Deep Learning

CS771: Introduction to Machine Learning

Purushottam Kar

A New Perspective on Non-linear Learning

Kernels allow us to nicely reuse linear algos to learn nonlinear models

- *Very powerful (and expensive too) – offer non-parametric learning*
- *Not all ML algos can be easily kernelized – e.g. those that use L_1 regularization*
- *In general, algos that use L_2 distances and dot products are kernelizable*

Other techniques exist to perform non-linear learning as well

- *kNN is one such prominent example – also a non-parametric algo*
- *Decision trees offer very good performance and very fast prediction too*
- *Other "parametric" methods such as splines, sinusoids popular in statistics*

Another successful non-linear learning technique is deep learning

- *Predates kernel learning and machine learning itself by decades*
- *Not very popular till recently due to lack of data, computational power*
- *Very successful and well-researched technique currently*

From Kernel Learning to Deep Learning

Notice that kernel learning essentially involves learning a linear model over new features. The new features are given by the kernel map ϕ_K

- *The num of features is large (infinite?) which causes kernel algos to be slow*
- *Several techniques to speed up kernel methods address this exact problem*
- *Landmarking/Nystrom create new features using similarity values*
- *Random feature methods also create new features from rank 1 kernels*

Given a budget k can we directly learn k good features?

- *In some sense, deep learning does exactly this*
- *Several deep networks basically run a linear ML algo on top of learnt features*
- ***Key difference**: instead of first learning good features and then learning a linear model on top of those features, deep learning learns both jointly*
- ***Drawbacks**: non-convex problem, over parameterized, can be bulky/slow*

Kernel Learning viewed as Deep Learning

Consider the quadratic kernel $K_{\text{quad}} = (\langle \mathbf{x}, \mathbf{y} \rangle + 1)^2$ on $\mathcal{X} = \mathbb{R}^2$

The feature map for K_{quad} is ϕ_{quad} where for $\mathbf{x} = (\mathbf{x}_1, \mathbf{x}_2) \in \mathbb{R}^2$

$$\phi_{\text{quad}}(\mathbf{x}) = \left[1, \sqrt{2} \cdot \mathbf{x}_1, \mathbf{x}_1^2, \sqrt{2} \cdot \mathbf{x}_1 \cdot \mathbf{x}_2, \mathbf{x}_2^2, \sqrt{2} \cdot \mathbf{x}_2\right] \in \mathbb{R}^6$$

A linear model over ϕ_{quad} is represented as a vector $\mathbf{w} \in \mathbb{R}^6$

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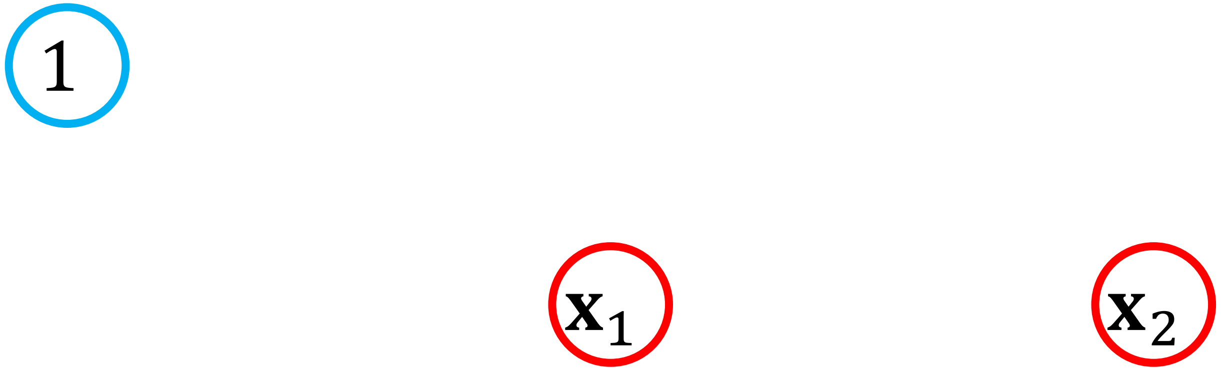

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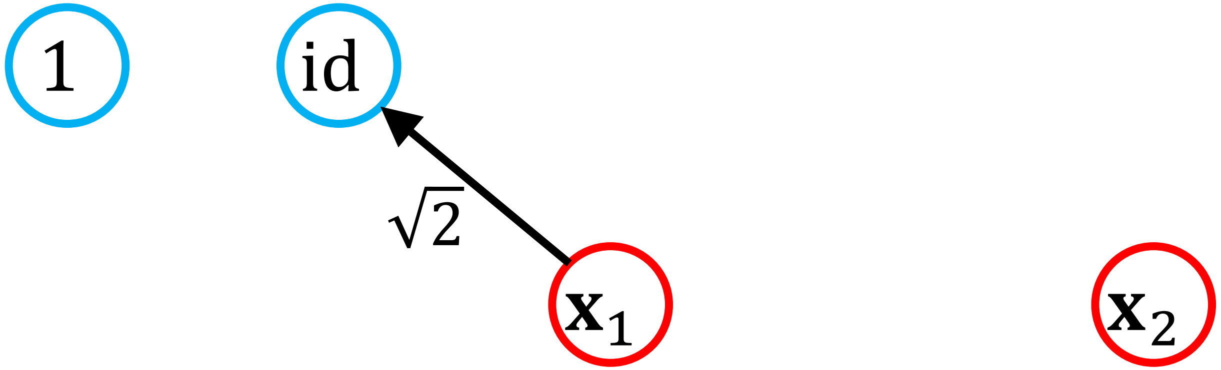

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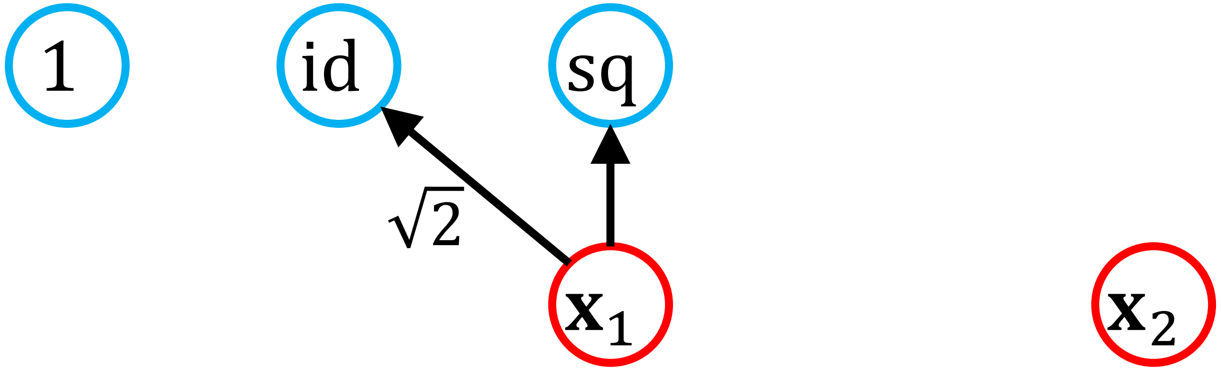

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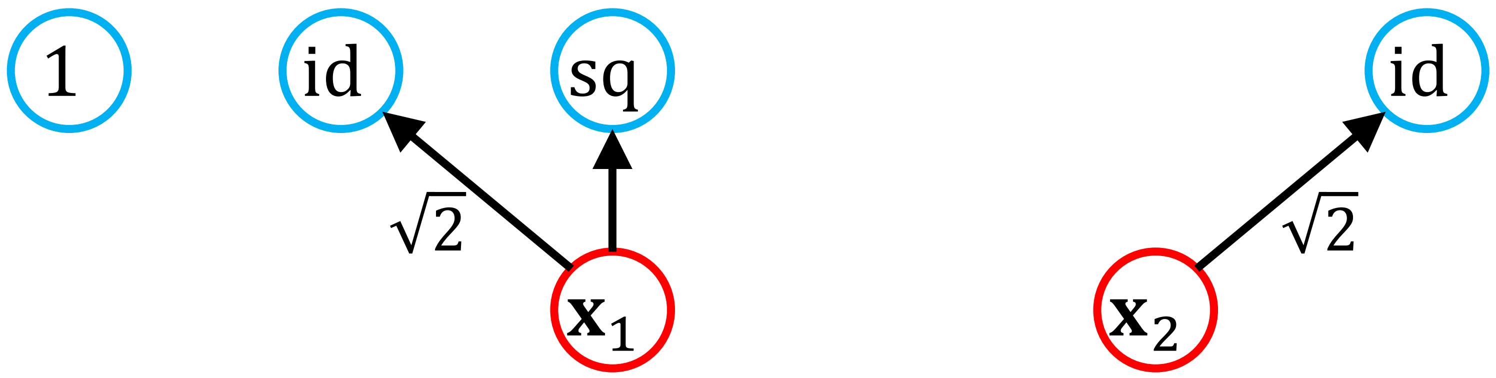

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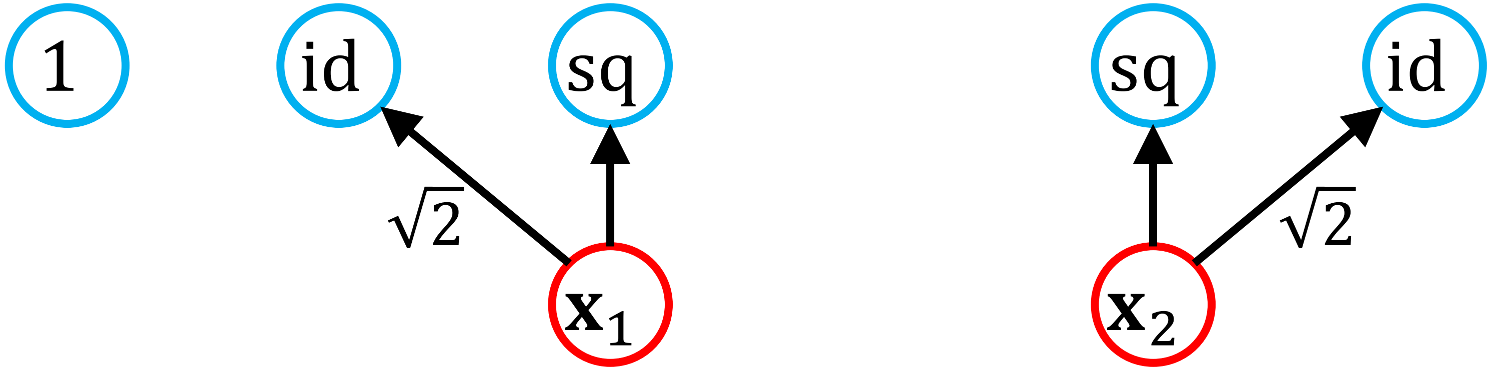

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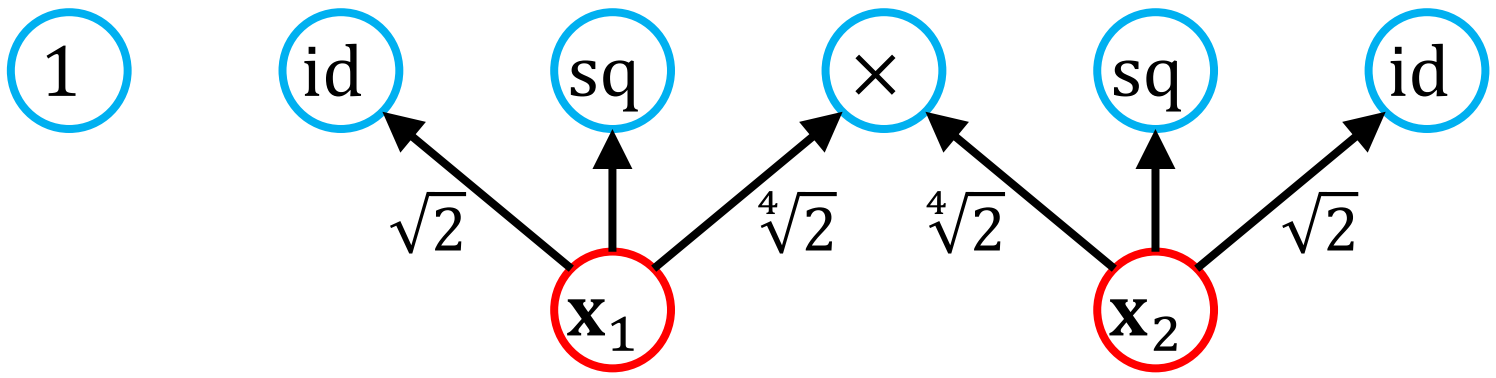

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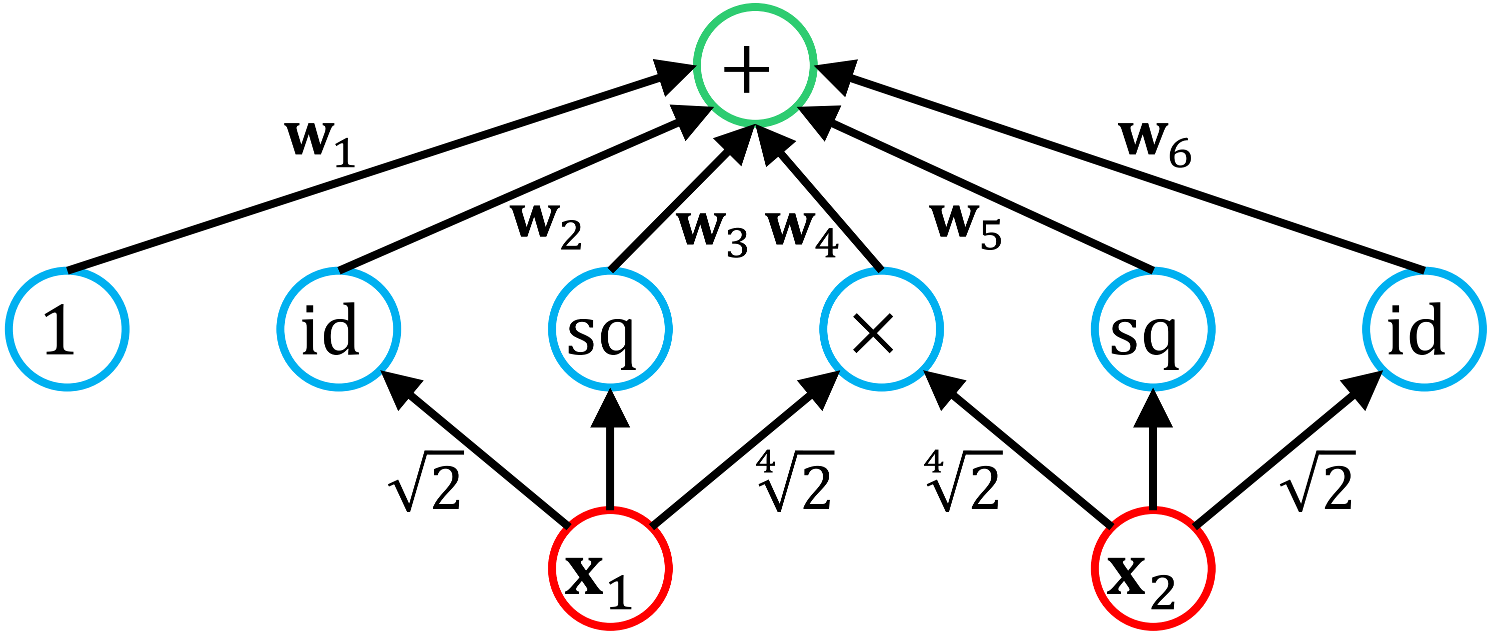

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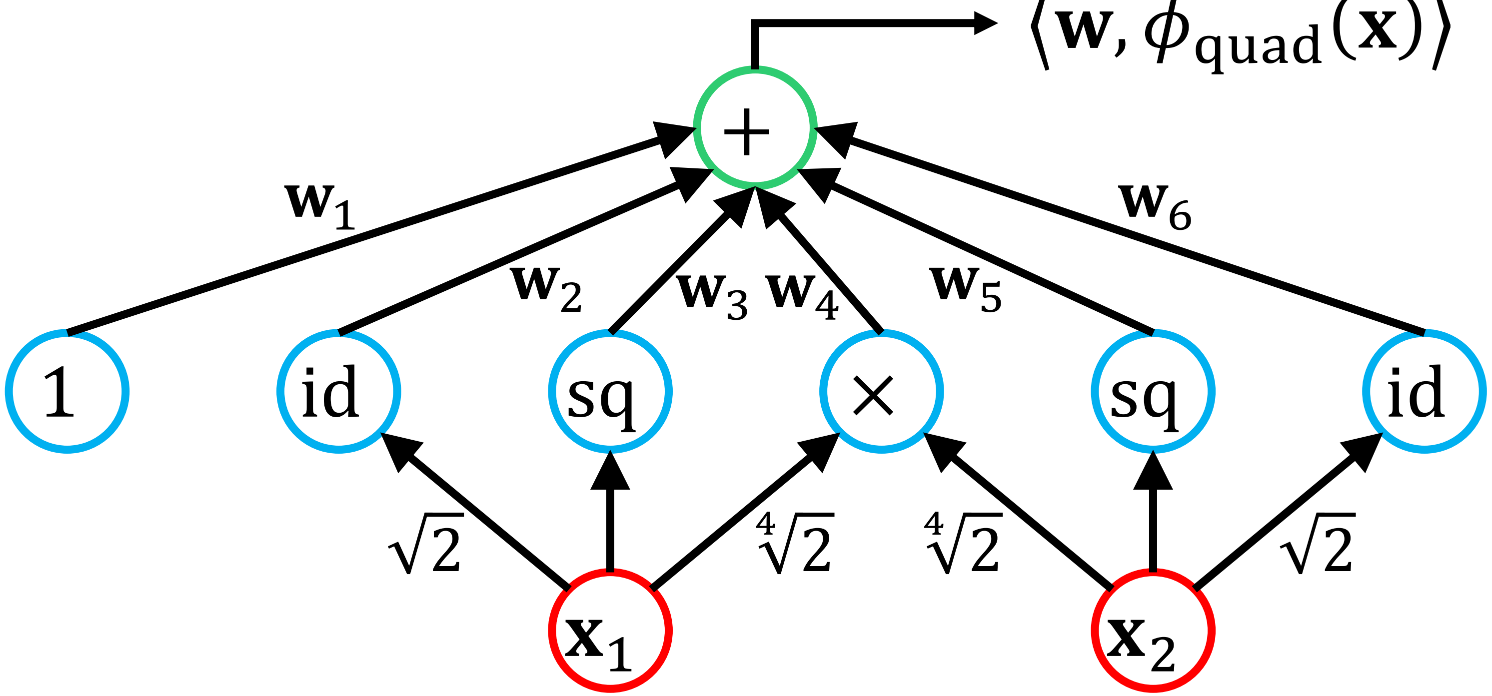

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Training kernel SVM/RR tunes these weights

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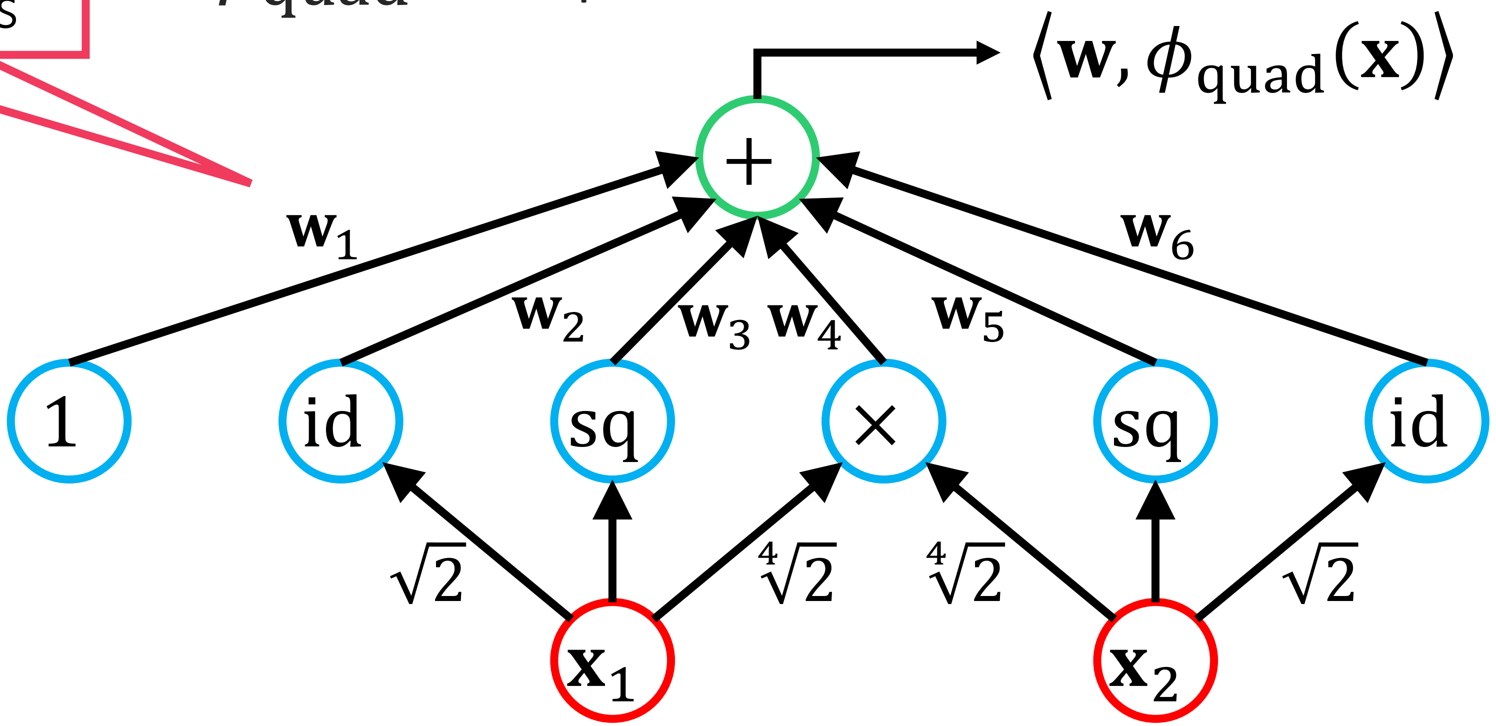

