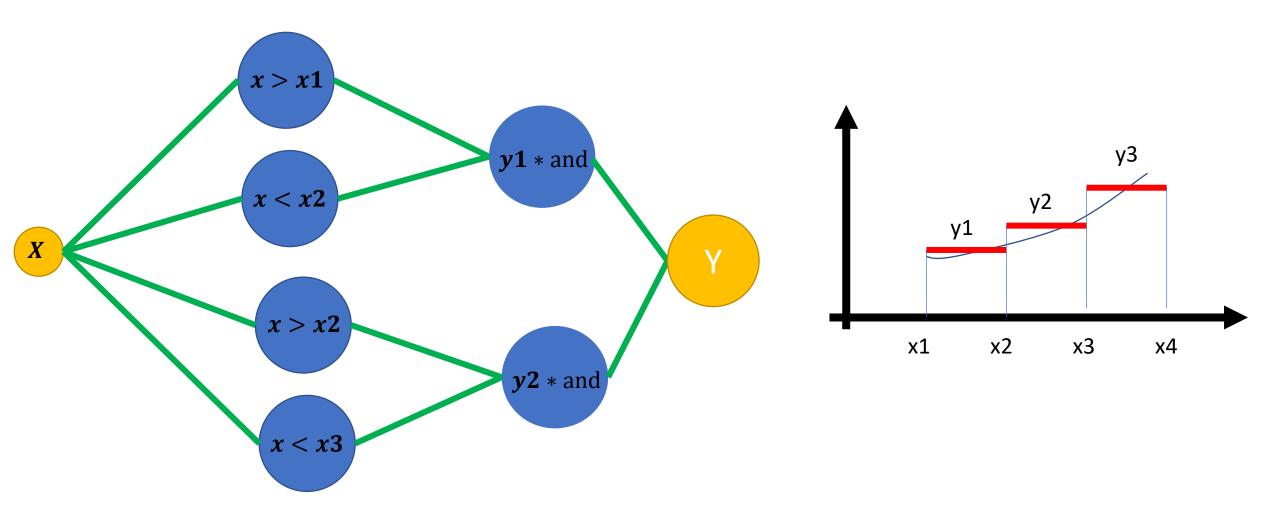
Universality of NN: Intuition



Universality of NN: Intuition



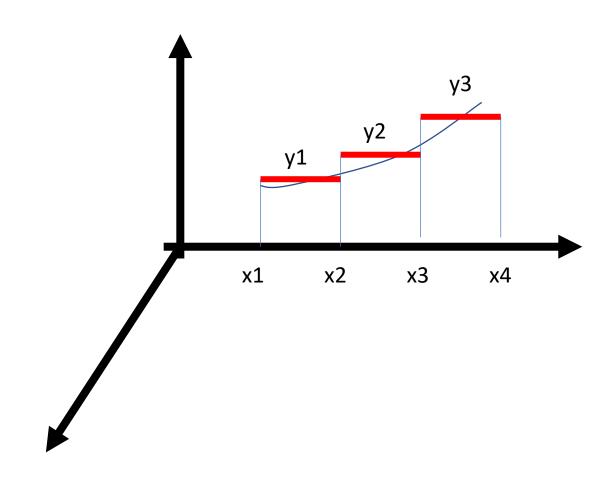
Universality of NN: Intuition



...

How does the depth help?

How does the number of features affect this?



What does the universality tell us?

Bias

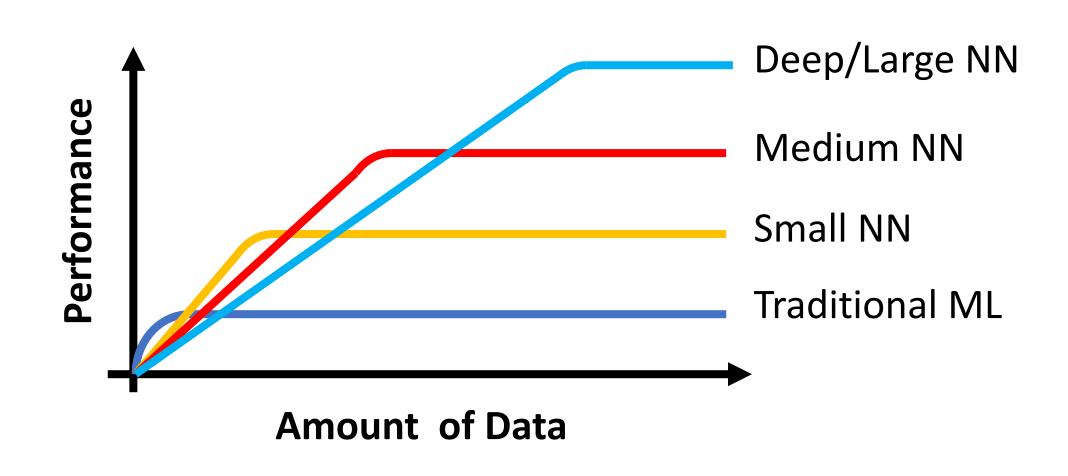
can be arbitrary small

if we allow for enough number of nodes or depth.

What do you think is going to happen to variance?

How can we deal with the increase in variance?

Data for NN



Summary

- Introduced NN
- Notation
- Universality of NN

Next ...

