

# When Neurons Fail

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July 25th, 2016



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1 Motivations

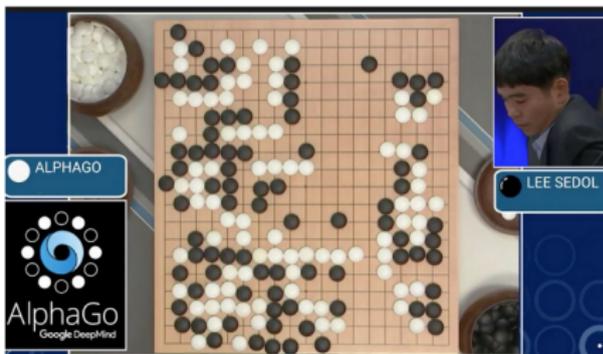
2 Problem statement

3 Results

# NNs everywhere



*"Do you want to tag Morgan Freeman?"*



## Model

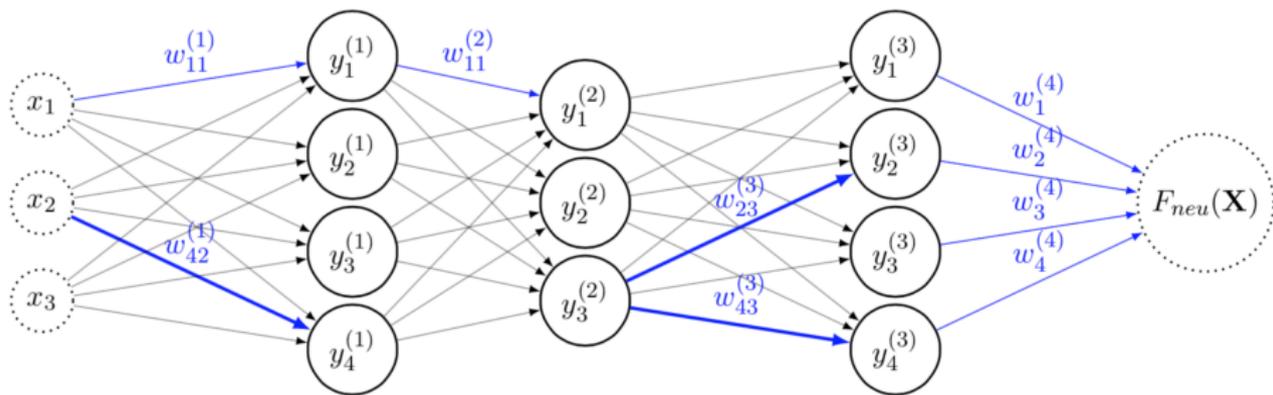


Figure : Feed forward neural network

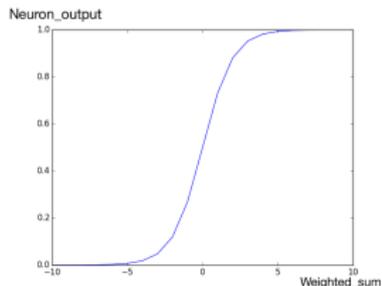
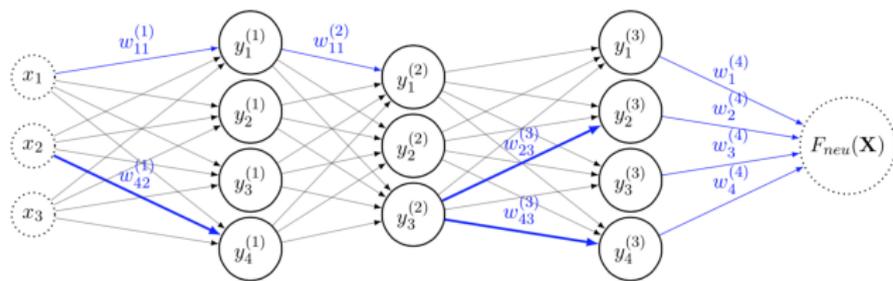
Nodes: neurons