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A 3 layer network

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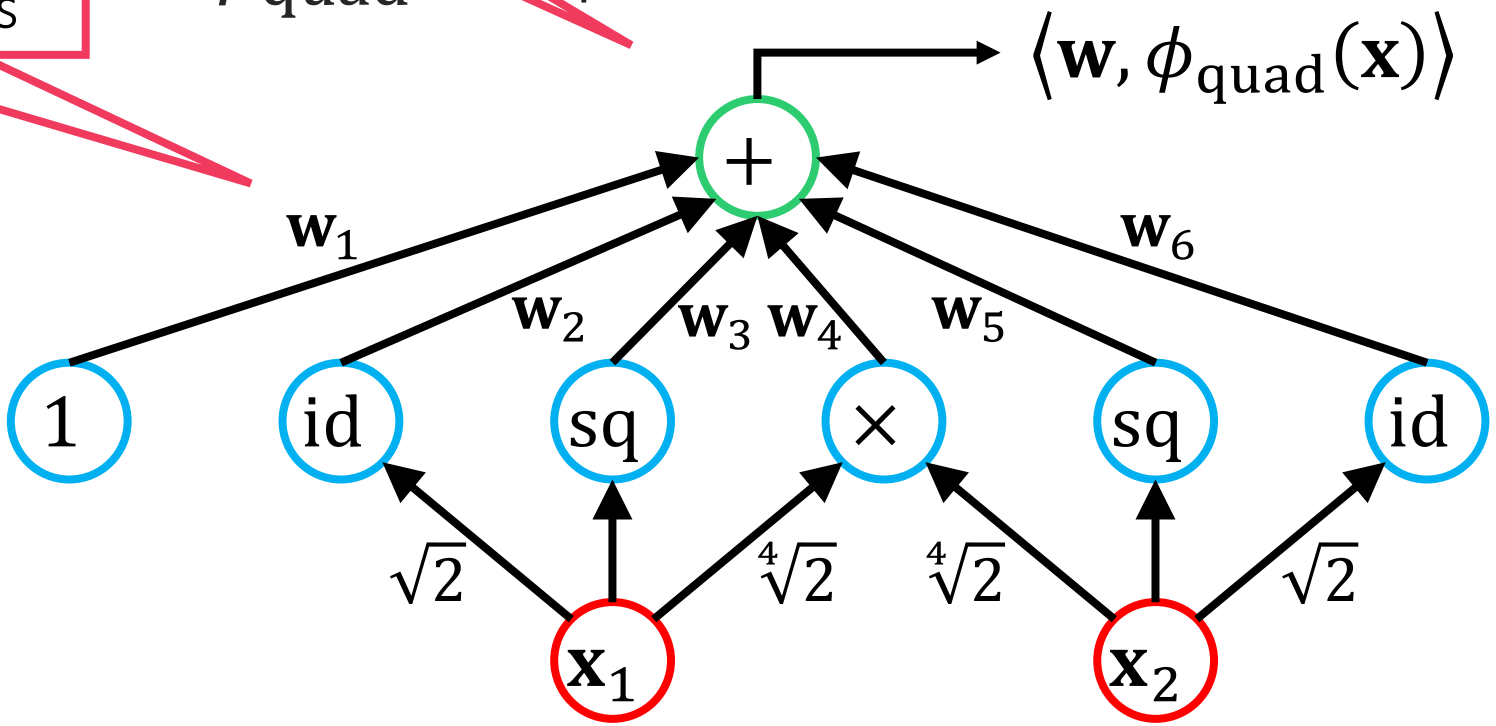

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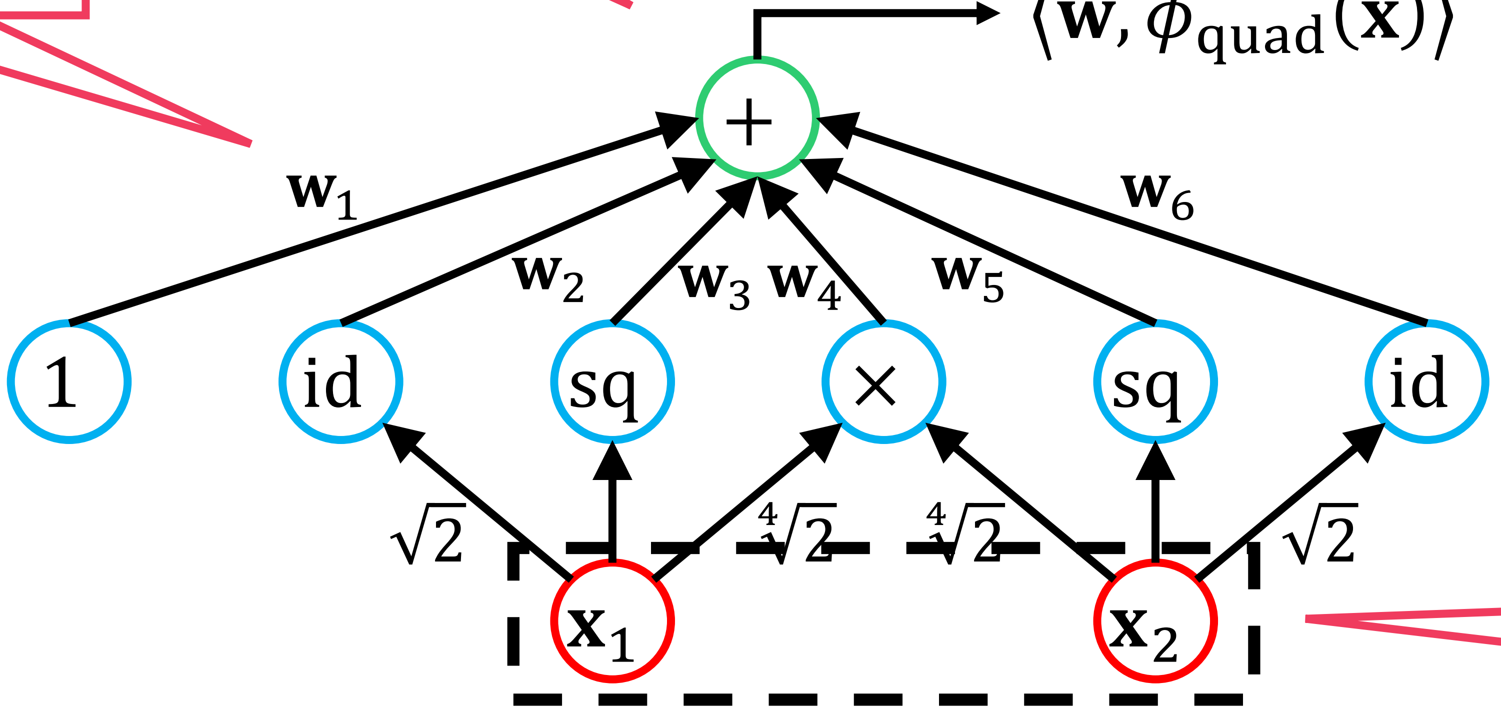

Input layer

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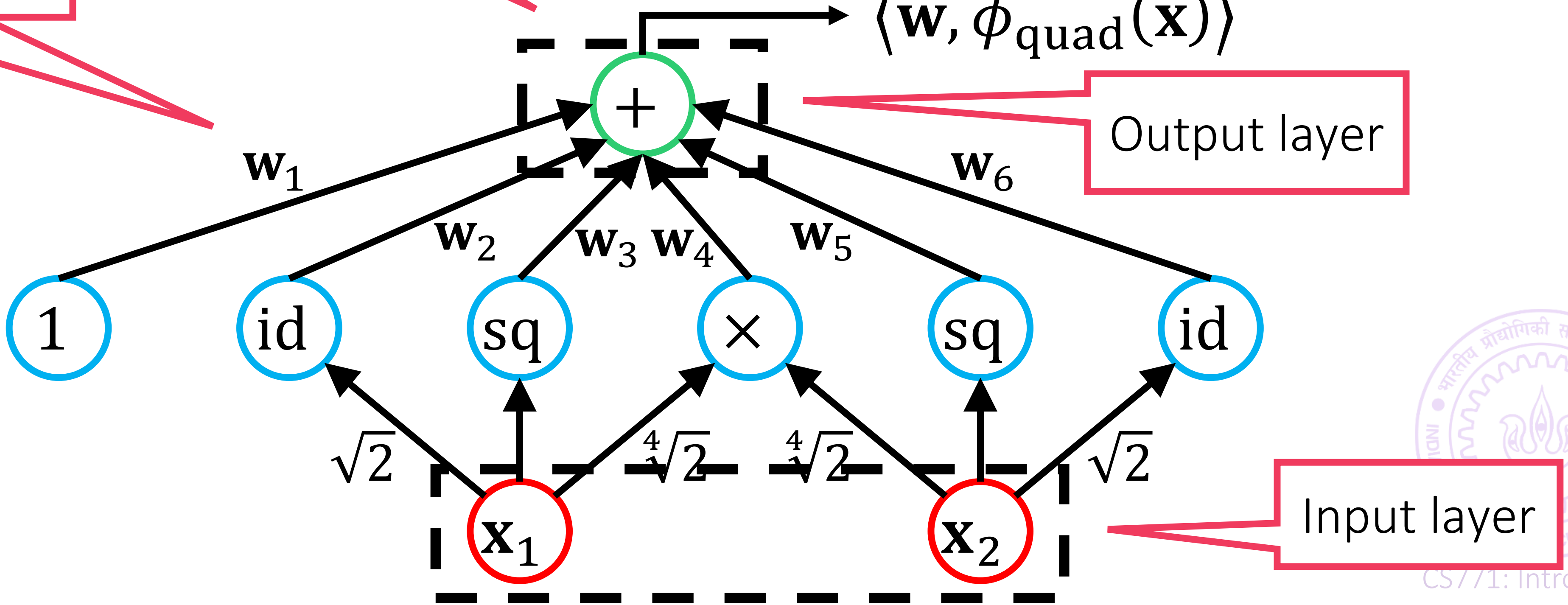

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A 3 layer network

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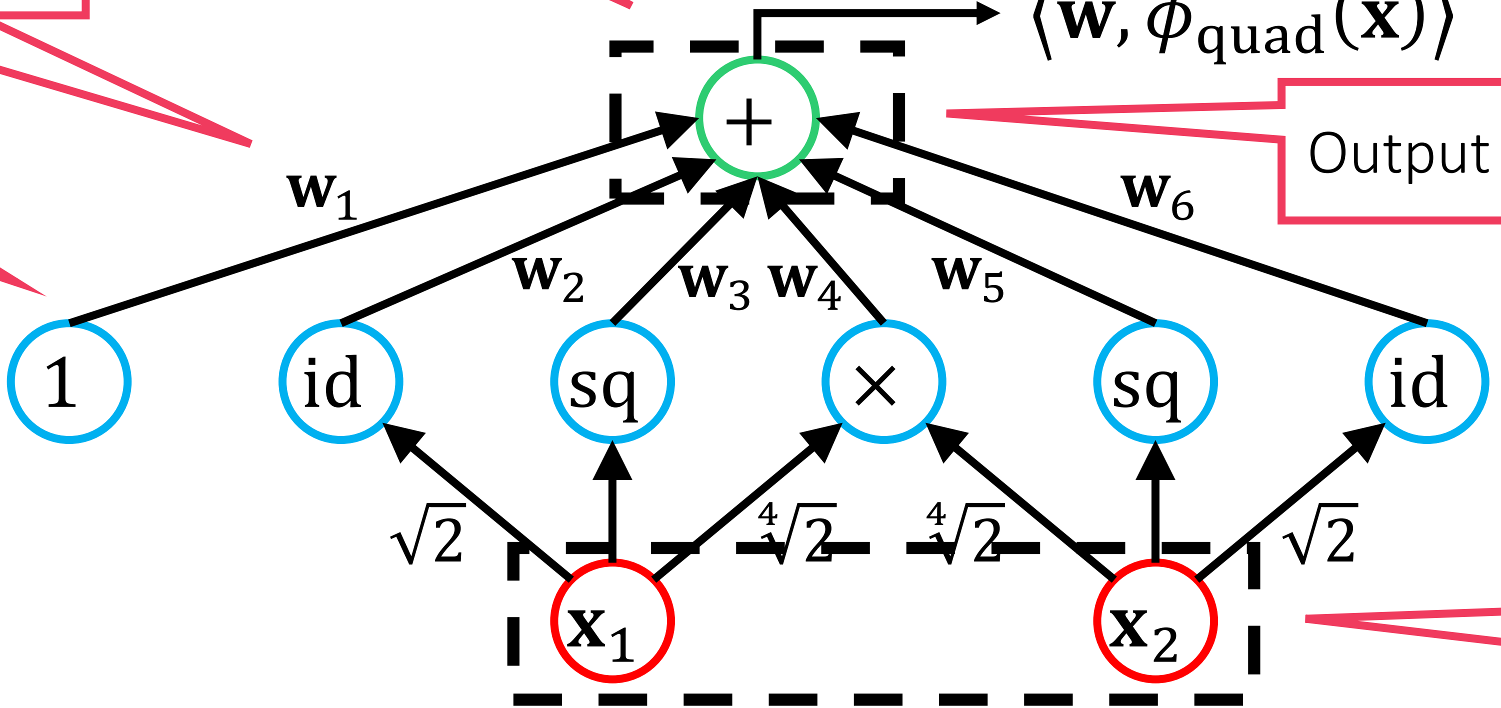
I/O layers are called "visible"



Output layer

Input layer

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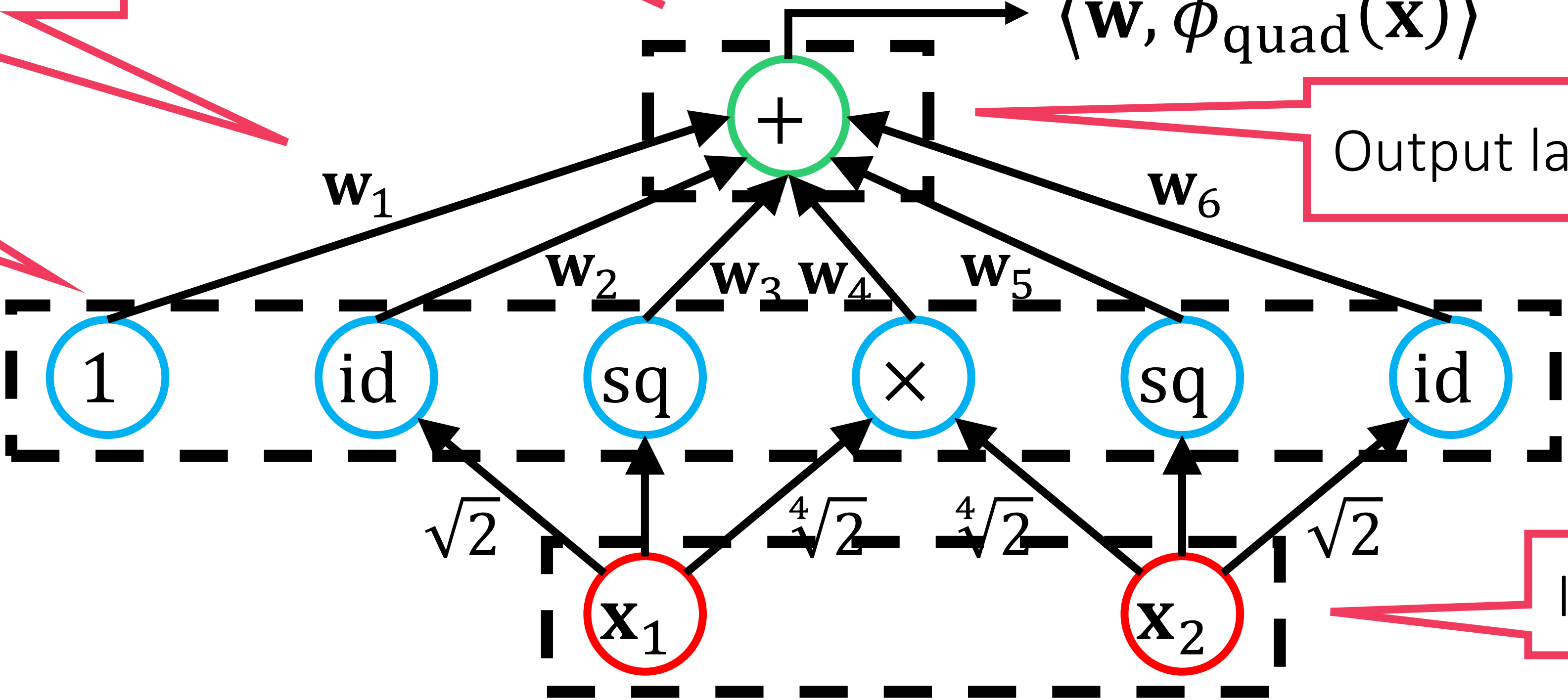
I/O layers are called “visible”

“Hidden” layer Usually many of these

Output layer

Input layer



The “Neuron” in Deep/Neural Networks

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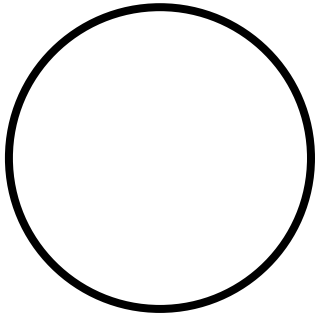

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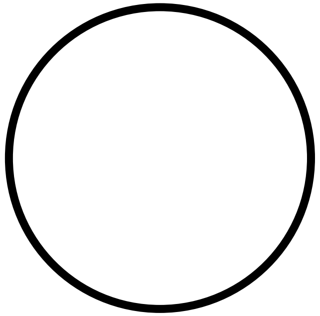

$\mathbf{x}_1$ $\mathbf{x}_2$ … $\mathbf{x}_\mathrm{d}$

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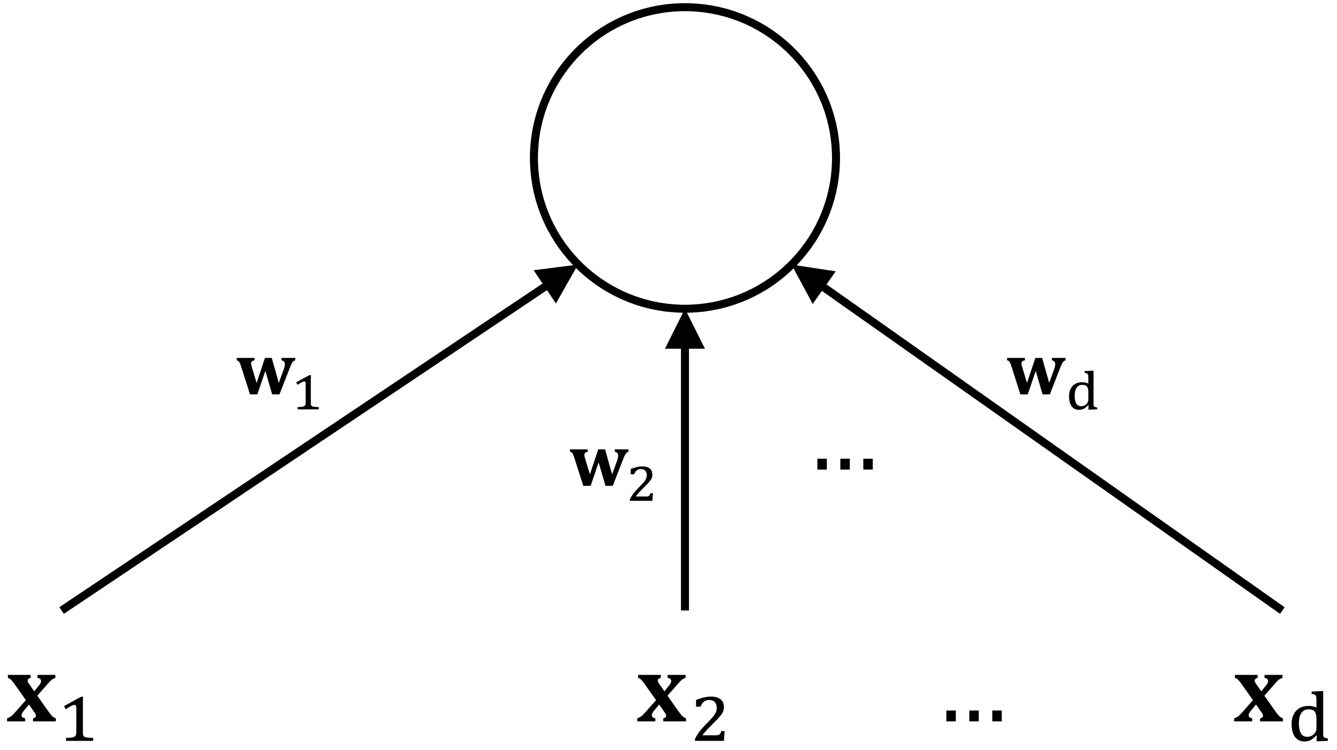

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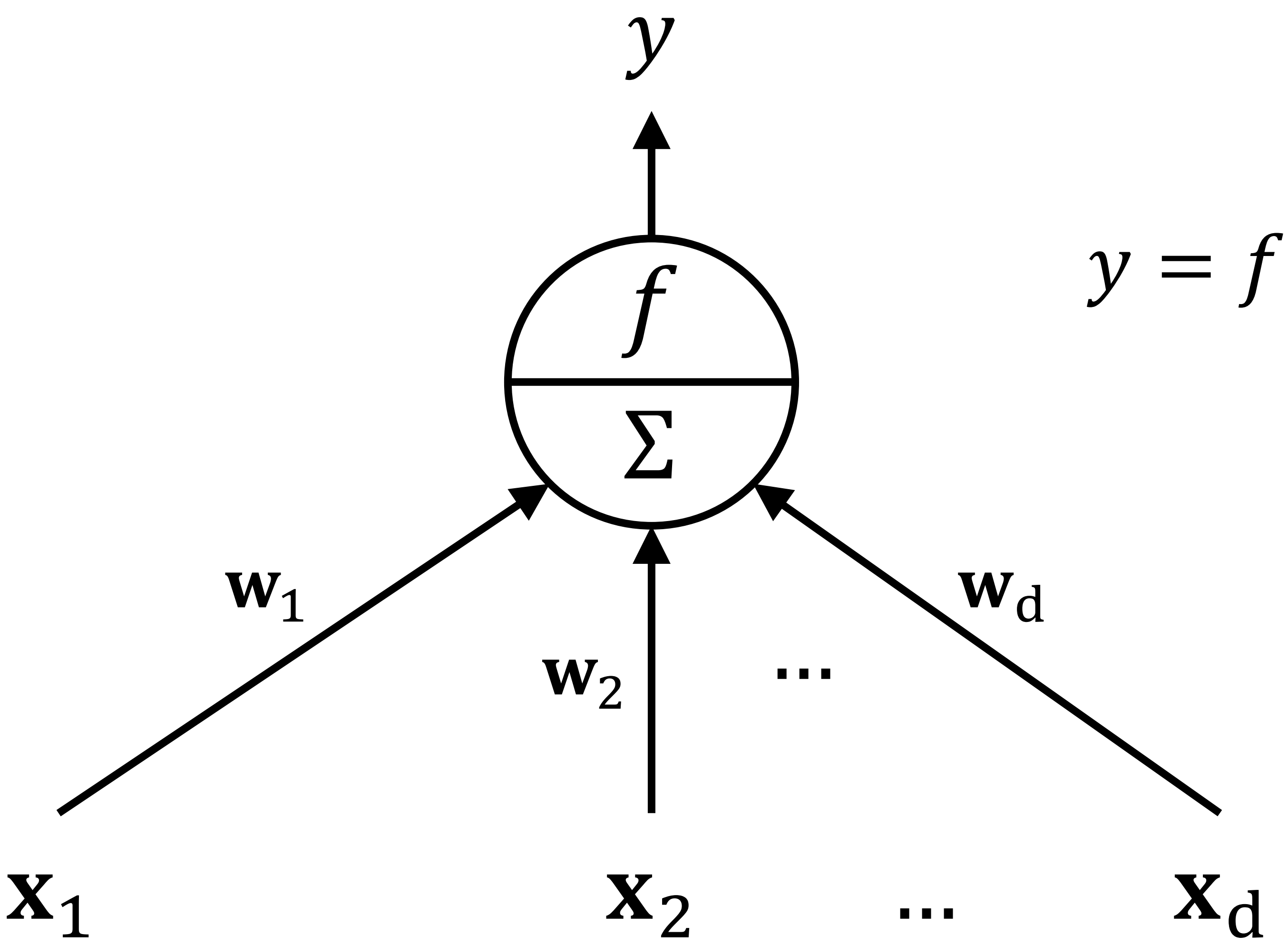

$$y = f\left(\sum_{i=1}^{d} \mathbf{w}_i \cdot \mathbf{x}_i\right)$$

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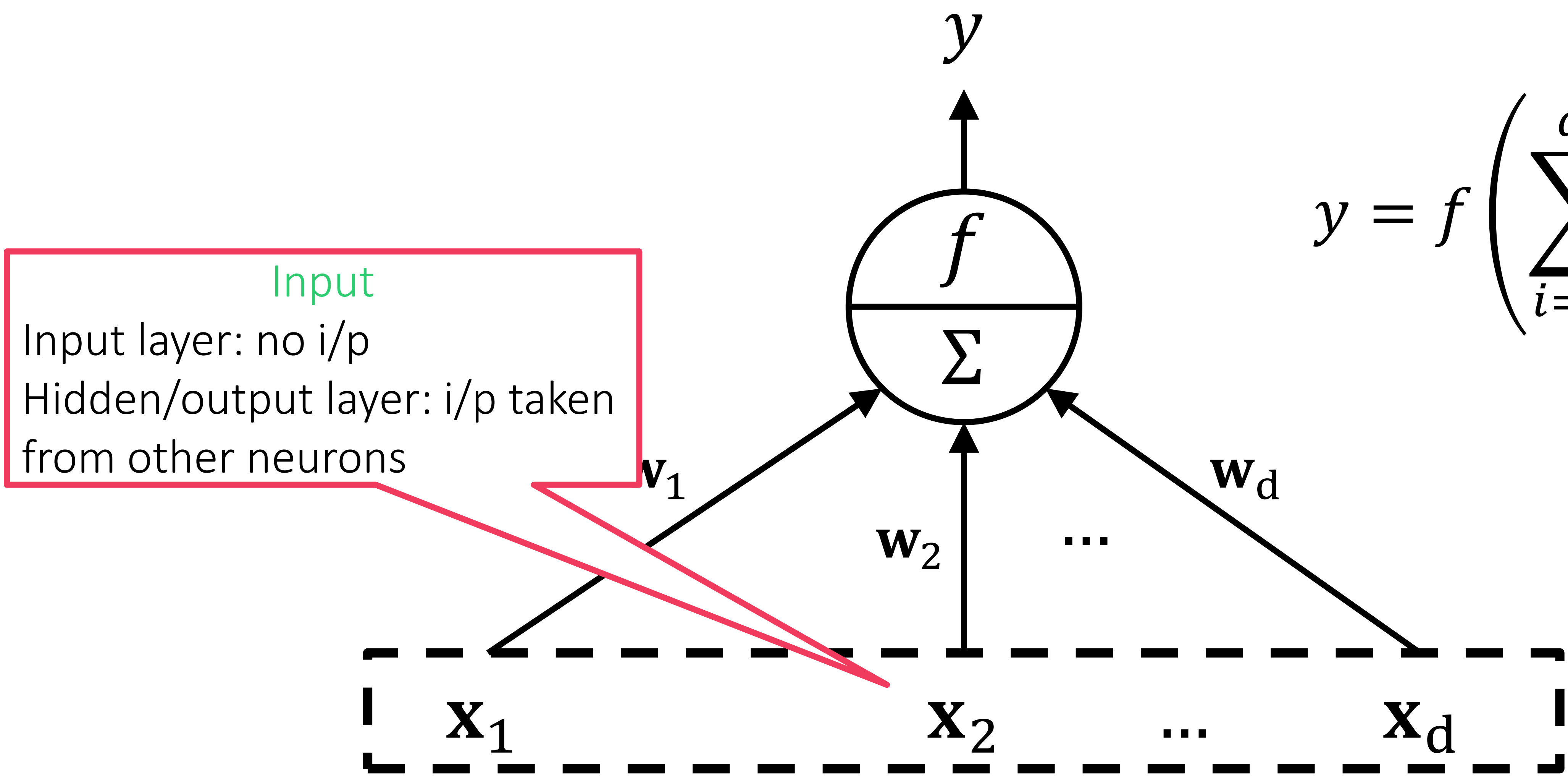

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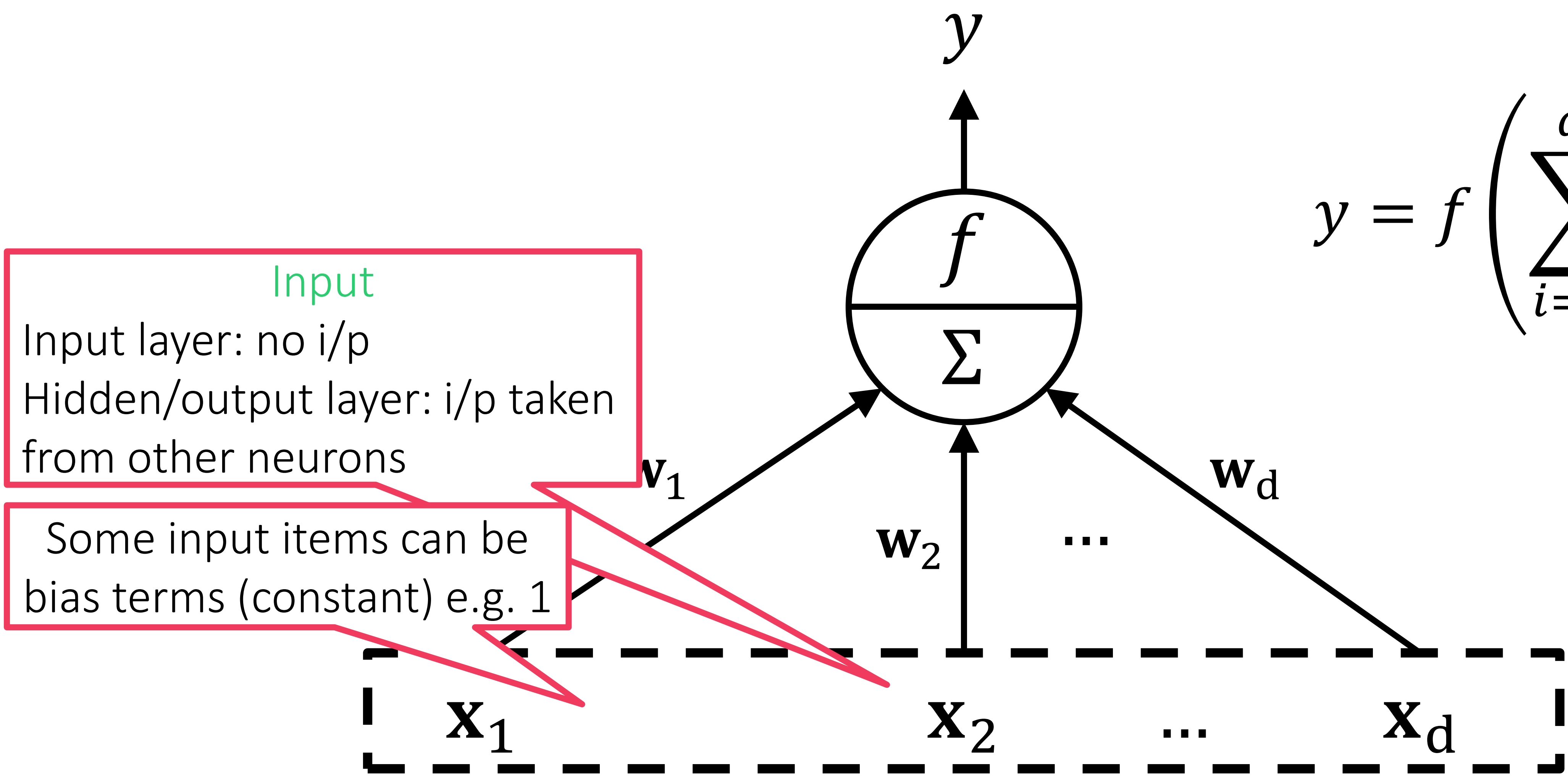

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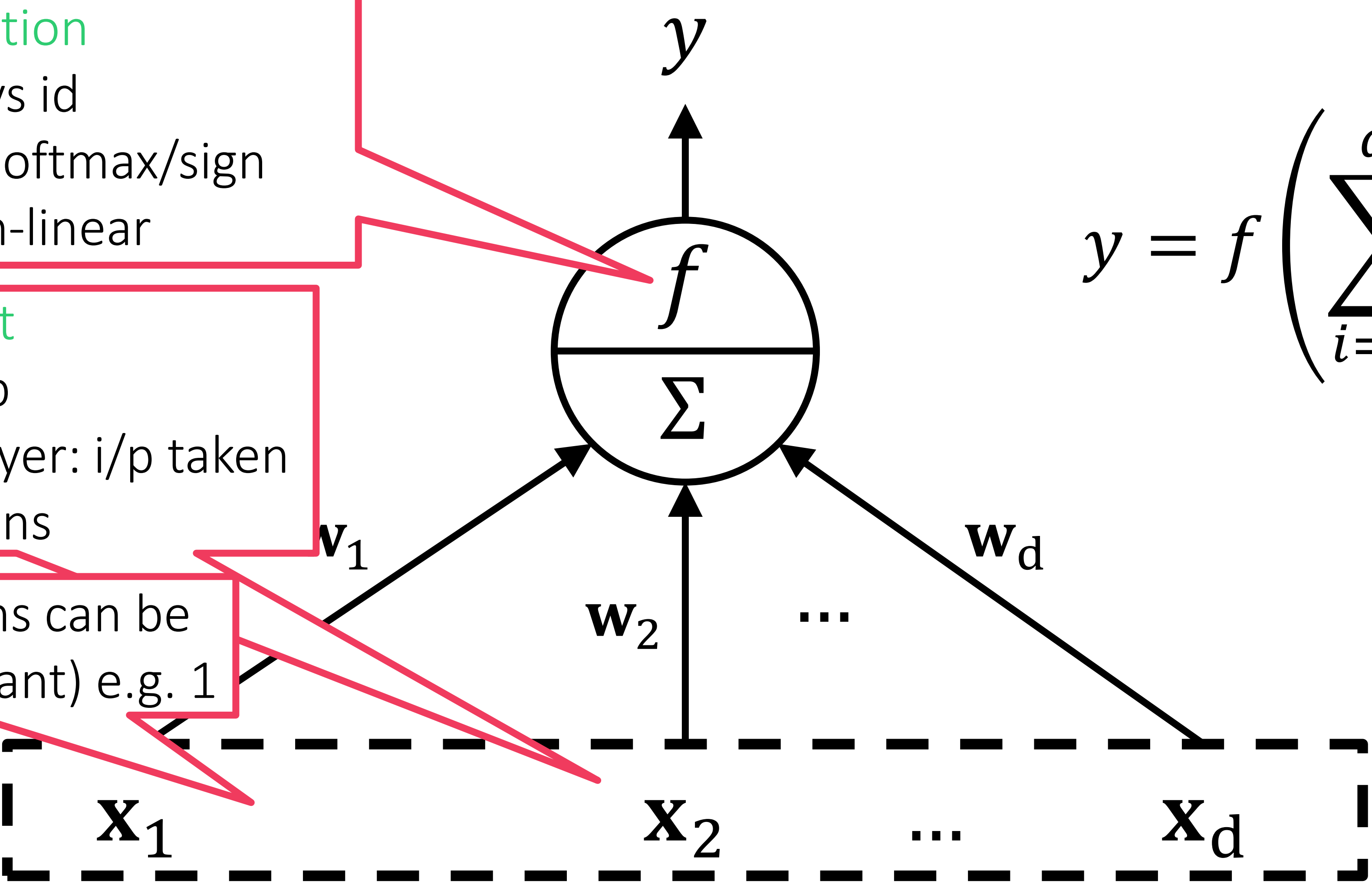
The “Neuron” in Deep/Neural Networks

Activation
Input layer: always id
Output layer: id/softmax/sign
Hidden layer: non-linear

Input
Input layer: no i/p
Hidden/output layer: i/p taken from other neurons

Some input items can be bias terms (constant) e.g. 1



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in Deep/Neural Networks

Output
Output layer: final o/p
Input/hidden layer: o/p to other neurons

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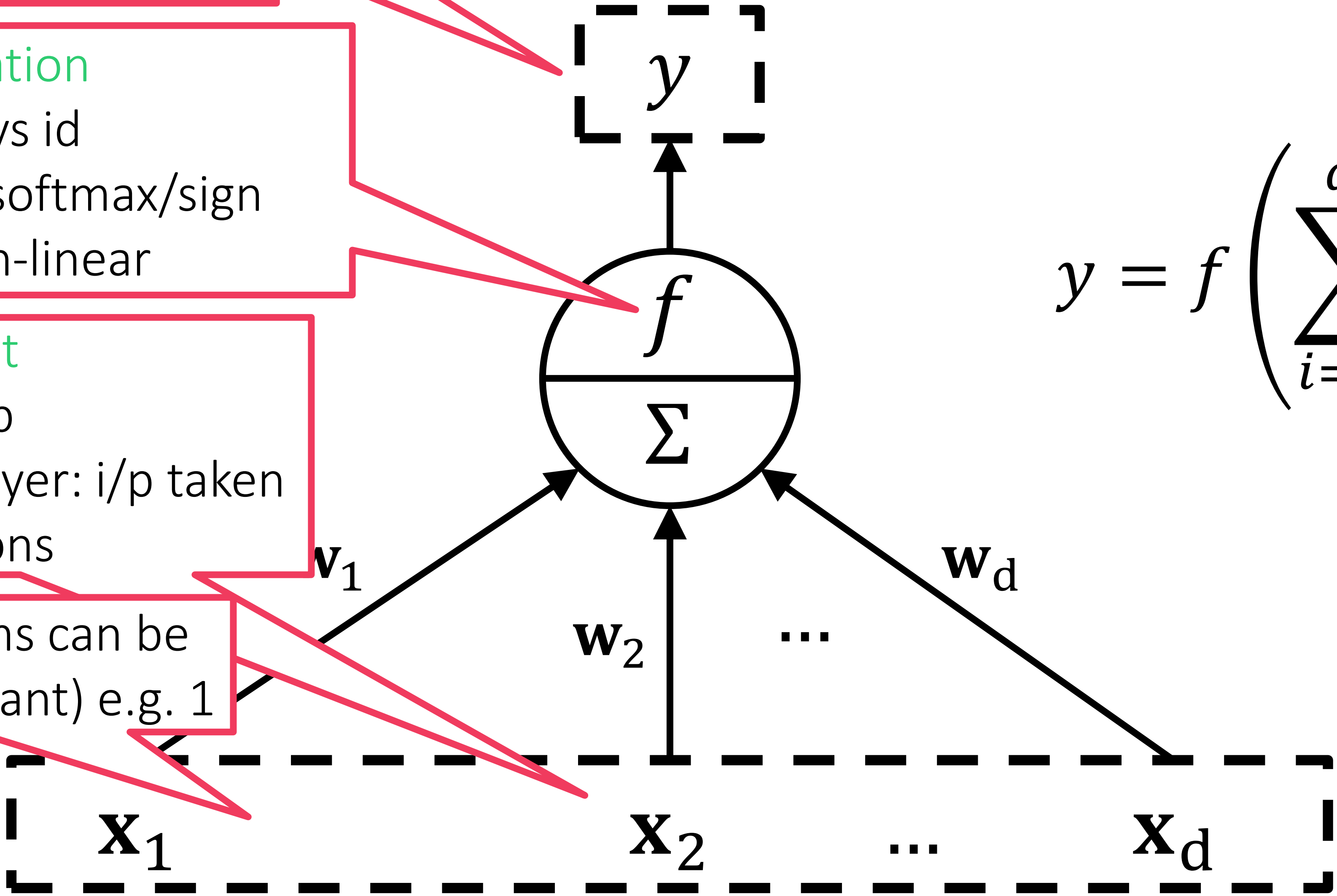

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Output

Output layer: final o/p

Input/hidden layer: o/p to other neurons

If no hidden layer then the network is just a generalized linear model, also called a **perceptron**

Activation

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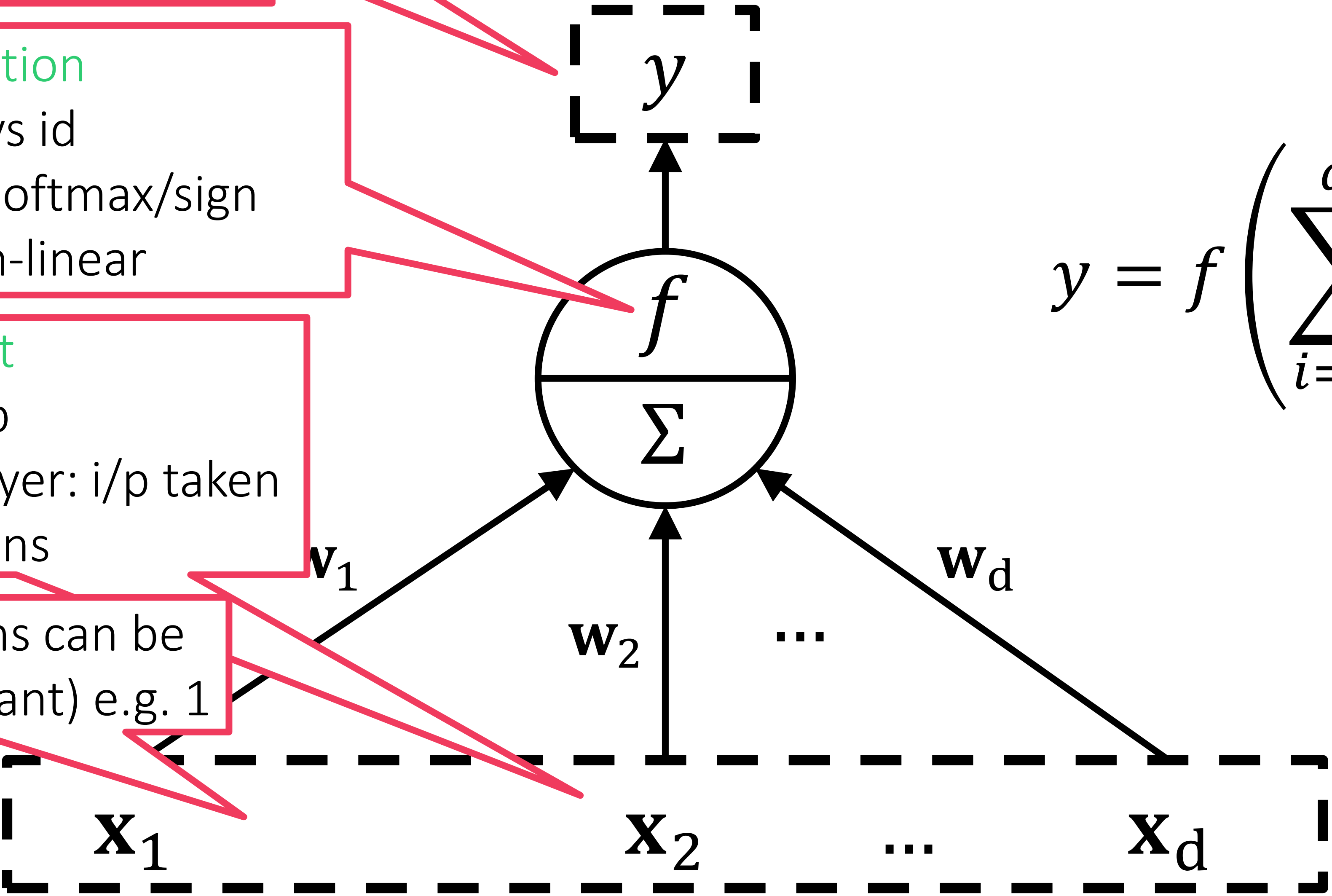

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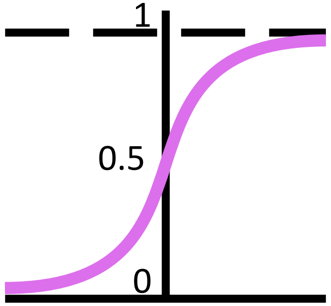
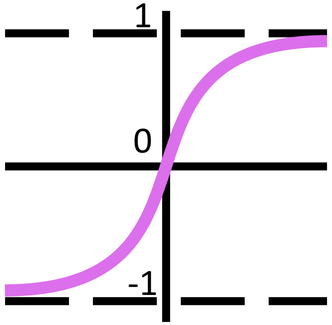
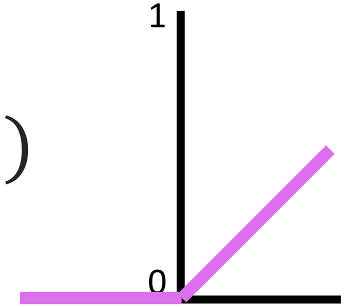
Common Activation Functions