Links: synapses

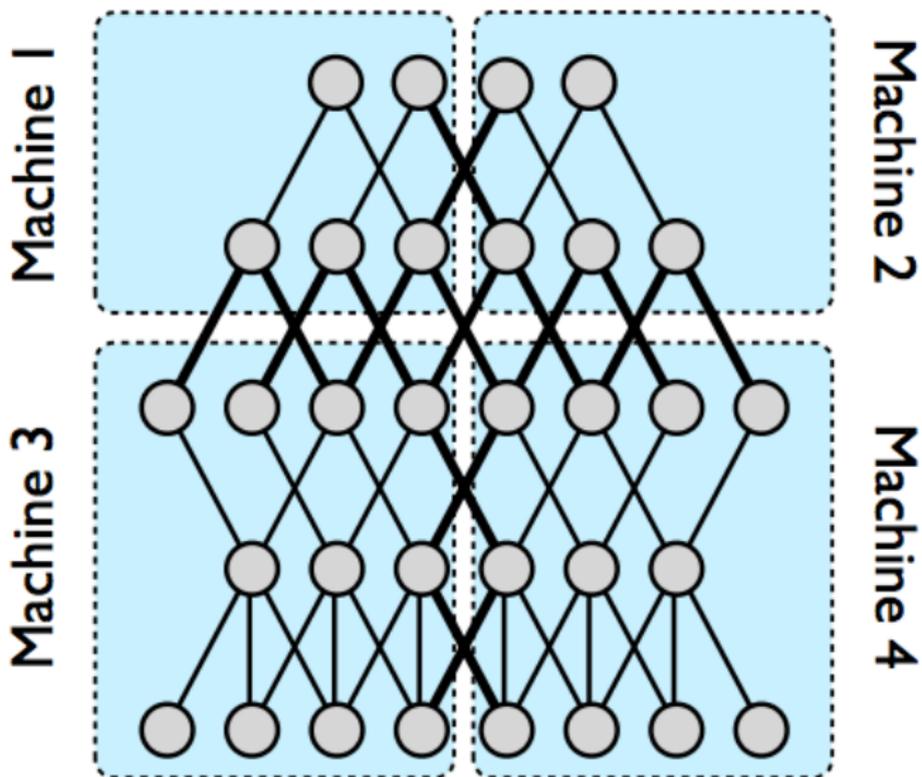
## Model

$$F_{neu}(\mathbf{X}) = \sum_{i=1}^{N_L} w_i^{(L+1)} y_i^{(L)}$$

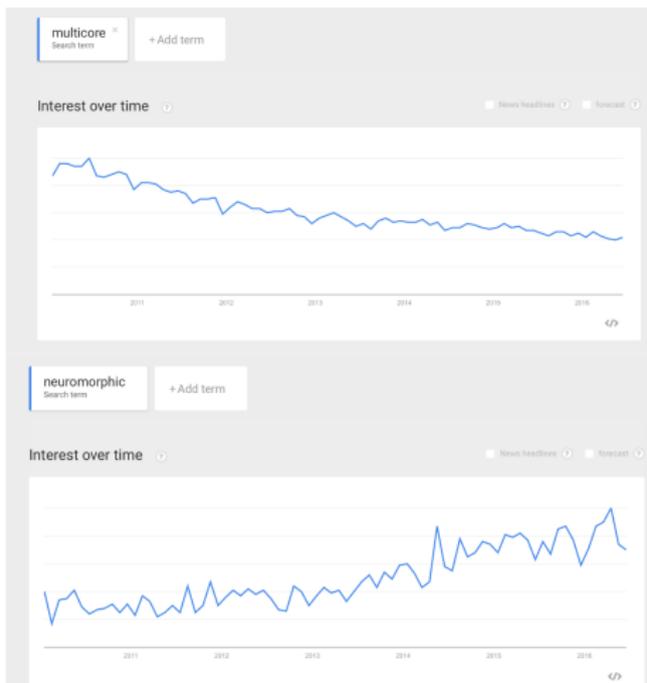
with  $y_j^{(l)} = \varphi(s_j^{(l)})$  for  $1 \leq l \leq L$ ;  $y_j^{(0)} = x_j$  and  $s_j^{(l)} = \sum_{i=1}^{N_{l-1}} w_{ji}^{(l)} y_i^{(l-1)}$