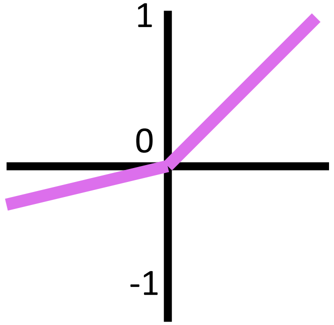


Sigmoid $\sigma(t) = \frac{\exp(t)}{\exp(t)+1}$

Tan Hyperbolic $\tanh(t) = \frac{\exp(2t)-1}{\exp(2t)+1} = 2\sigma(2t) - 1$



Rectified Linear Unit (ReLU) $r(t) = [t]_+ = \max(t, 0)$



Leaky ReLU $r(t) = \max(\beta \cdot t, t)\,, \beta \in [0,1]$

Others e.g. smoothed (exponential, softplus) ReLU, maxout

Sigmoid/tanh have a problem of vanishing gradients

Notice that the curves of these functions flatten out in both directions

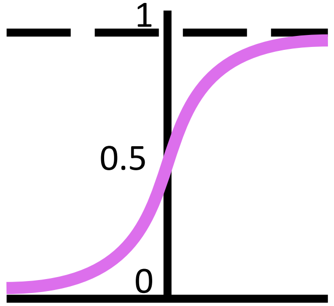
(Leaky) ReLU does not have this problem – very popular

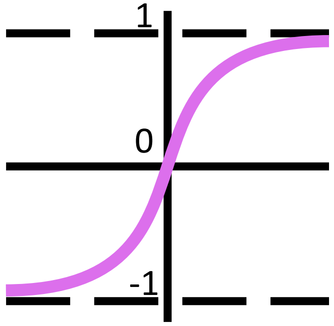
Also offer cheap gradient computations since they are piecewise linear

(Leaky) ReLU networks always learn piecewise linear functions

***Proof**: by induction on number of hidden layers (base case – no hidden layer)*

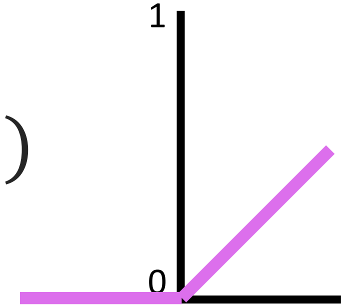
Common Activation Functions





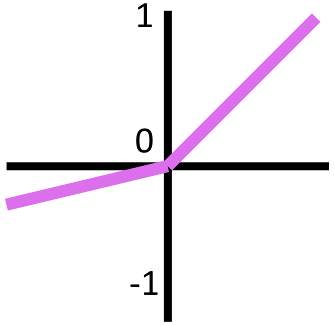
Sigmoid $\sigma(t) = \frac{\exp(t)}{\exp(t)+1}$

Tan Hyperbolic $\tanh(t) = \frac{\exp(2t)-1}{\exp(2t)+1} = 2\sigma(2t) - 1$



Rectified Linear Unit (ReLU) $r(t) = [t]_+ = \max(t, 0)$

Leaky ReLU $r(t) = \max(\beta \cdot t, t), \beta \in [0,1]$



Others e.g. smoothed (exponential, softplus) ReLU, maxout

Sigmoid/tanh have a problem of vanishing gradients

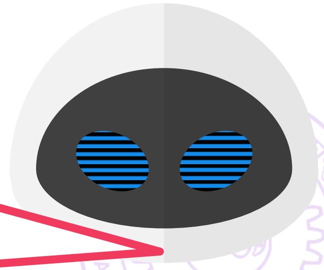
Notice that the curves of these functions flatten out in both directions

(Leaky) R

Also offe

(Leaky) R

Output layer neurons are usually given a task-specific activation e.g. identity for regression problems, sign for binary/multilabel classification problems, softmax for multiclassification problems



Proof*: by induction on number of hidden layers (base case – no hidden layer)*

Toy Example

Input sent to first hidden layer with two nodes

Each node first computes its pre-activation *value*

$$a_i = \left(\mathbf{w}^i\right)^\top \mathbf{x}, i = 1,2, \mathbf{w}^i, \mathbf{x} \in \mathbb{R}^d$$

Non-linear activation applied to each preactivation

$$h_i = f(a_i), i = 1,2$$

The vector $\mathbf{h} \in \mathbb{R}^2$ sent to next layer as input

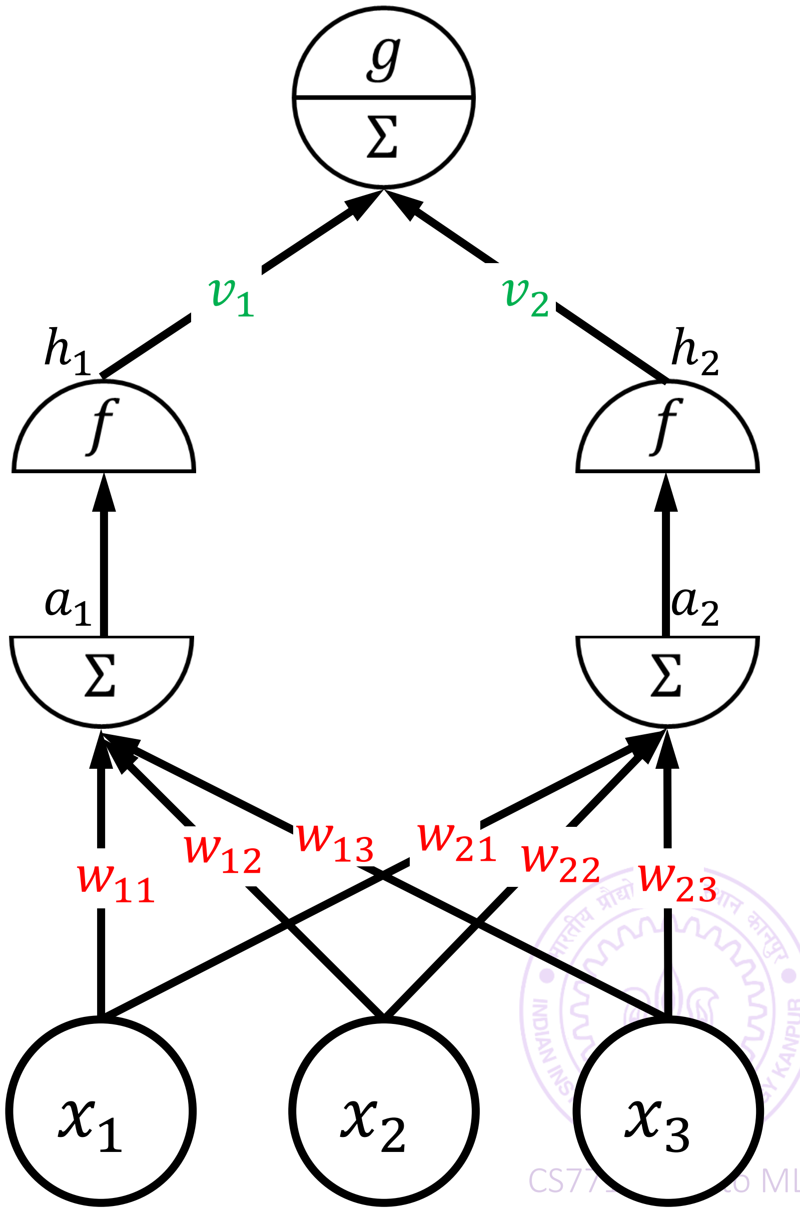
Process of preactivation, activation etc repeats

Shorthand: let $W = [\mathbf{w}^1, \mathbf{w}^2] \in \mathbb{R}^{d \times 2}$

Function computed by this network is

$$g\left(\mathbf{v}^\top f(W^\top \mathbf{x})\right)$$

This nesting of functions gives DN their power



Feedforward Deep Networks

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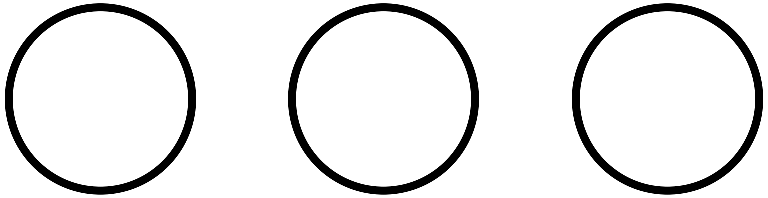

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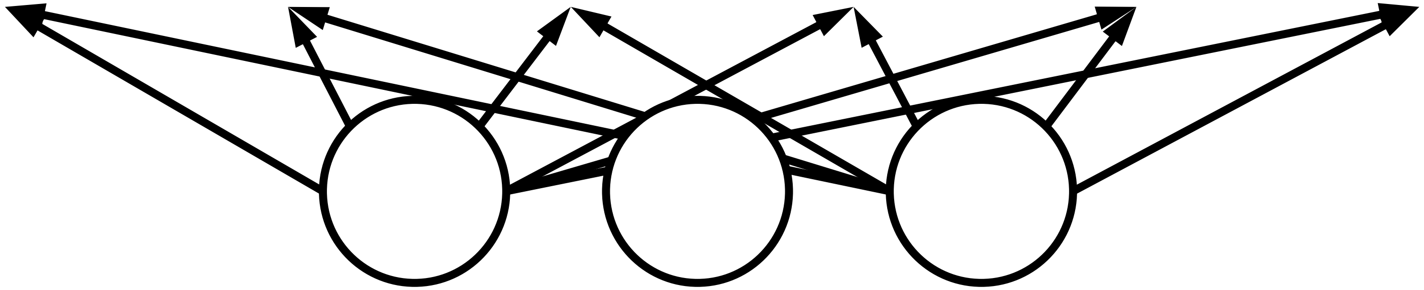

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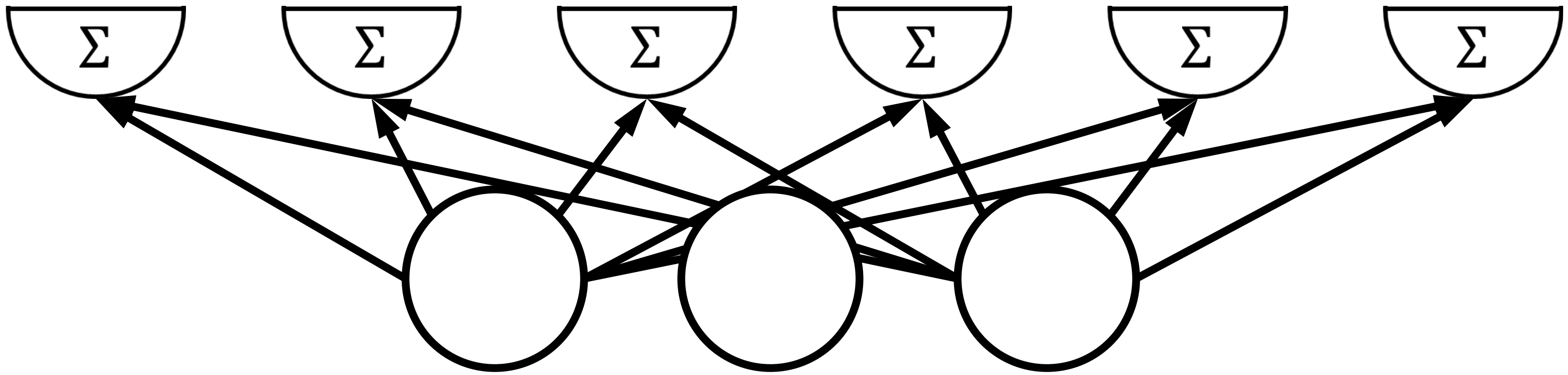

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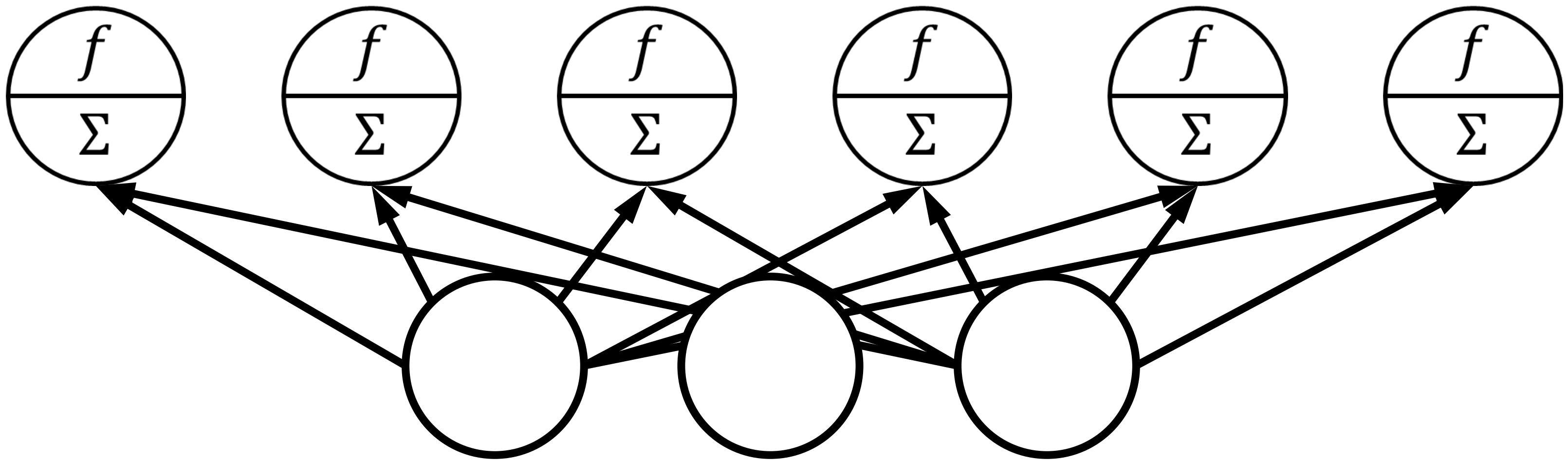

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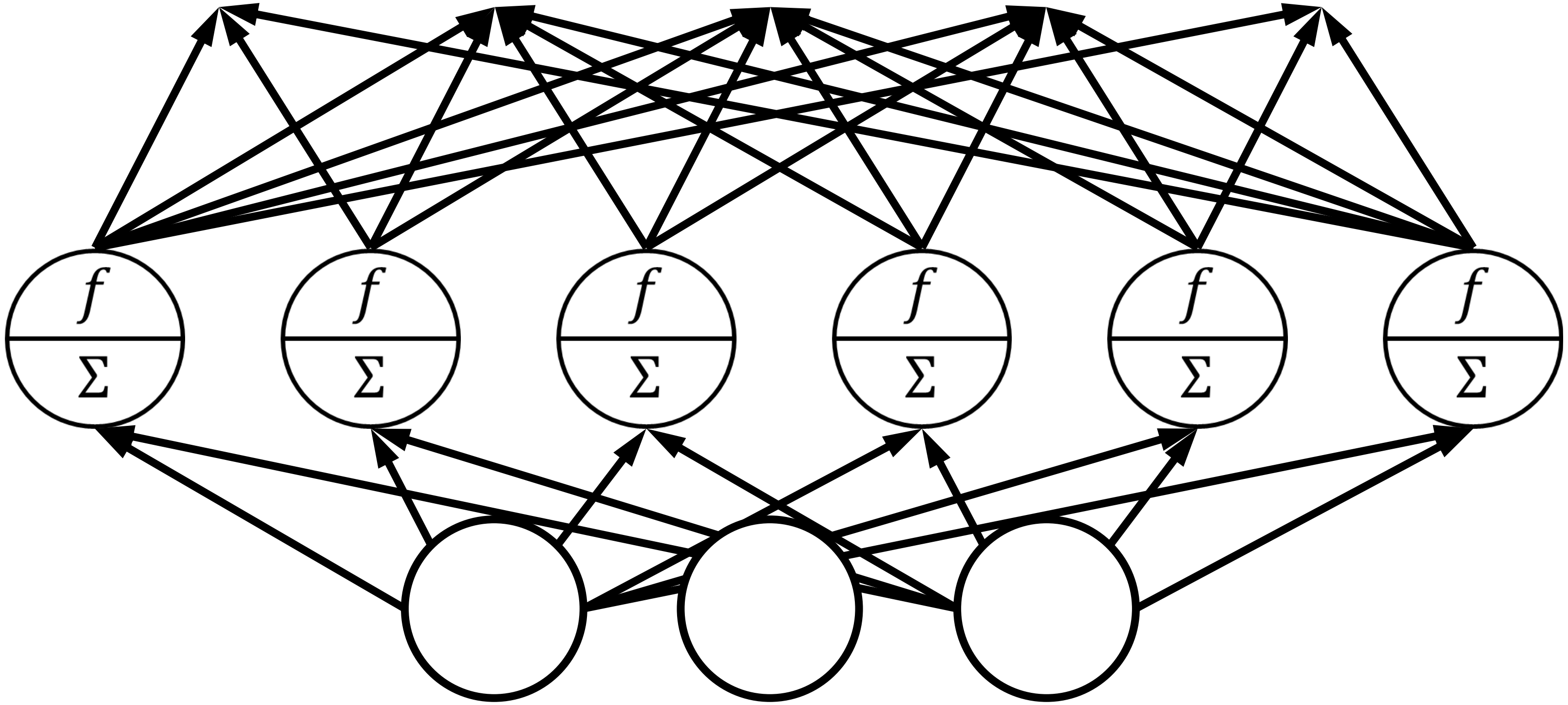

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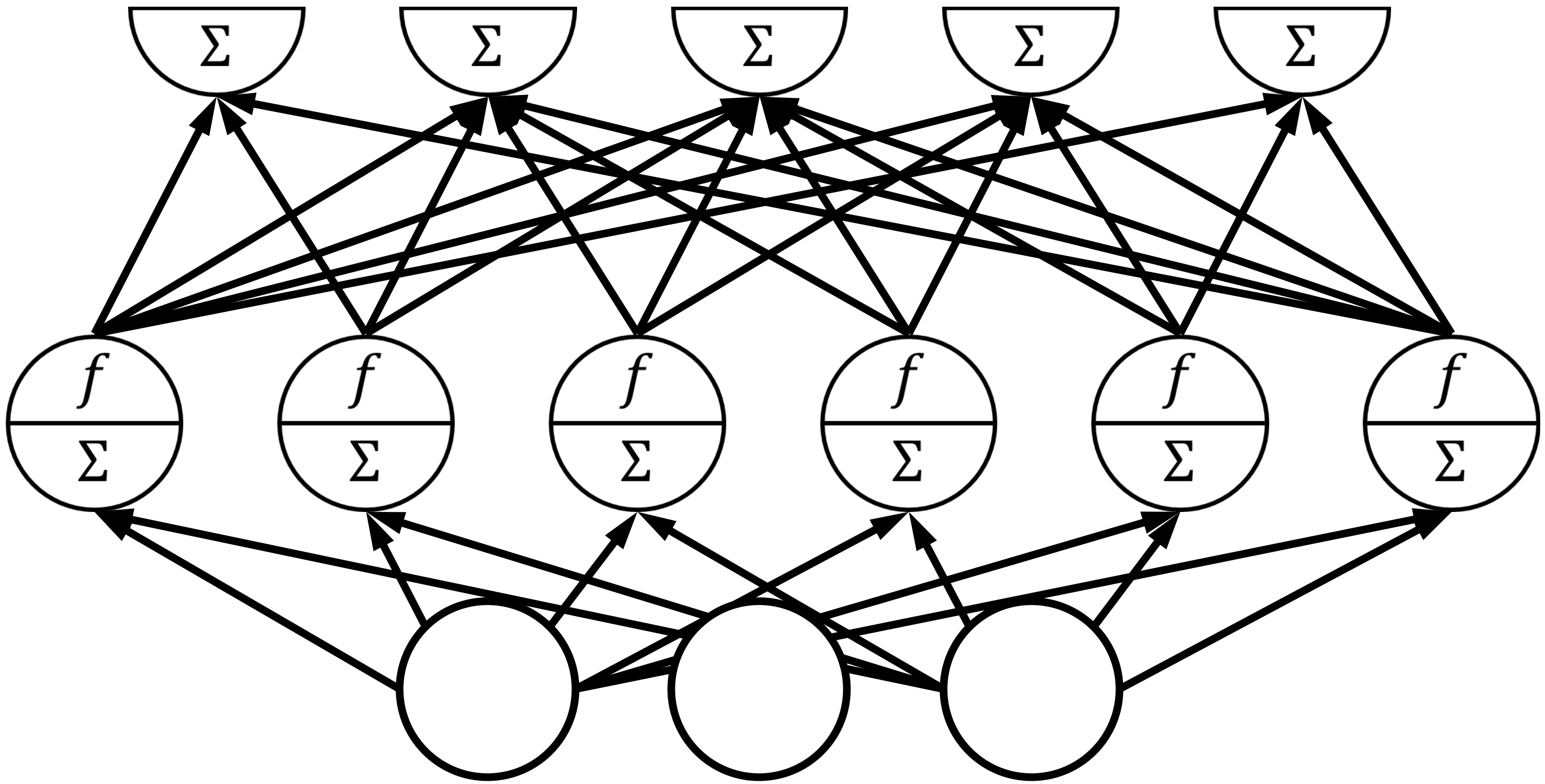