## Software simulated NN

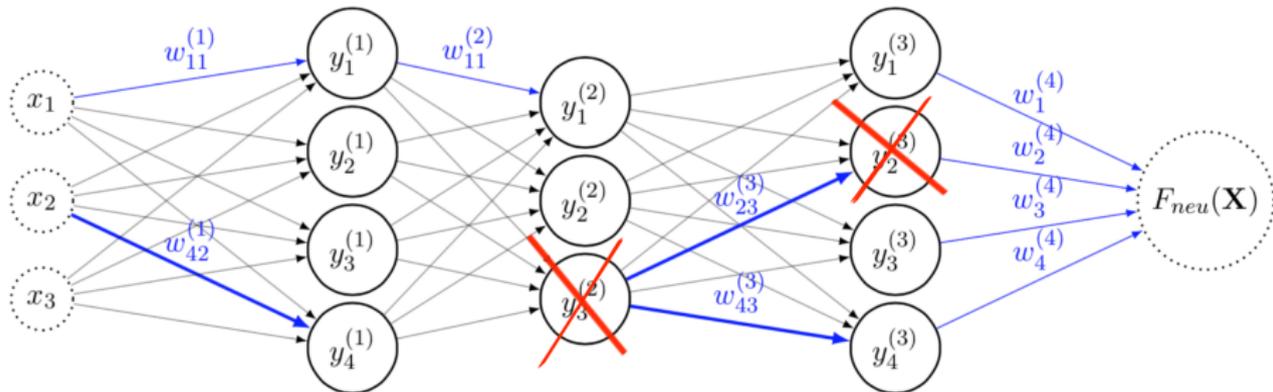


## Hardware-based NNs



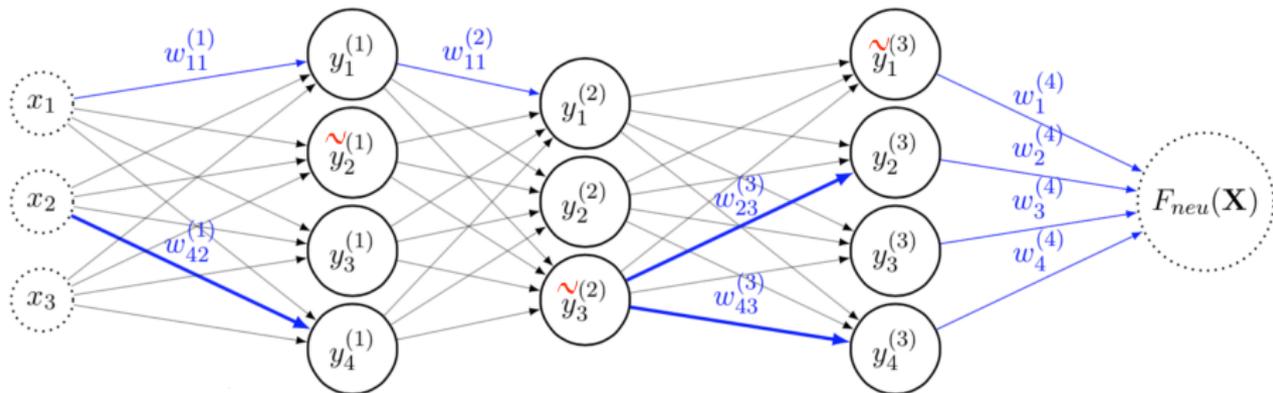
SyNAPSE (DARPA, IBM), Human Brain Project (SP9 on neuromorphic), Brains in Silicon at Stanford...

## How robust is this?



Crash failure: a component stops working.

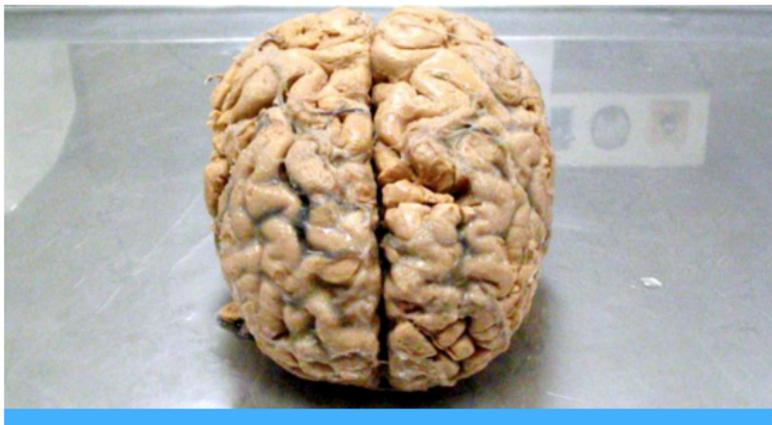
## How robust is this?



Byzantine failure: a component sends arbitrary values.

# Biological plausibility

## Examples of extreme robustness in nature



**A man who lives without 90% of his brain is challenging our concept of 'consciousness'**

The father of two lives a normal life.

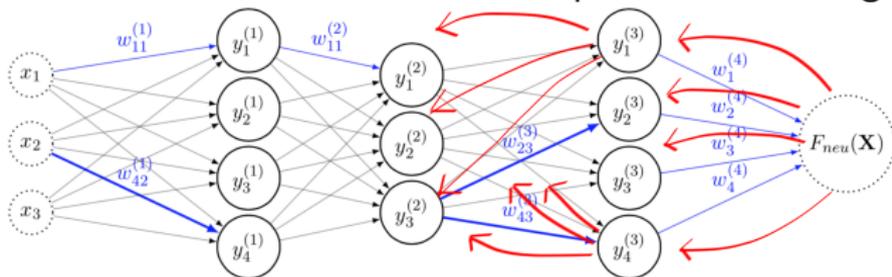
1

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<sup>1</sup>Feuillet et al., 2007. Brain of a white-collar worker. *Lancet (London, England)*, 370(9583), p.262.

## Classical training leads to non-robust NN

E: difference between desired and actual outputs on a training set



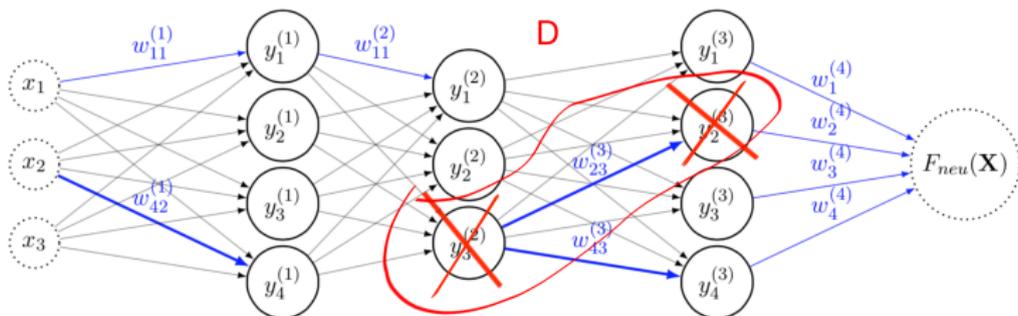
$$\Delta w_{ij}^{(l)} = -\frac{dE}{dw_{ij}^{(l)}}$$

$\exists$  robust weight distribution  $\mapsto$  Reach them with learning !

## Dropout

Randomly switch neurons off during the training phase

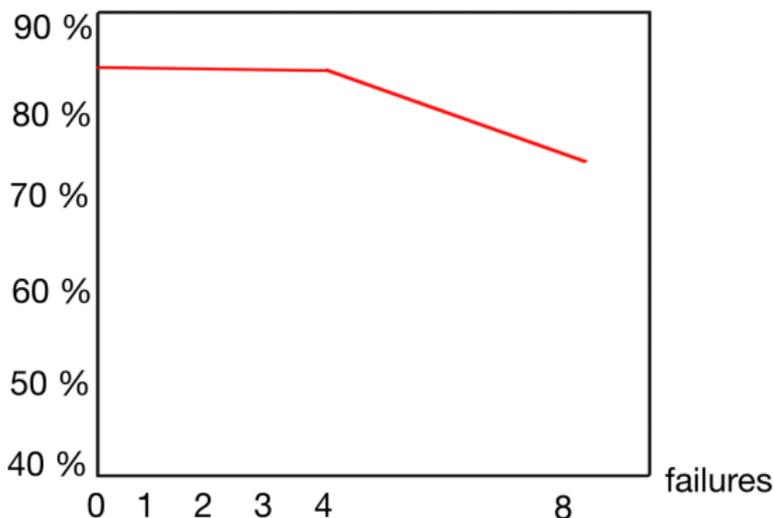
Kerlirzin and Vallet (1991, 1993), Hinton et al. (2012, 2014)



$$\text{Minimize } E_{av} = \sum_D E^D P(D) \text{ where } P(D) = (1 - p)^{|D|} p^{(N-|D|)}$$

## Experimentally observed robustness

generalisation rate



2

- Over-provisioning
- Upper-bound ?