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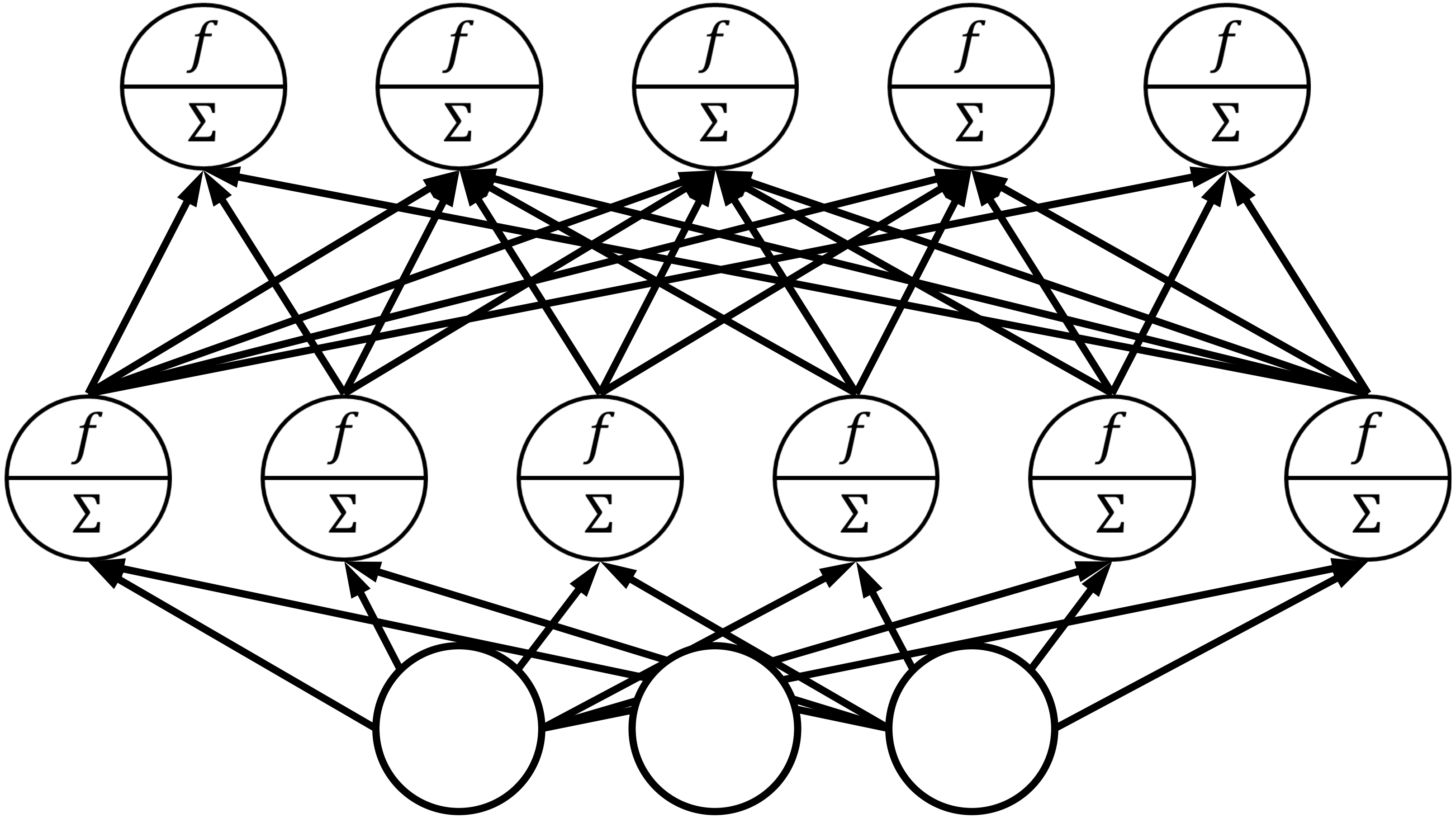

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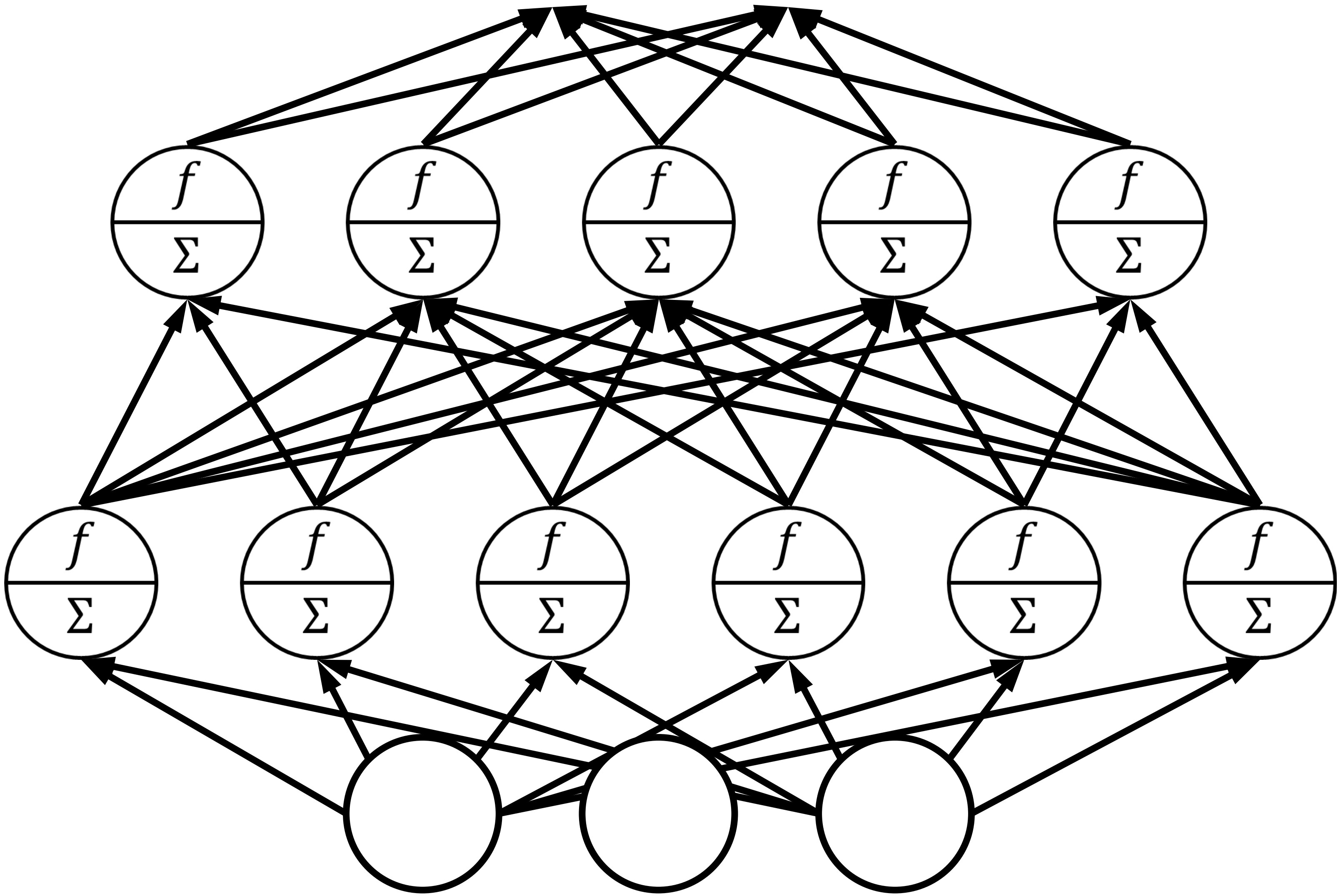

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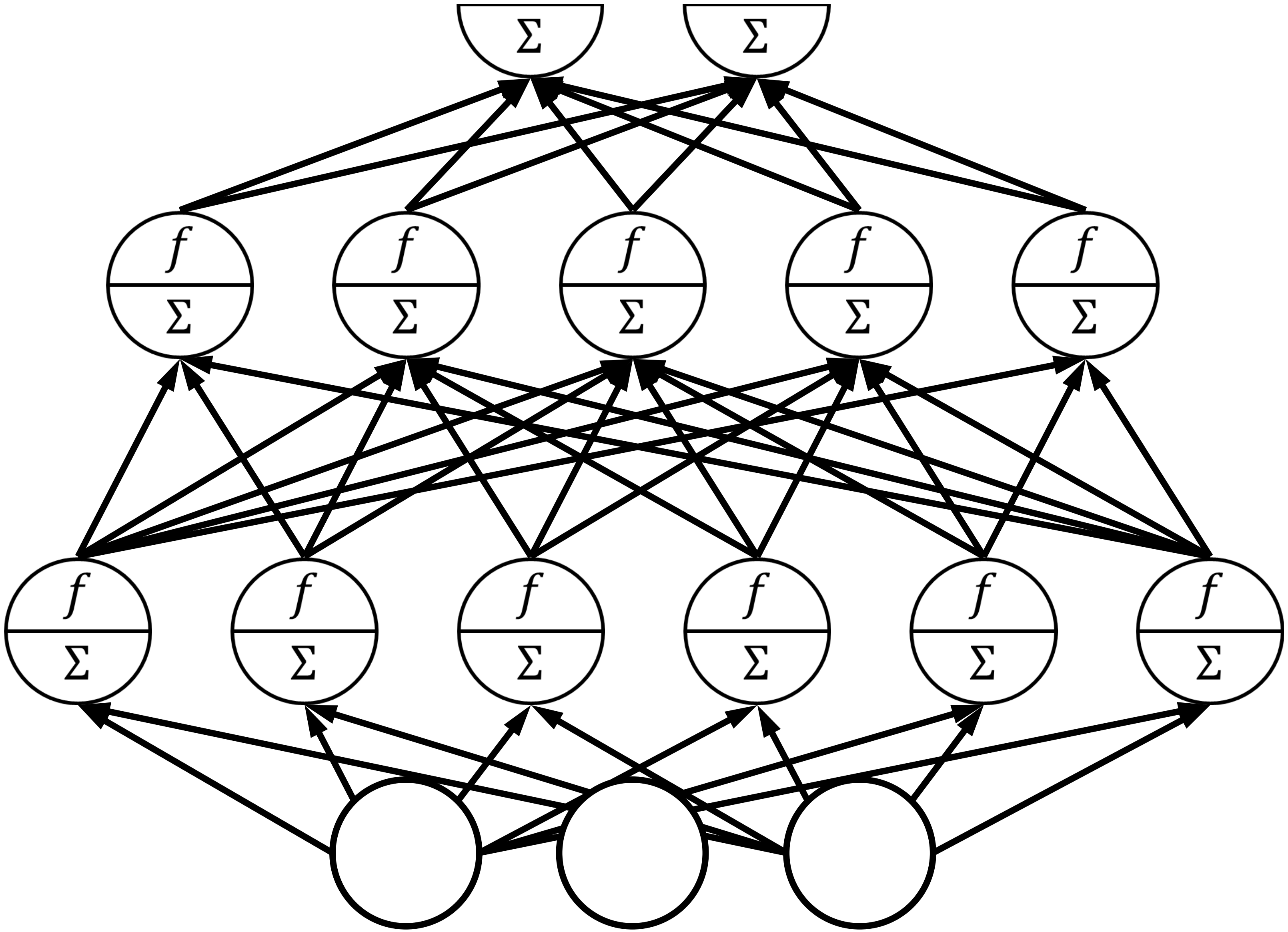

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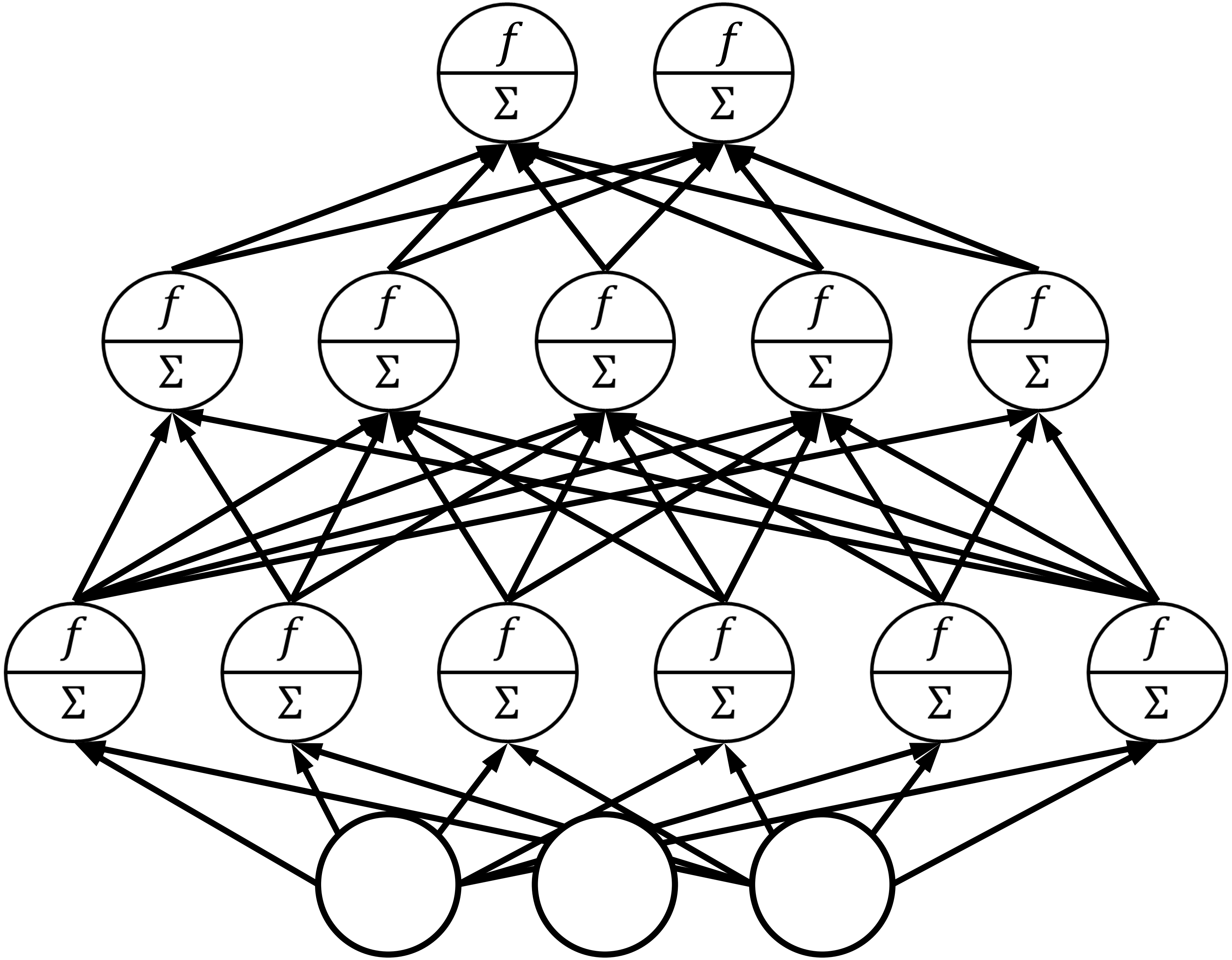
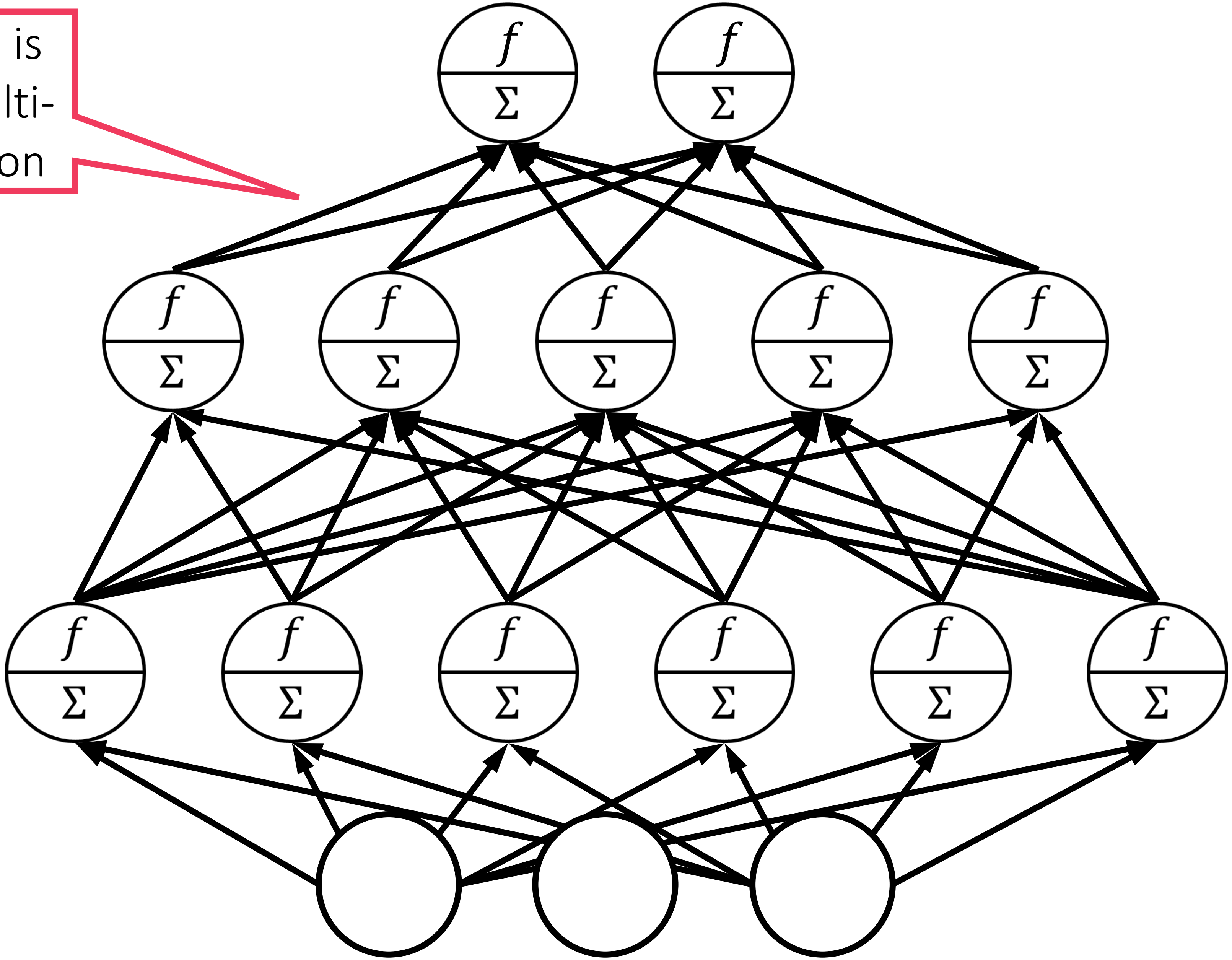


Feedforward Deep Networks

This architecture is often called a Multi-layered perceptron



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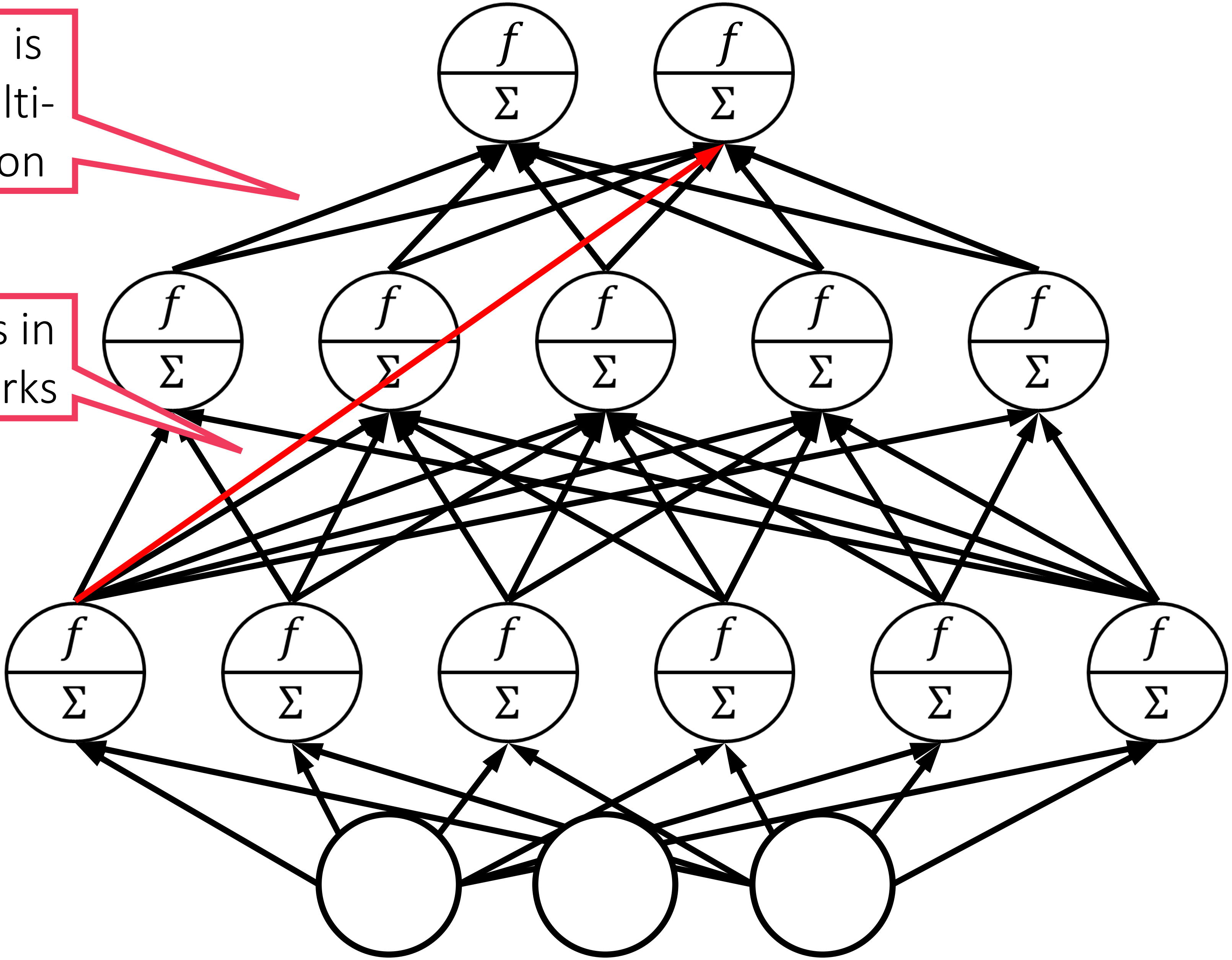
Cannot skip layers in classical FF networks