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<sup>2</sup>from Kerlirzin 1993, edited

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- 3 Results

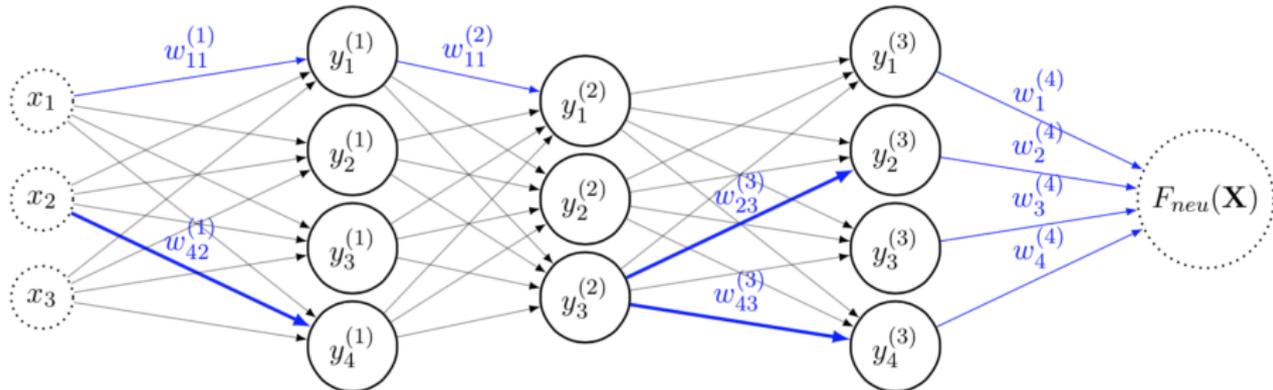
Given a precision  $\epsilon$ , derive a tight bound on failures to keep  $\epsilon$ -precision for a any neural network<sup>3</sup> approximating a function  $F$

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<sup>3</sup>note: learning is taken for granted

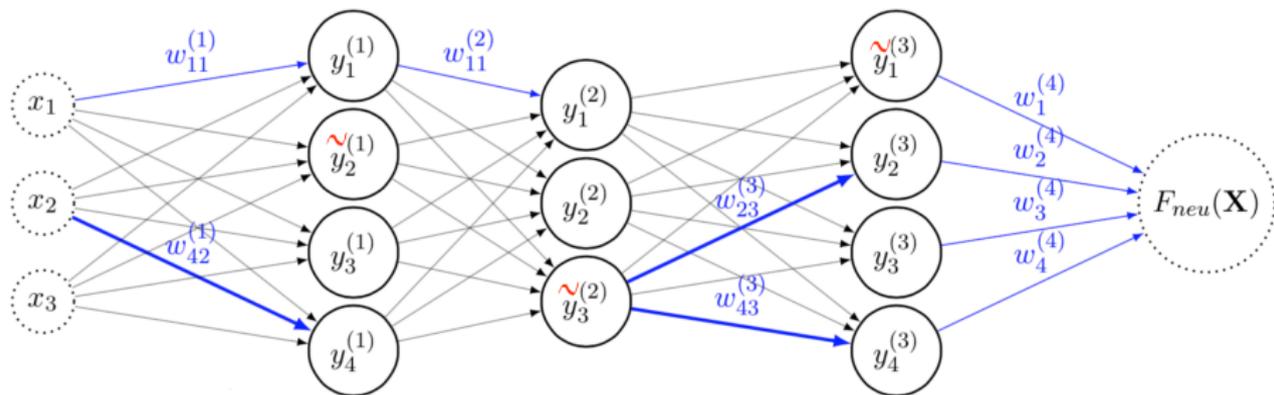
# Theoretical background: universality

Theorem<sup>4</sup>:  $\forall(F, \epsilon), \exists$  NN generating  $F_{neu}$  s.t  $\|F_{neu} - F\| < \epsilon$