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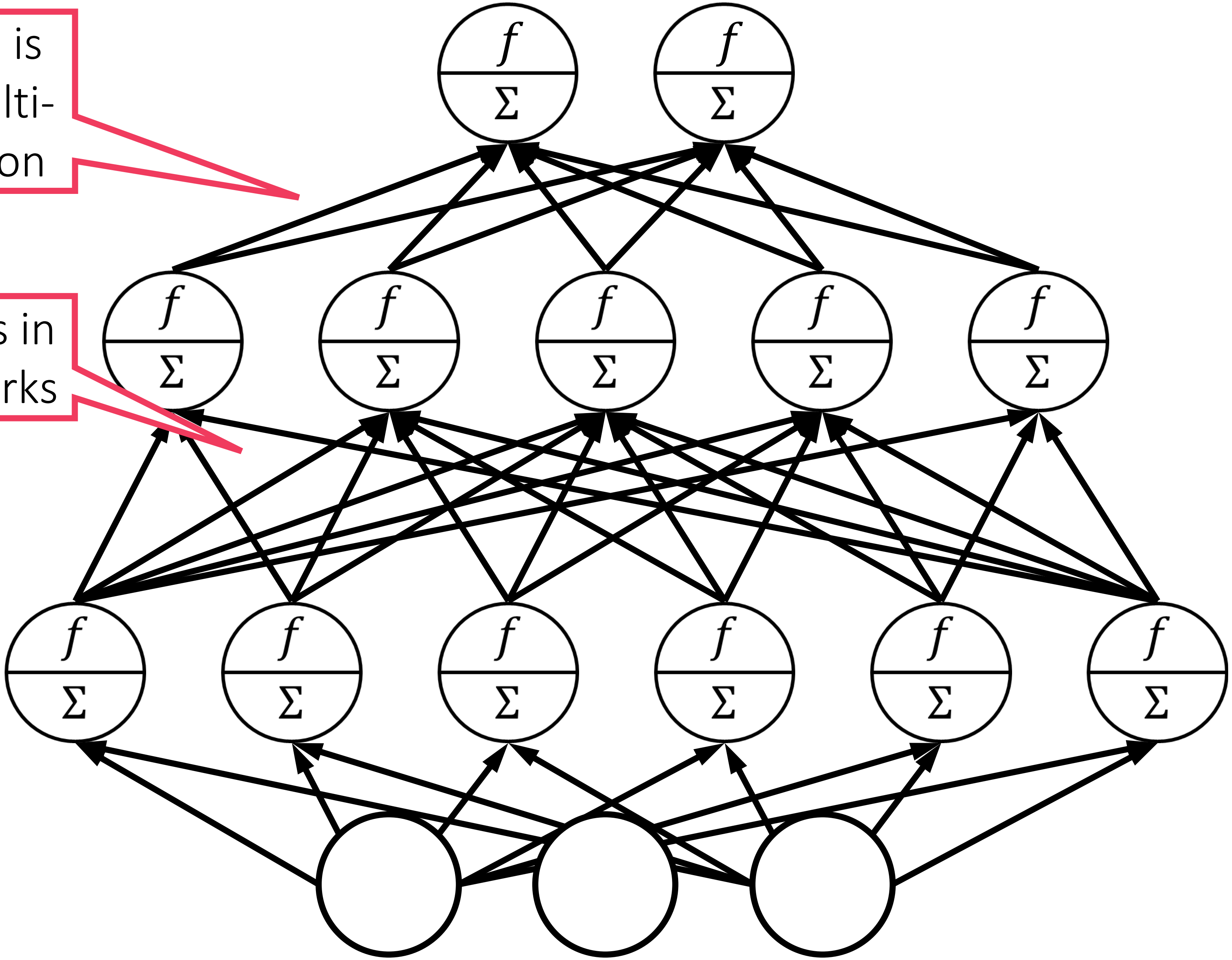

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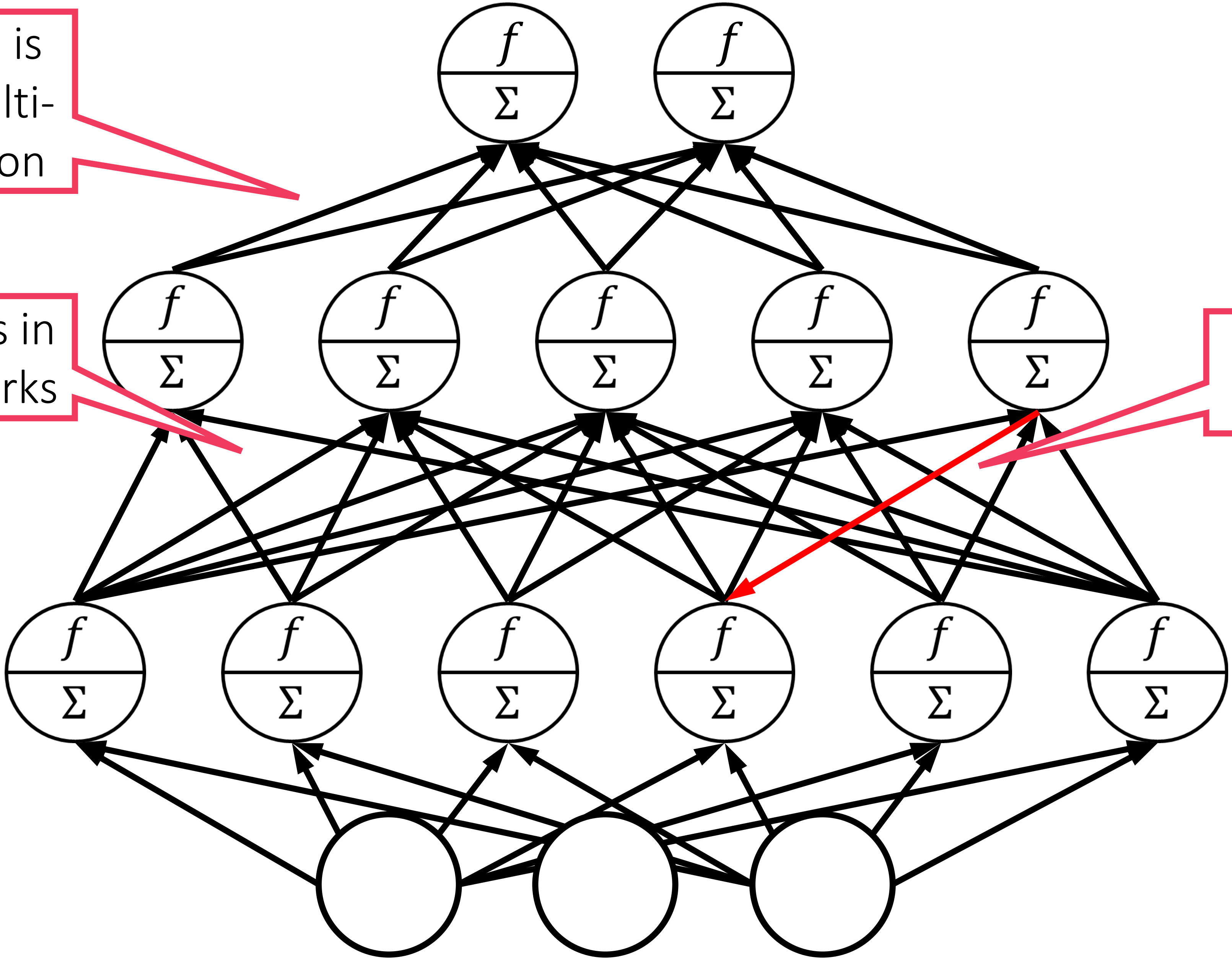

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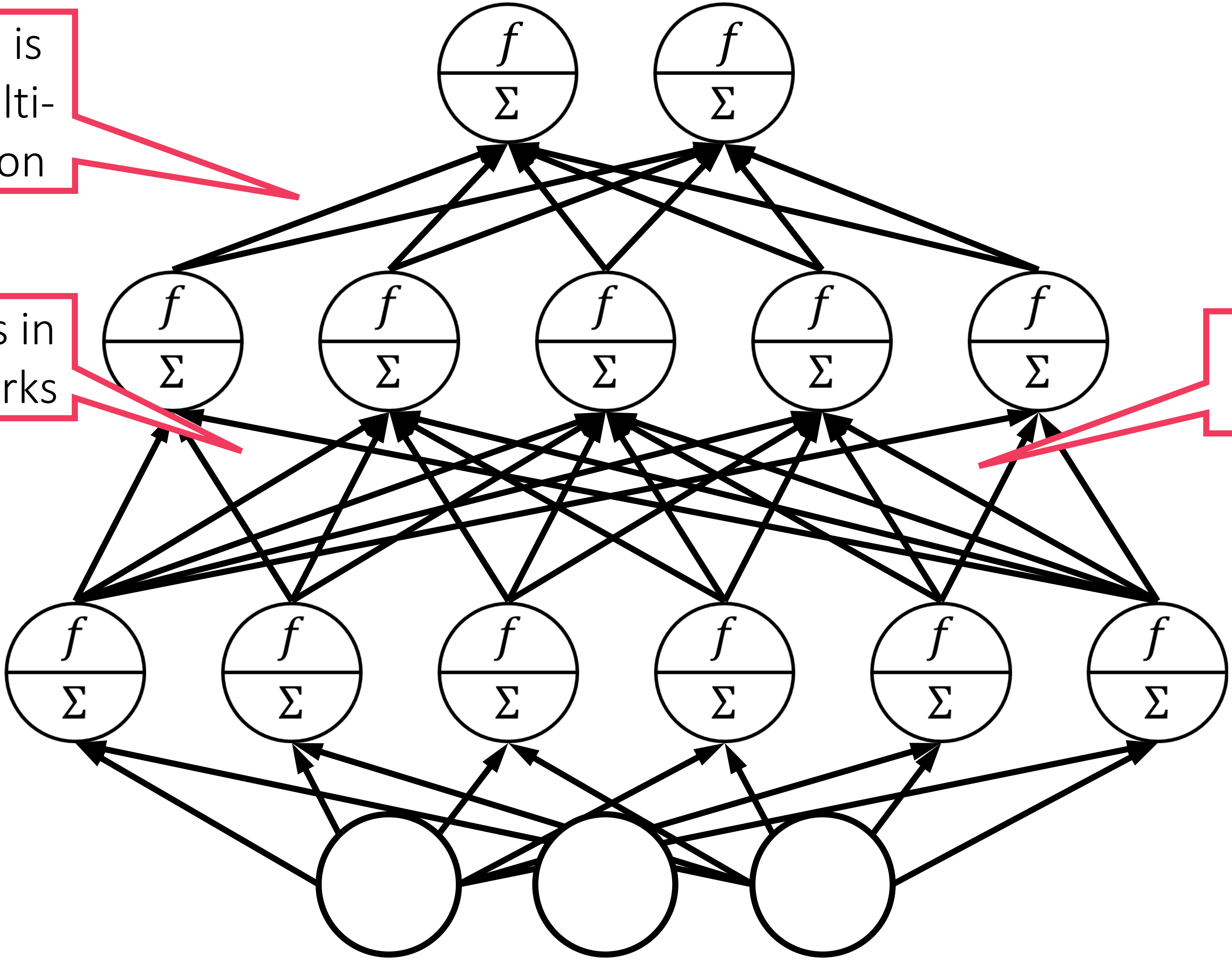

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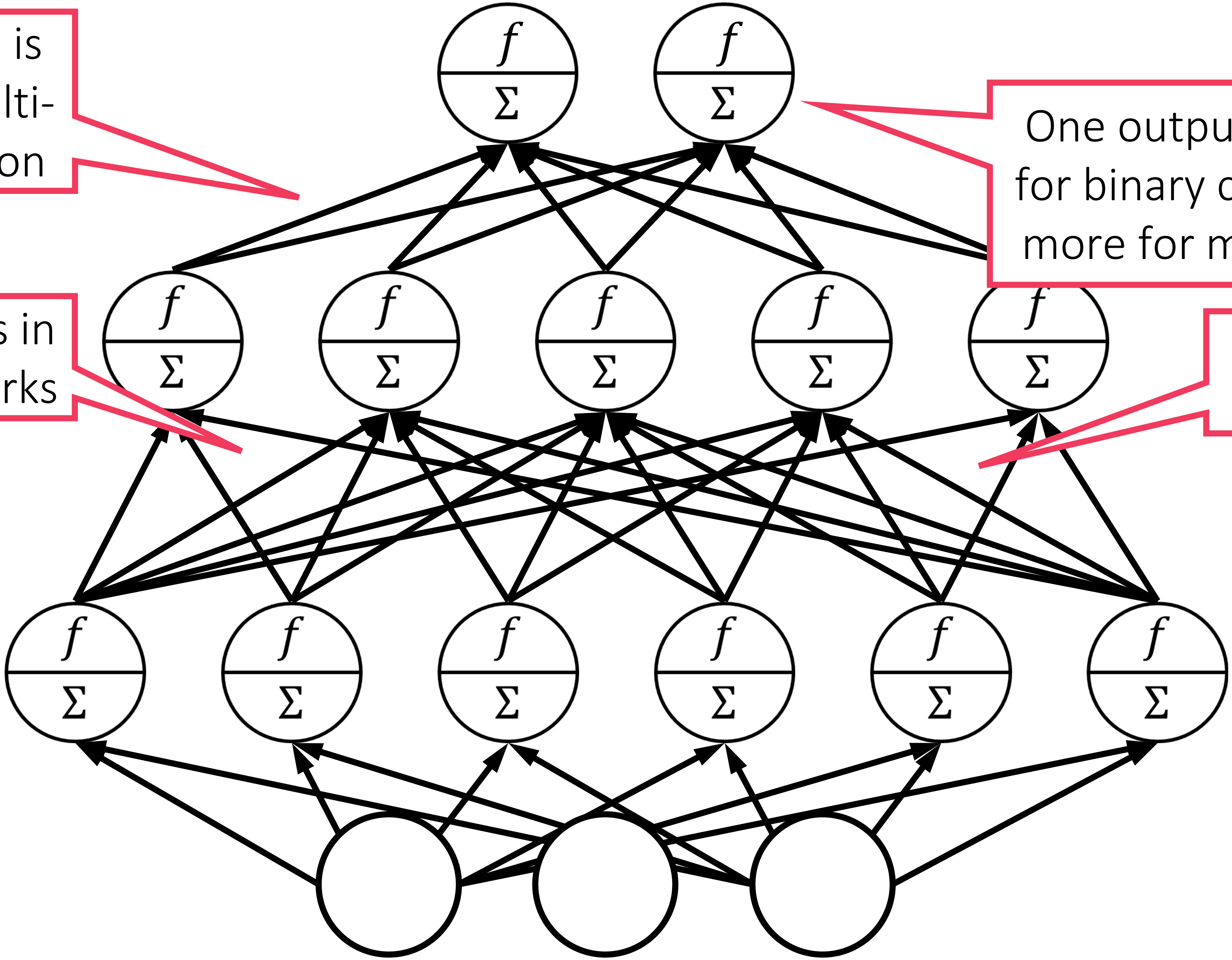

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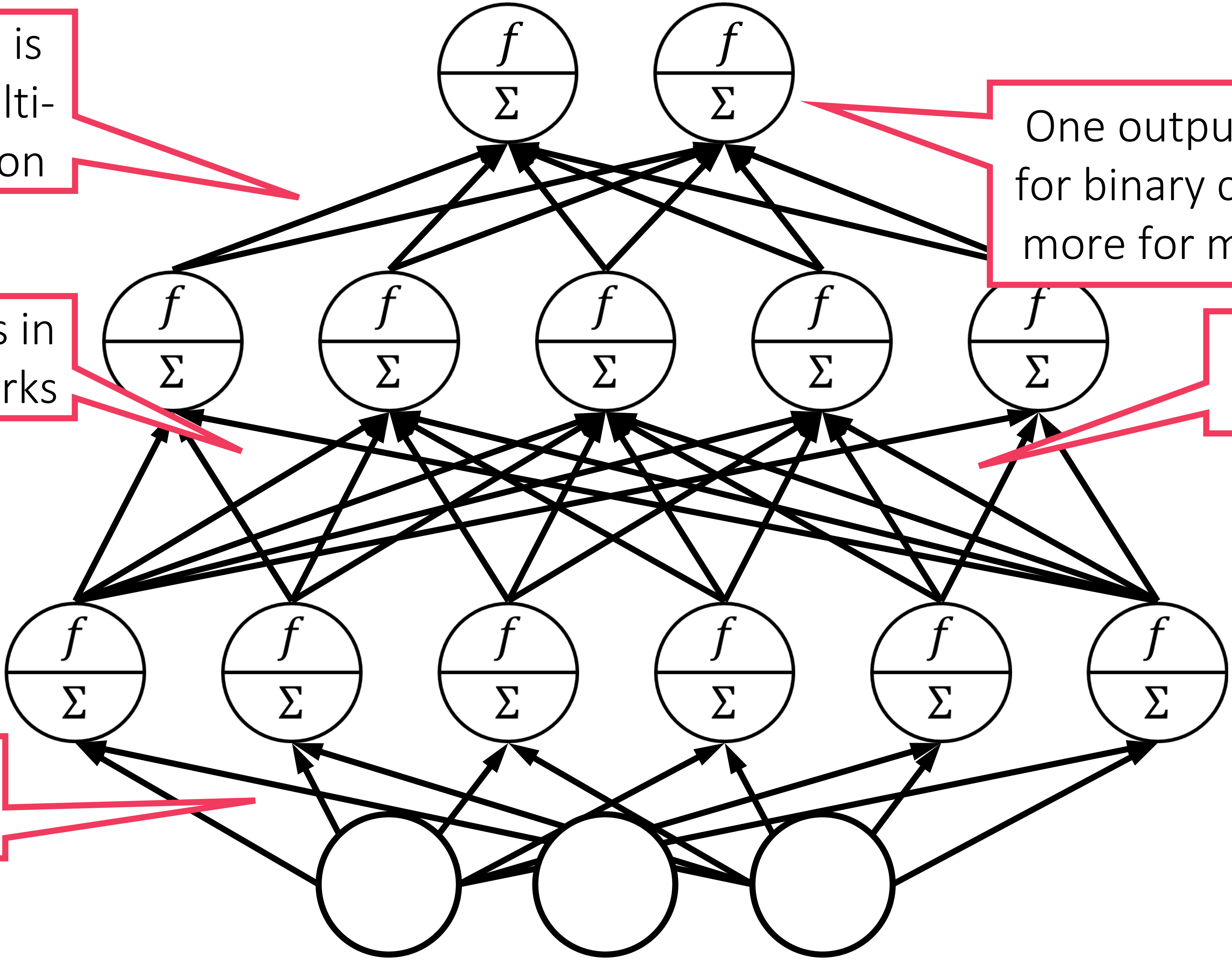
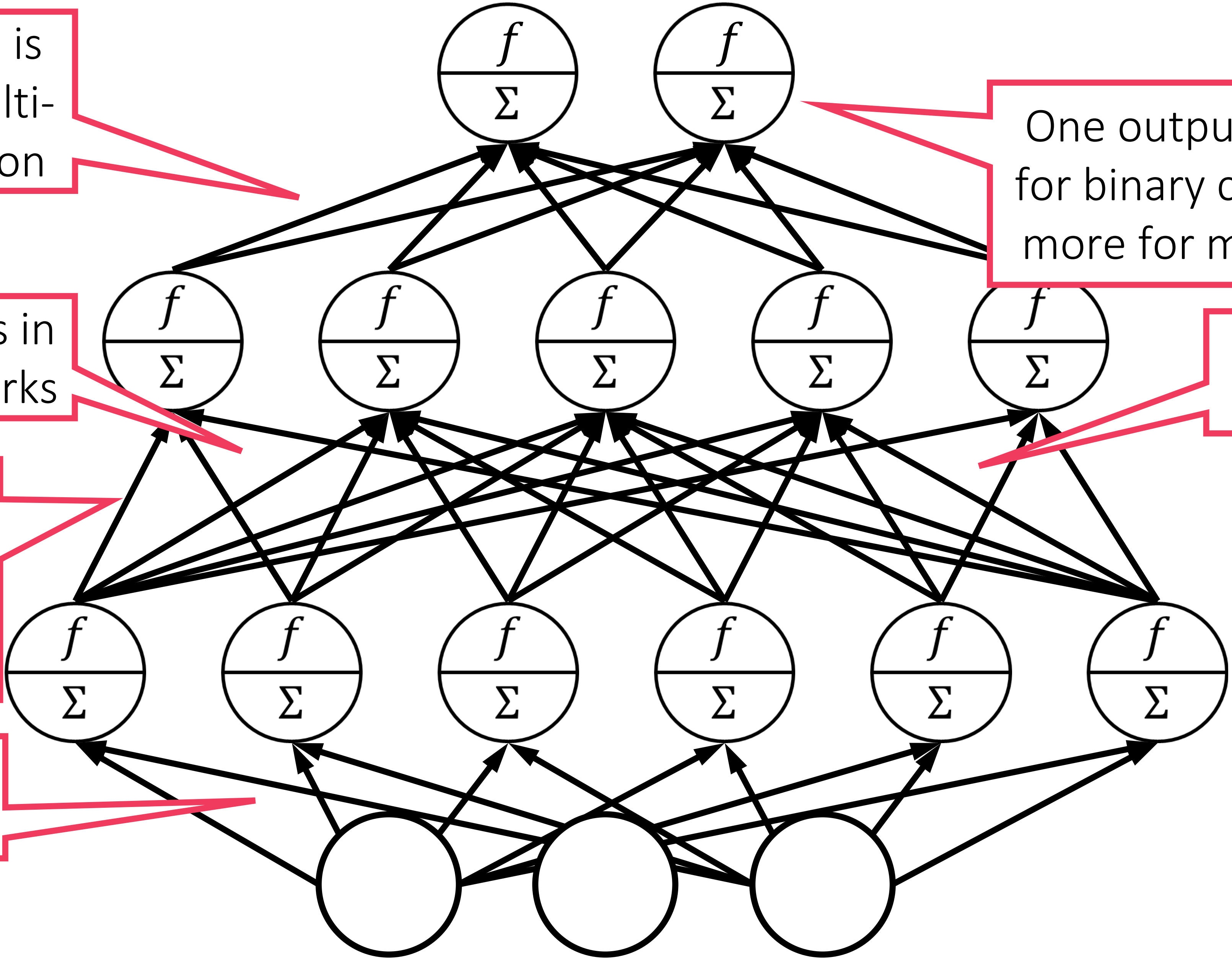