<sup>4</sup>Cybenko 1989, Horkink 1991

## Problem statement

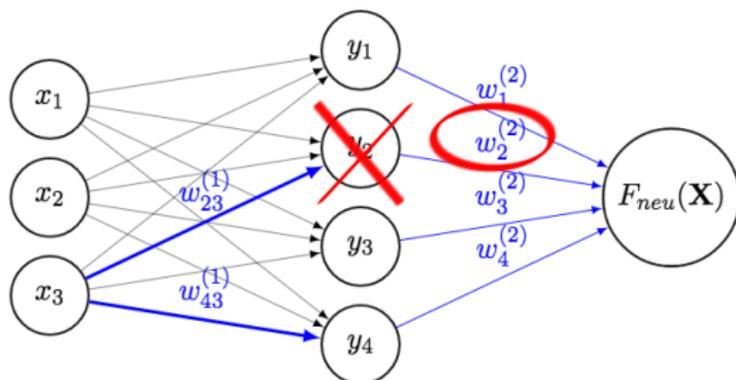


- Minimal networks are not robust <sup>5</sup>
- Given over-provision  $\epsilon'$  ( $\epsilon' < \epsilon$ ), what condition on failures to preserve  $\epsilon$ -precision?

<sup>5</sup>not to mention: impossible to derive

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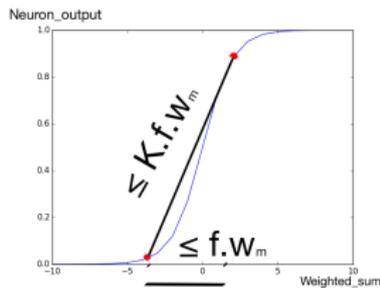
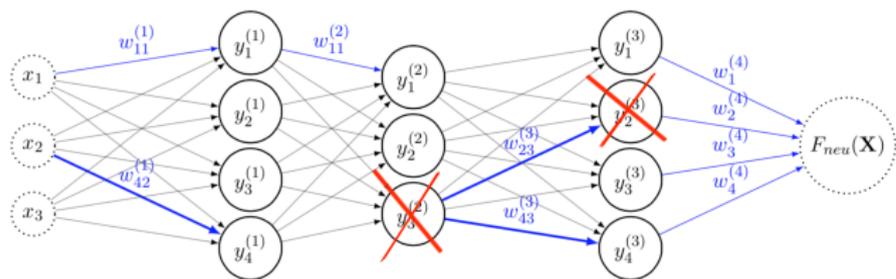
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$$f \leq \frac{\epsilon - \epsilon'}{W_m}$$

- More over-provision  $\mapsto$  more robustness
- Unequal weight distribution  $\mapsto$  single point of failure
- No Byzantine FT  $\mapsto$  bounded synaptic capacity

## Multilayer networks, Byzantine failures



- Failure at layer  $l$  propagates through layers  $l' > l$  (Byz and crash).
- Factors: weights, |layers|, |neurons|, Lipschitz coef. of  $\varphi$
- Total error propagated to the output should be  $\leq \epsilon - \epsilon'$

# Multilayer networks, Byzantine failures

- Bounded channel capacity (otherwise no robustness to Byzantine)

- Propagated error  $\leq C \sum_{l=1}^L \left( f_l K^{L-l} w_m^{(L+1)} \prod_{l'=l+1}^L (N_{l'} - f_{l'}) w_m^{(l')} \right)$

$C$ : capacity,  $K$ : Lipschitz coeff.,  $w_m^{(l)}$  maximal weight to layer  $l$   
 $N_l$ : |neurons|,  $f_l$ : |failures|

## How to read the formula

$$C \sum_{l=1}^L \left( f_l K^{L-l} w_m^{(L+1)} \prod_{l'=l+1}^L (N_{l'} - f_{l'}) w_m^{(l')} \right) \leq \epsilon - \epsilon'$$

## How to read the formula

$$C \sum_{l=1}^L \left( f_l K^{L-l} w_m^{(L+1)} \prod_{l'=l+1}^L (N_{l'} - f_{l'}) w_m^{(l')} \right) \leq \epsilon - \epsilon'$$

worst-case propagated error

## How to read the formula

$$C \sum_{l=1}^L \left( f_l K^{L-l} w_m^{(L+1)} \prod_{l'=l+1}^L (N_{l'} - f_{l'}) w_m^{(l')} \right) \leq \epsilon - \epsilon'$$

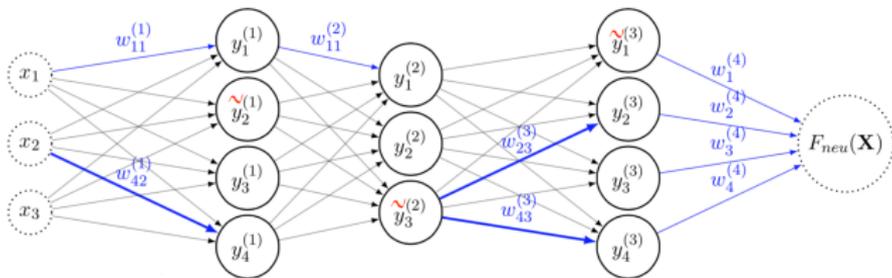
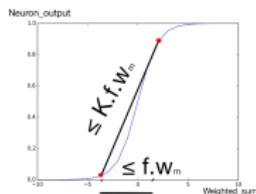
error margin permitted by the over-provision

## How to read the formula

$$C \sum_{l=1}^L \left( f_l K^{L-l} w_m^{(L+1)} \prod_{l'=l+1}^L (N_{l'} - f_{l'}) w_m^{(l')} \right) \leq \epsilon - \epsilon'$$

Error (at most  $C$  is transmitted) at  $f_l$  neurons in layer  $l$  propagating through  $l' > l$ .

$(N_{l'} - f_{l'})$  : only correct neurons propagating it, multiplying by  $K w_m^{(l')}$ .



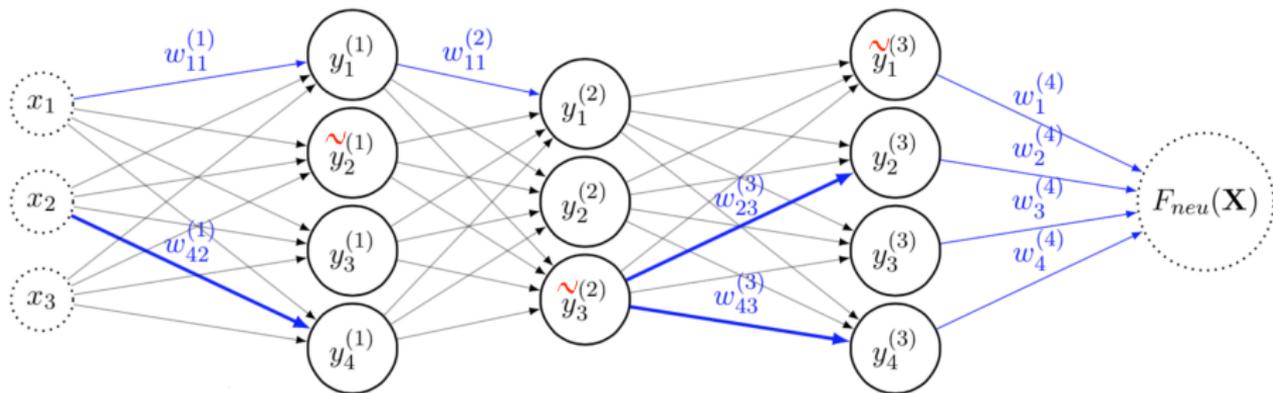
## Unbounded capacity

Taking  $C \mapsto \infty$

$$C \sum_{l=1}^L \left( f_l K^{L-l} w_m^{(L+1)} \prod_{l'=l+1}^L (N_{l'} - f_{l'}) w_m^{(l')} \right) \leq \epsilon - \epsilon'$$

Then  $\forall l f_l = 0$

No Byzantine FT.



- Generalization to synaptic failures.
- Applications of the bound (Memory cost, neuron duplication, synchrony)
- Other neural computing models.

## Questions ?

More details: <https://infoscience.epfl.ch/record/217561>