All weights are learnt

Feedforward Deep Networks



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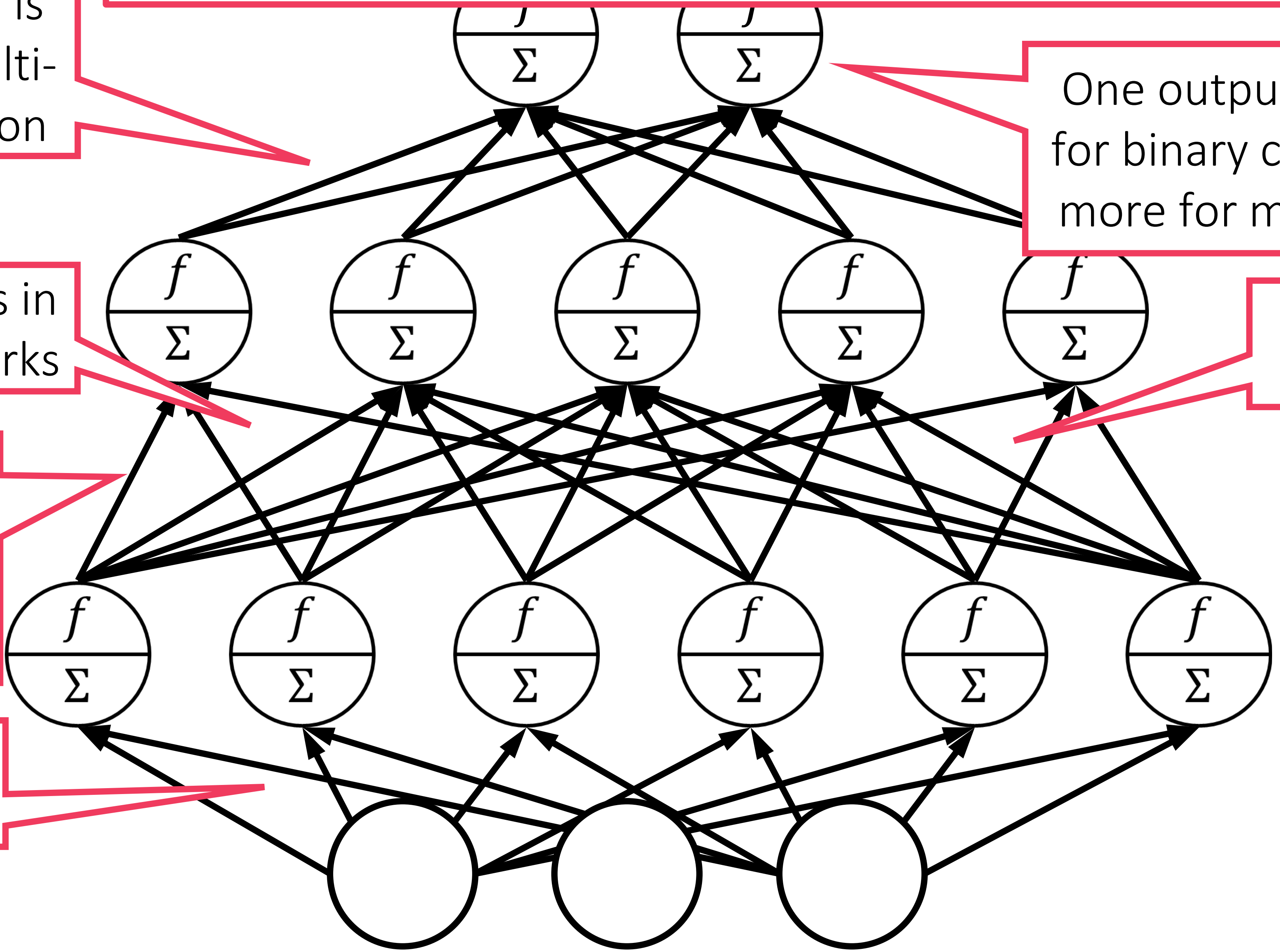

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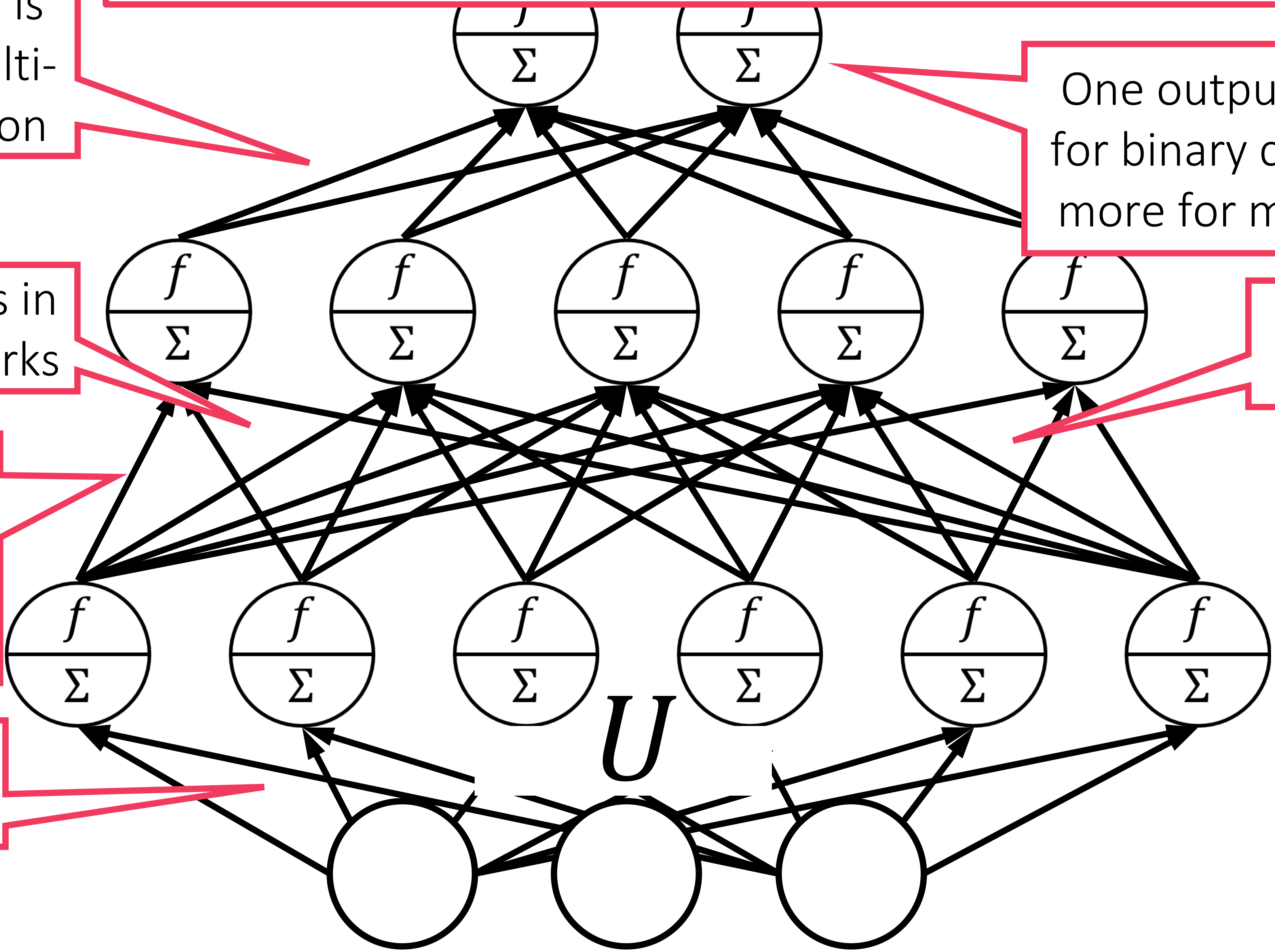

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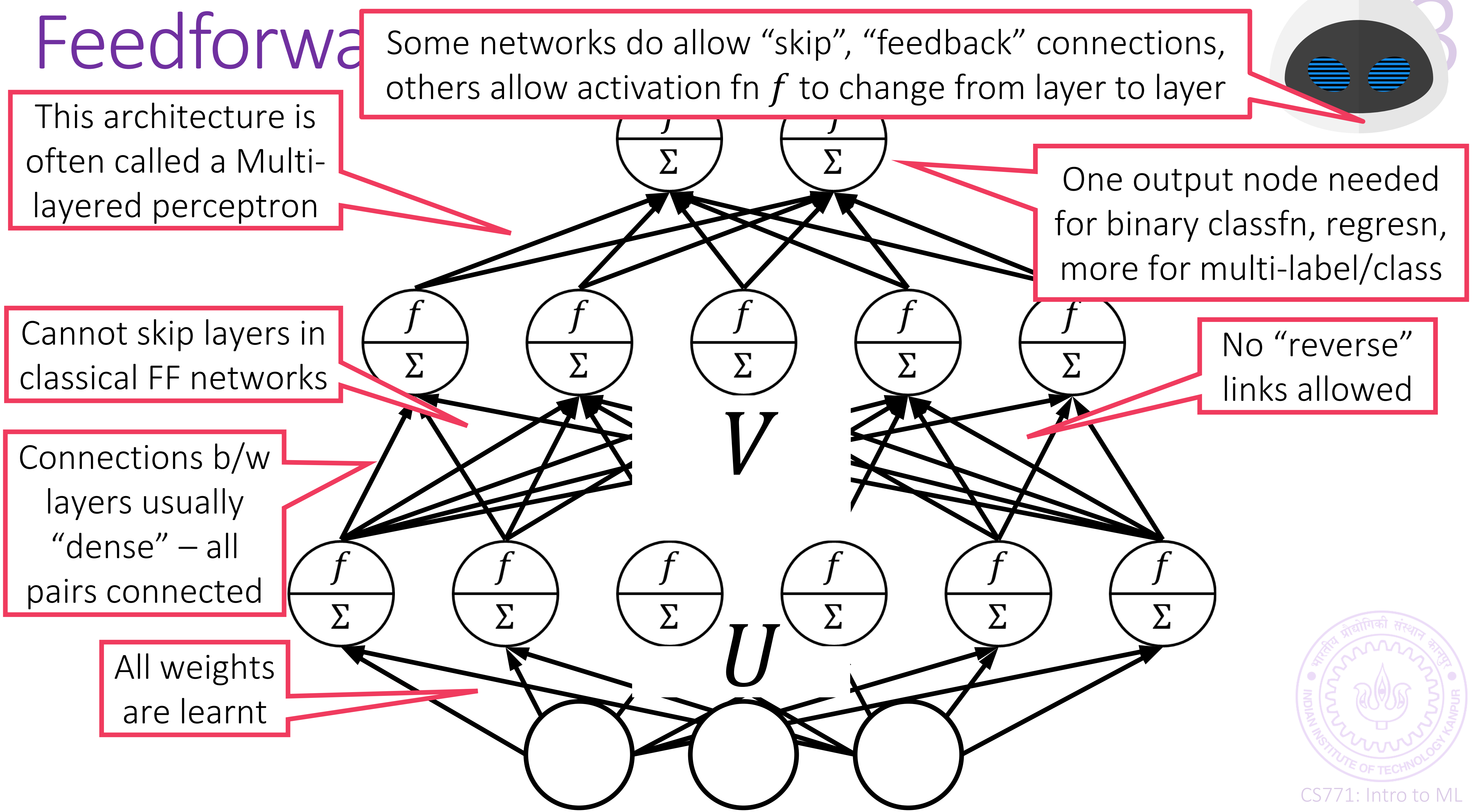

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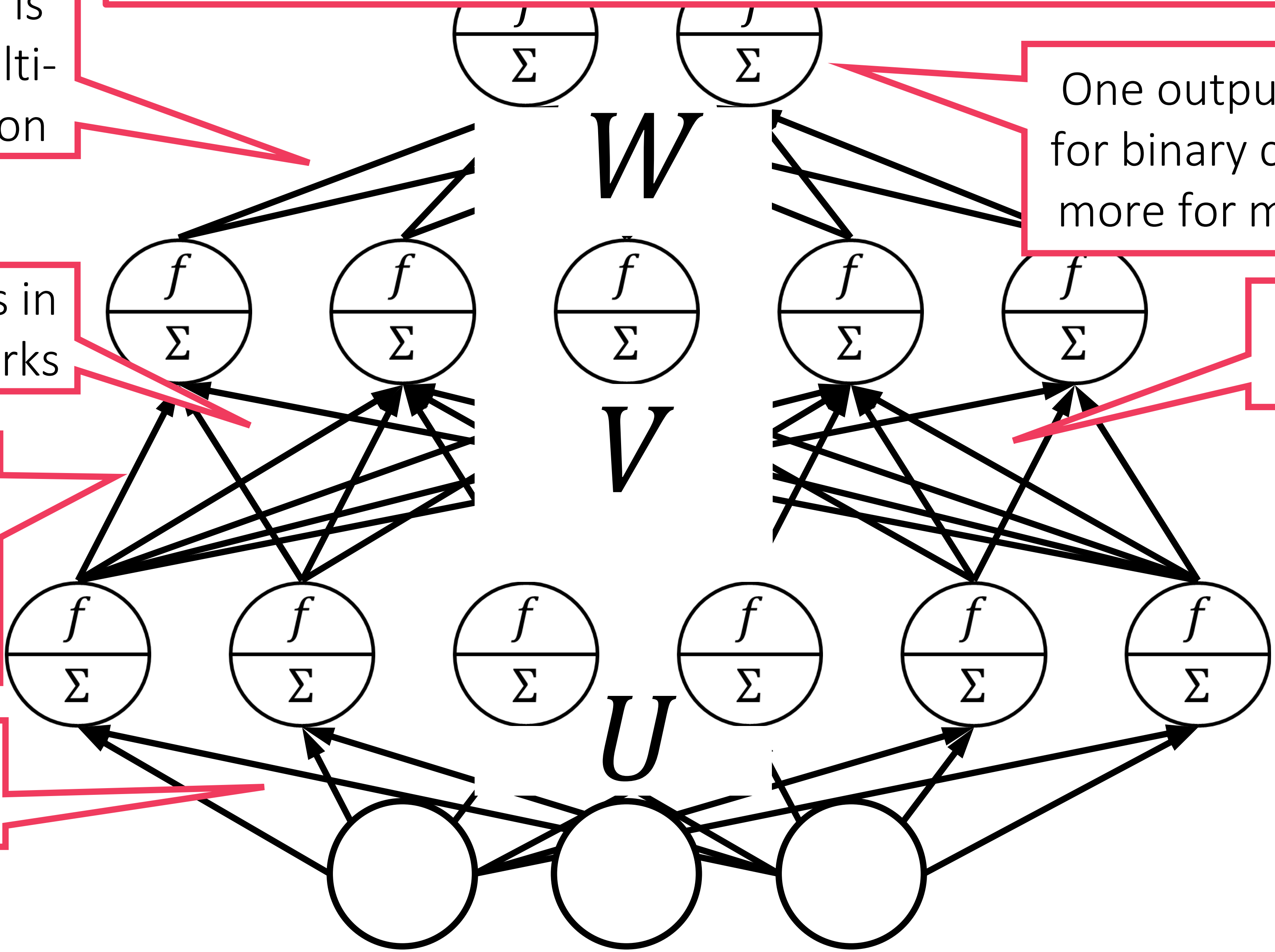

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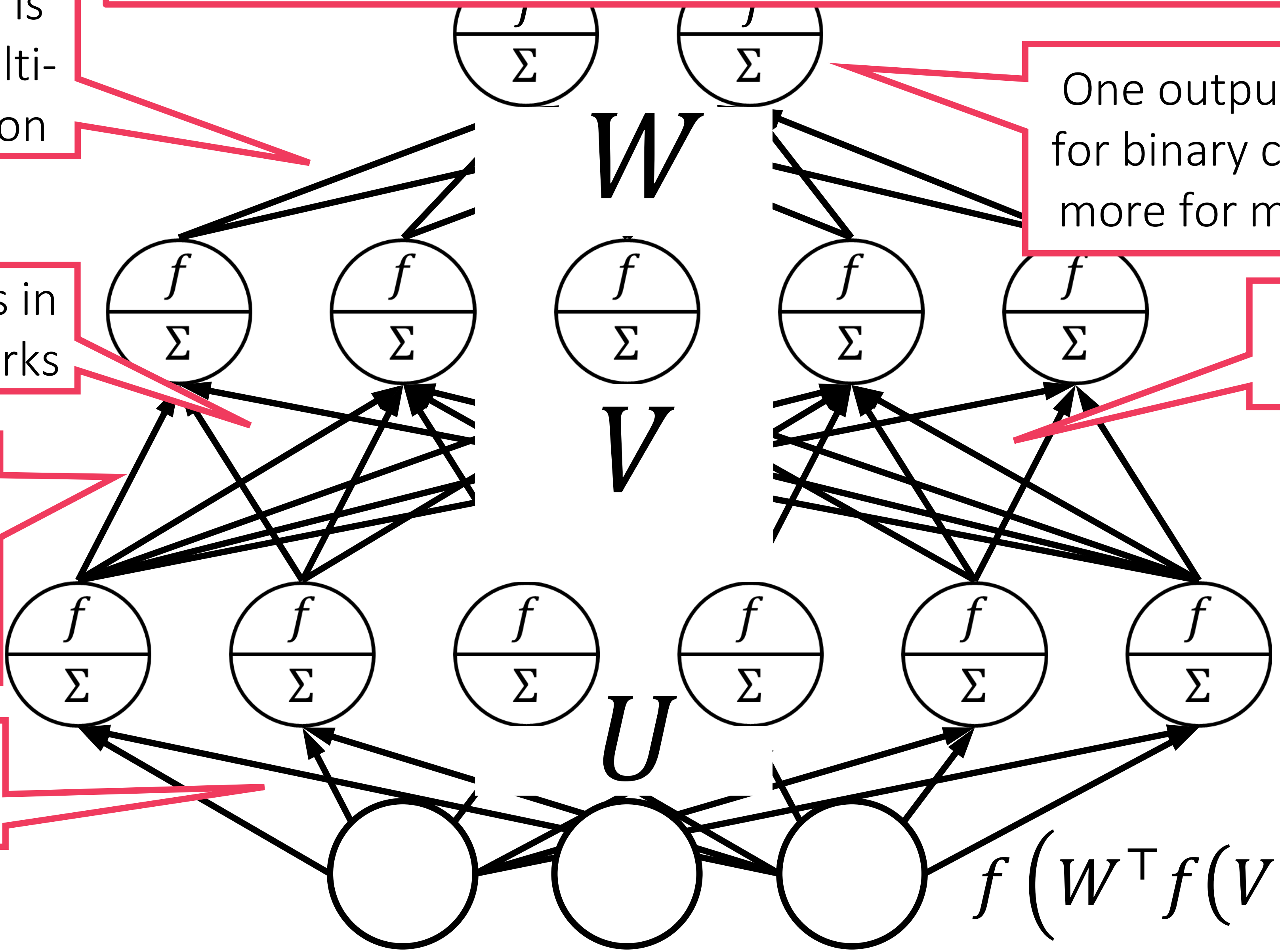

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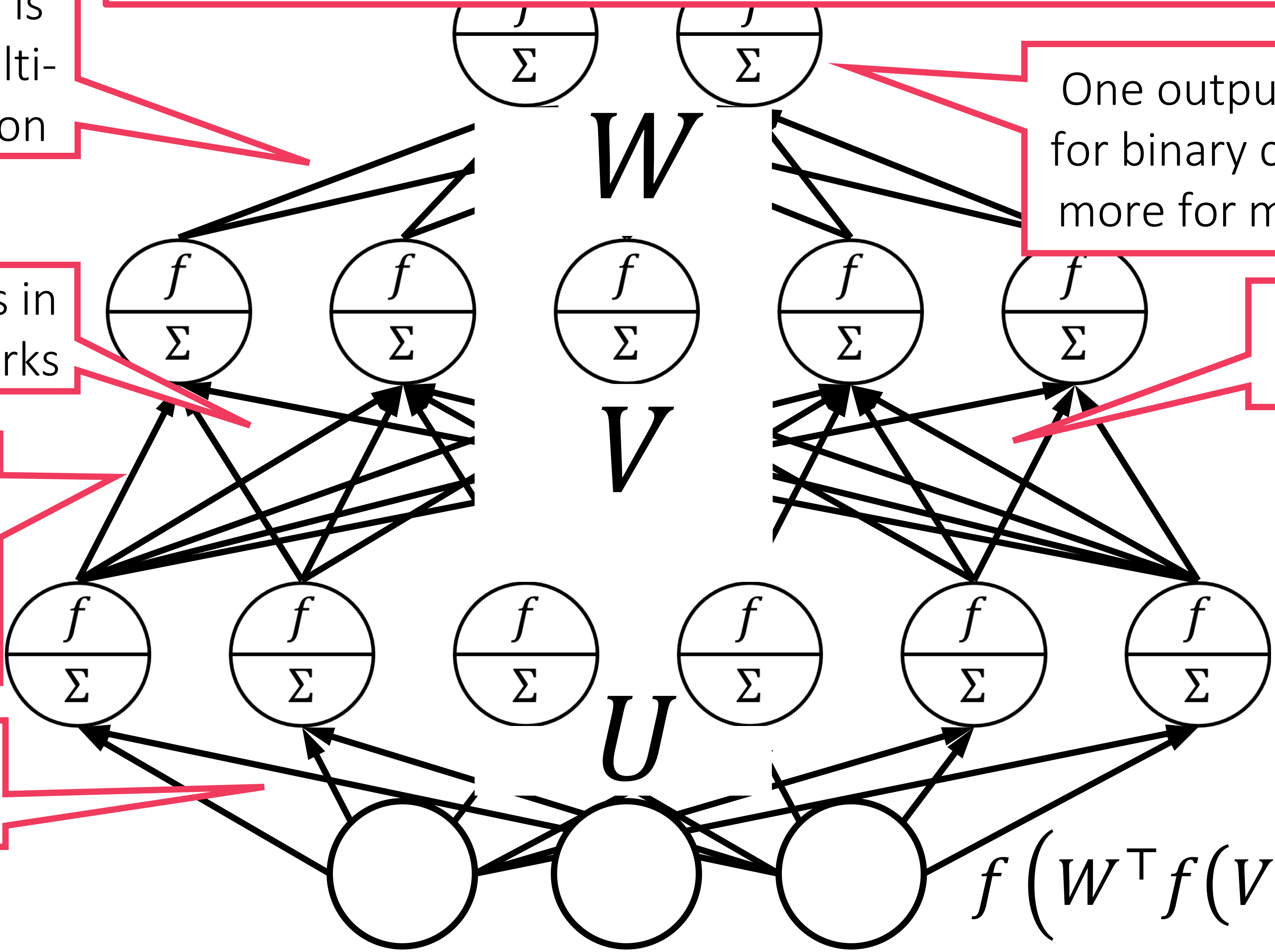

$U \in \mathbb{R}^{3\times 6}$

$V \in \mathbb{R}^{6\times 5}$

$W \in \mathbb{R}^{5\times 2}$

$$f\left(W^\top f(V^\top f(U^\top \mathbf{x}))\right)$$

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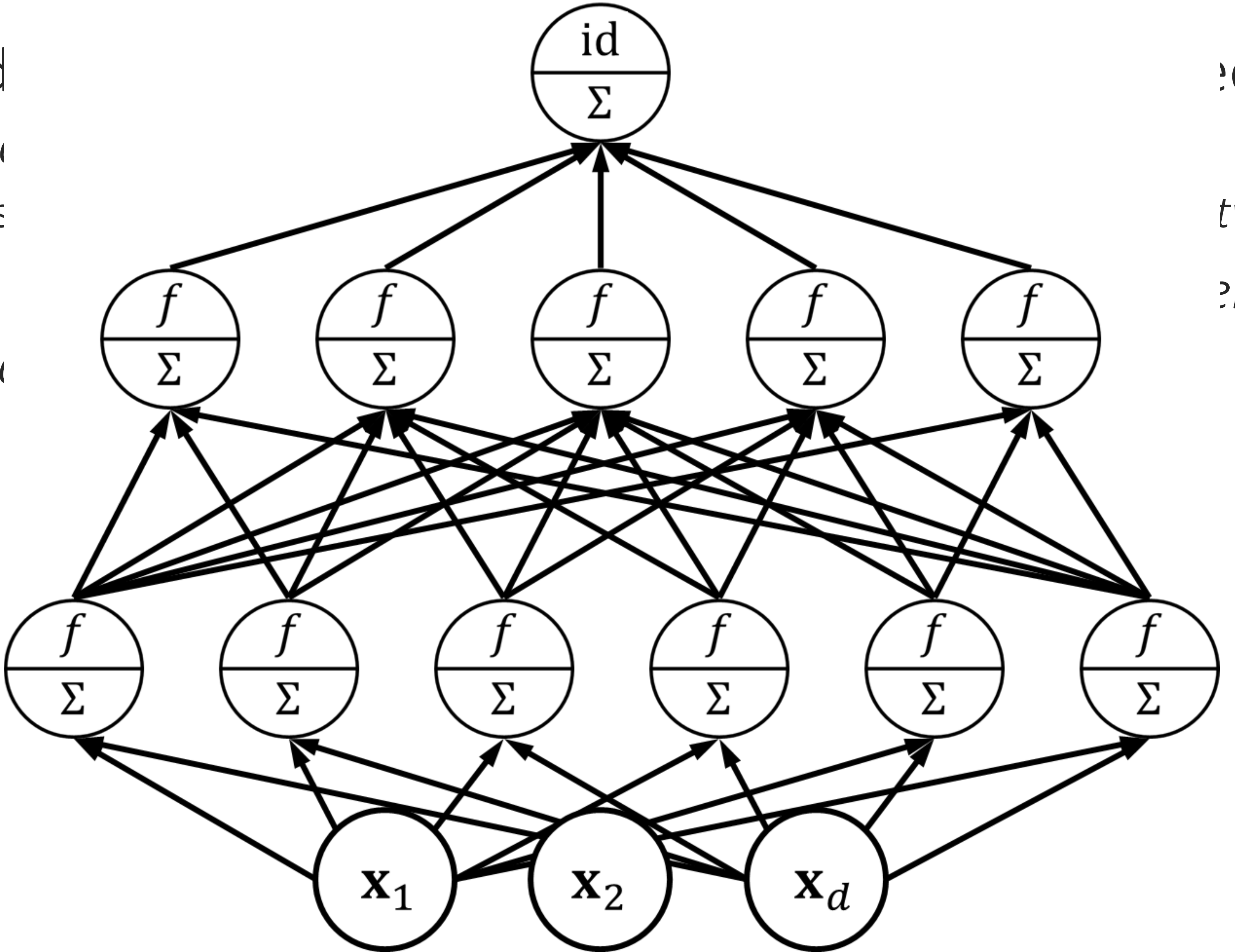

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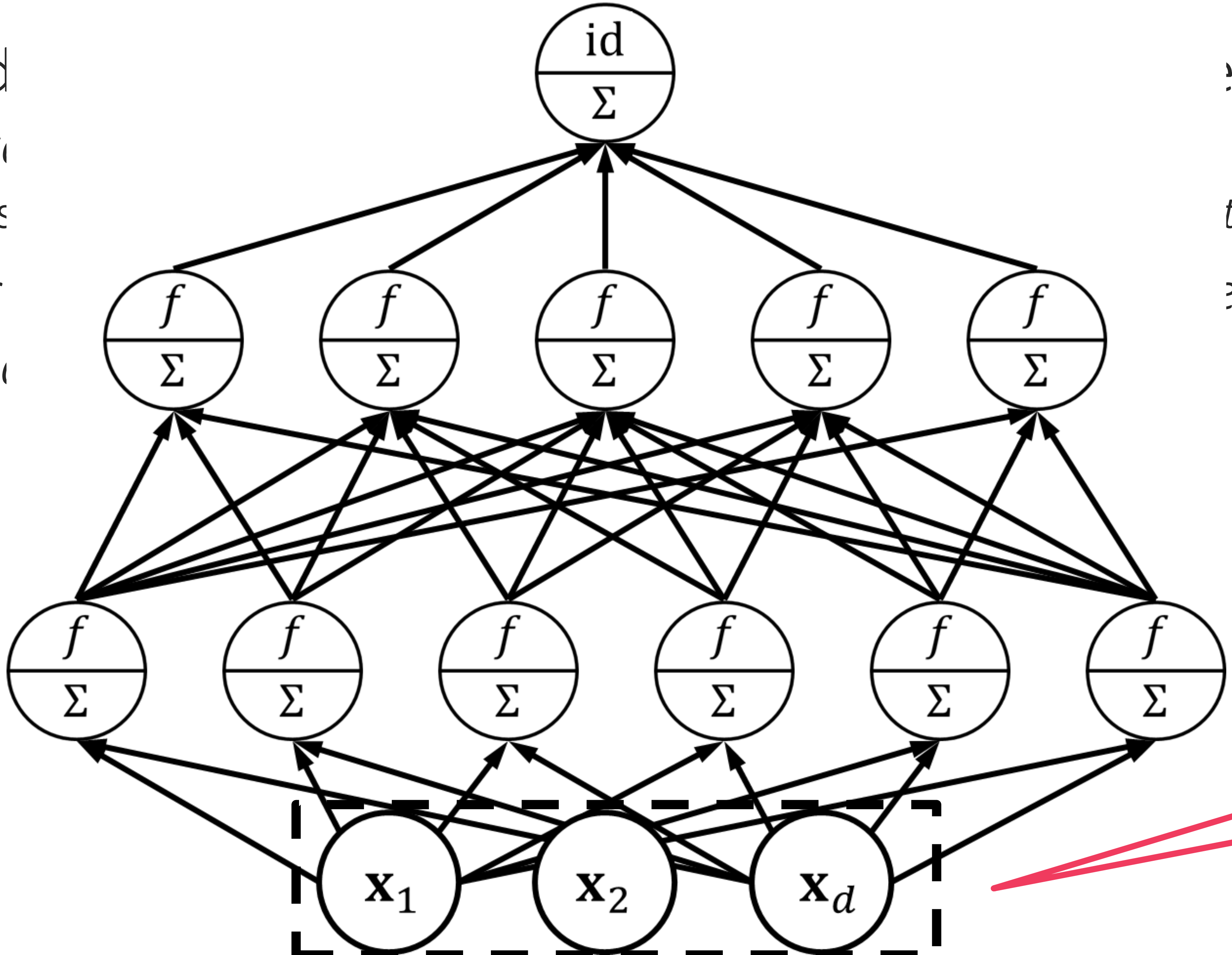

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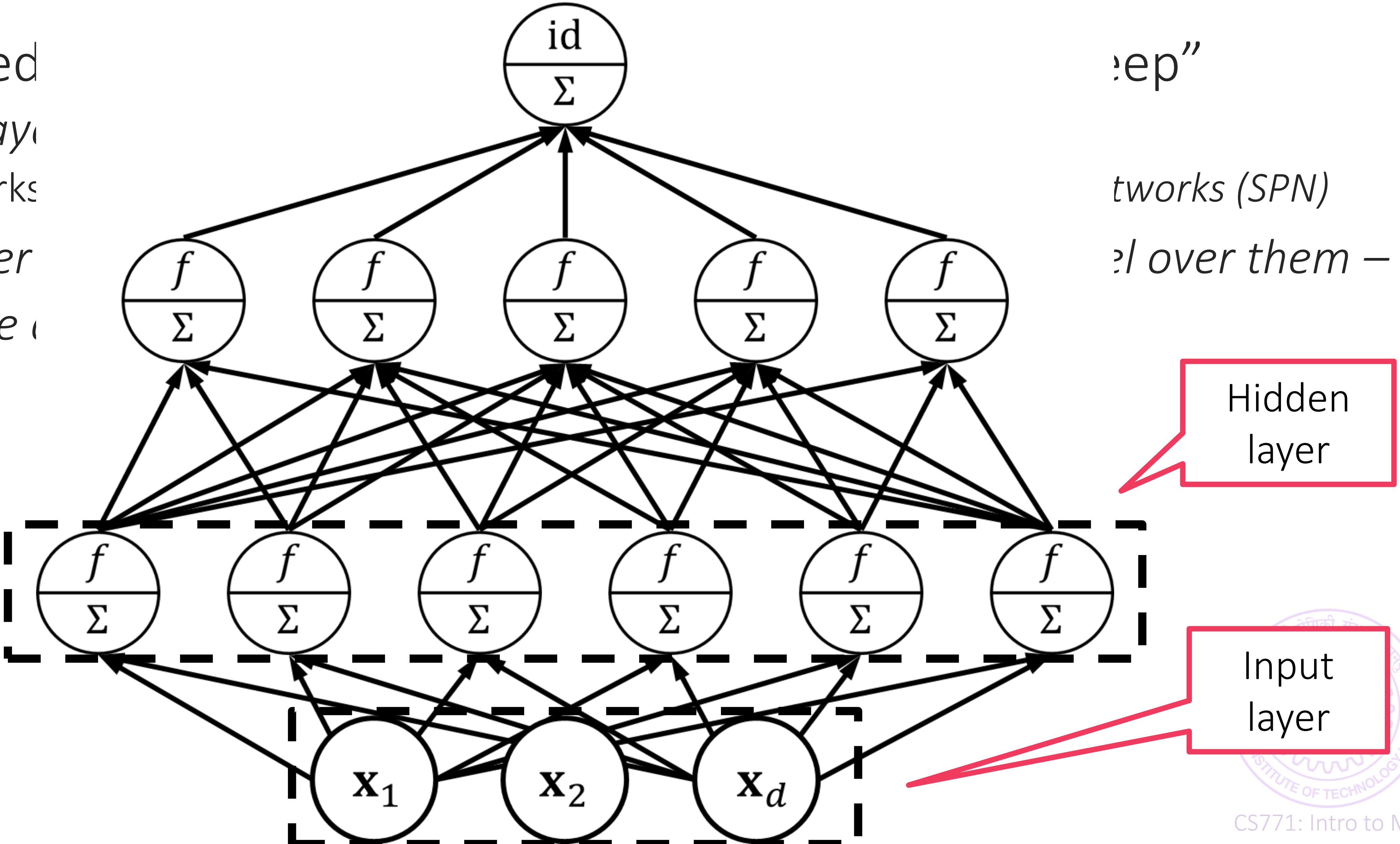

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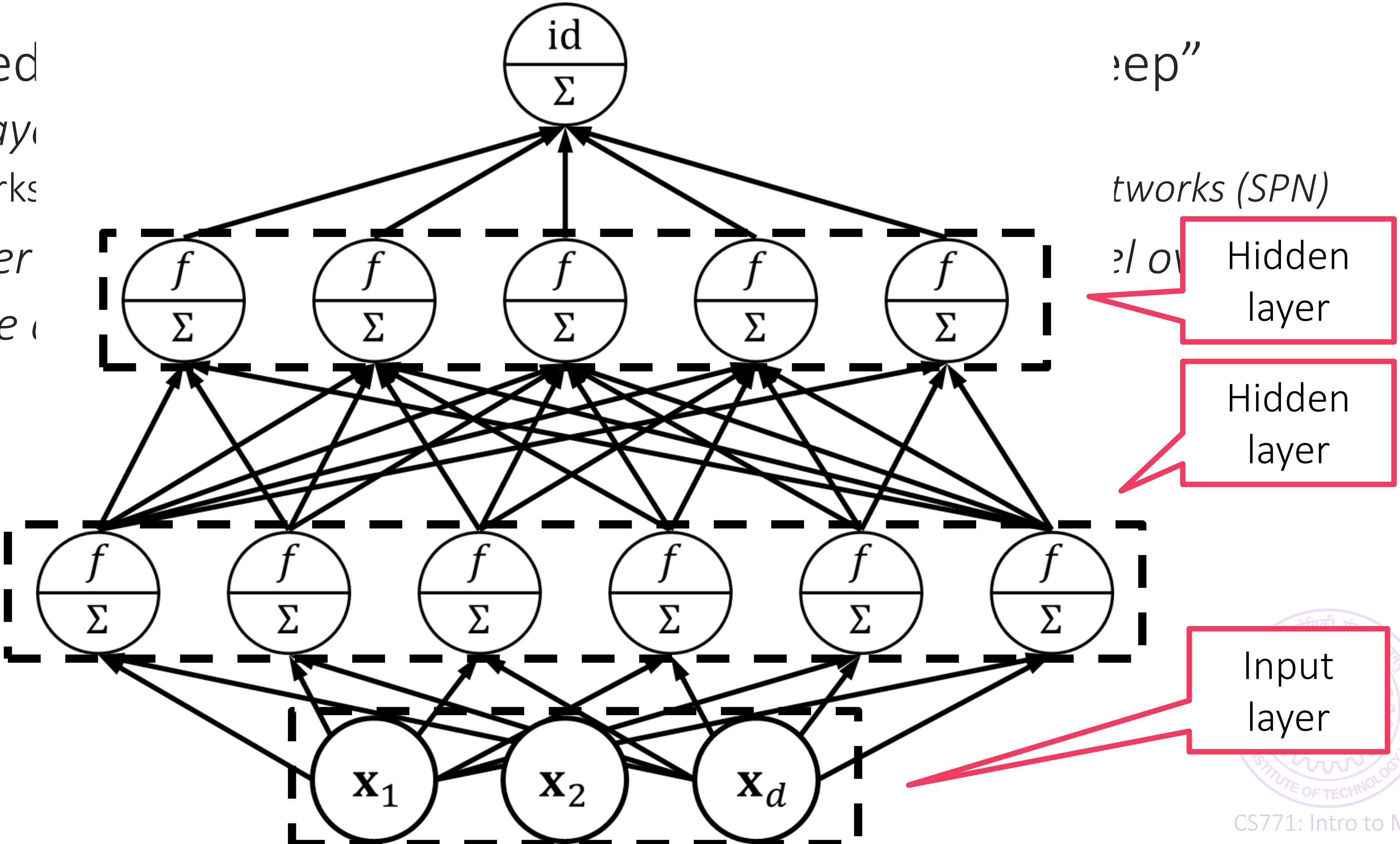

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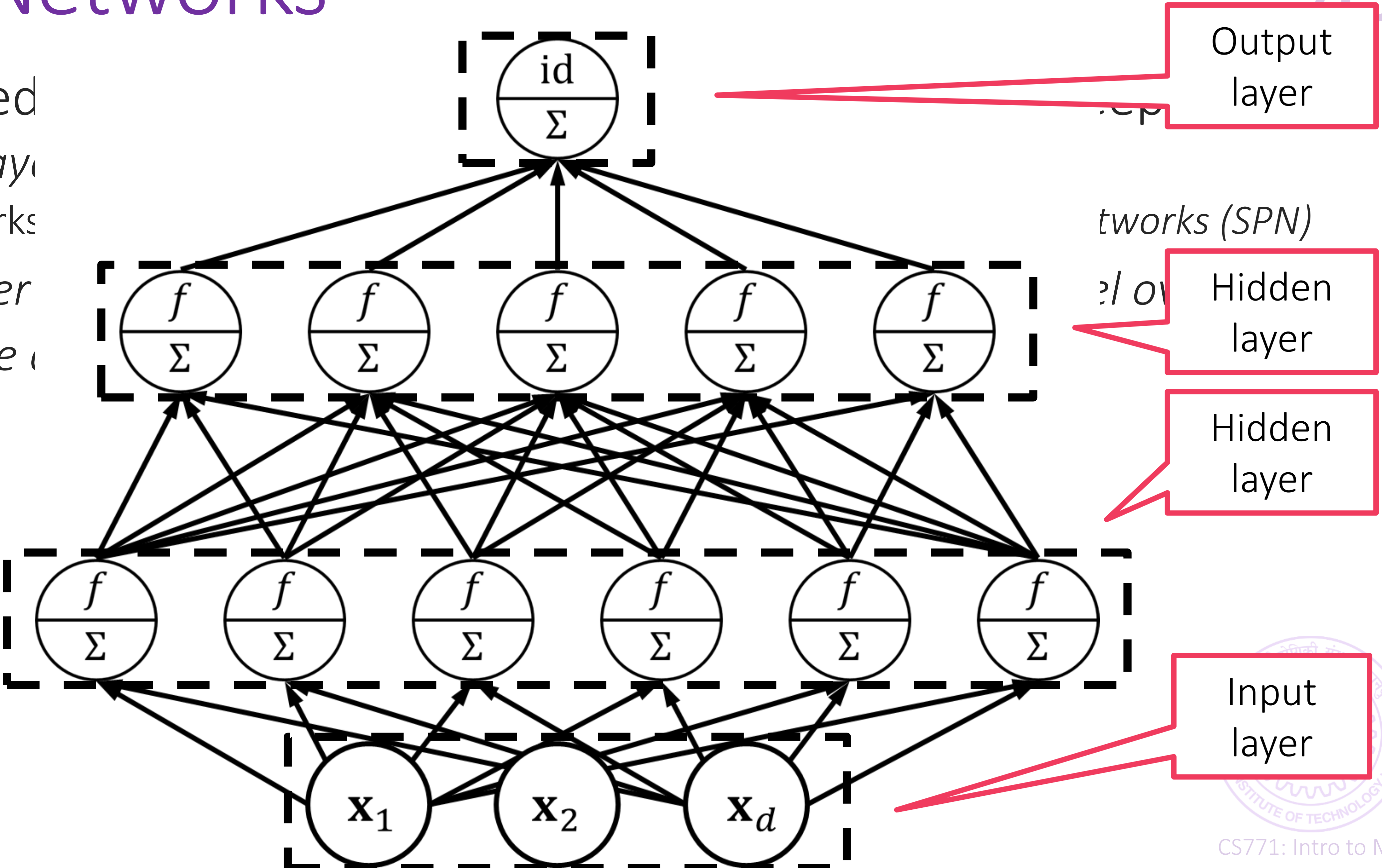

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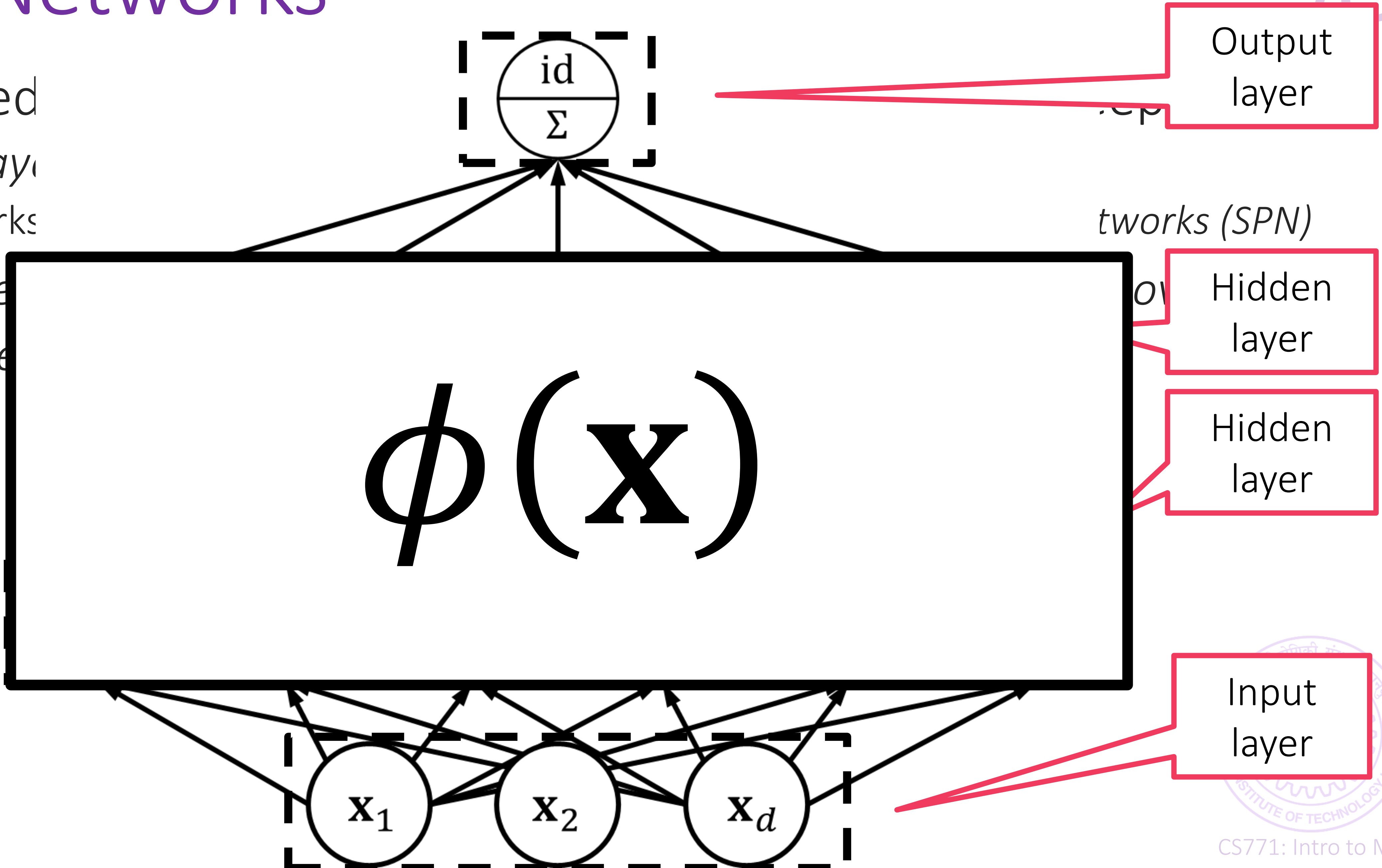

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Lower layers can be interpreted as computing useful features

Networks that learn polynomial etc features exist too – *Sum Product Networks (SPN)*

Last layer exploits all this hard work to learn a good linear model over them – can have any no. of layers, any no. of nodes in each layer

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Even (leaky) ReLU are piecewise linear, not linear – non-linearity is essential