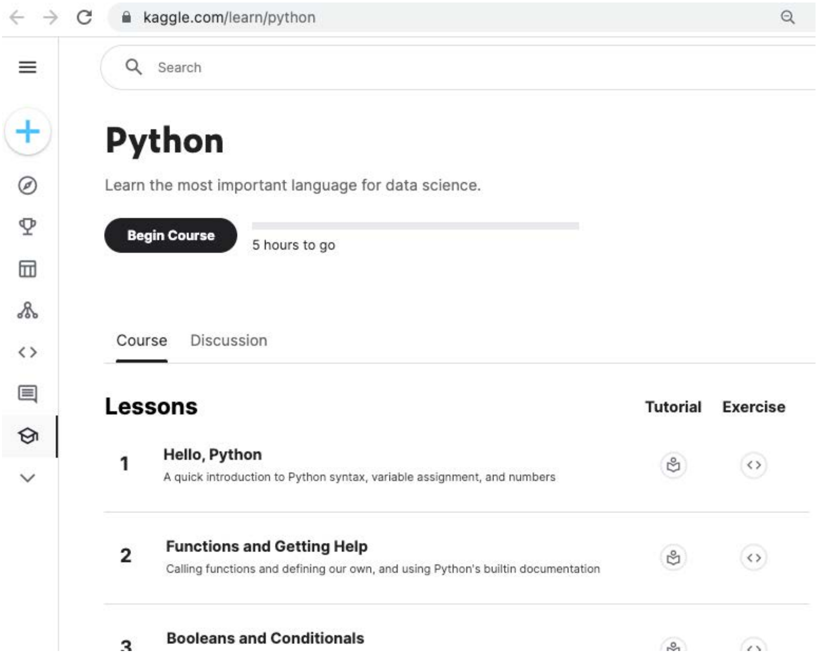
Lecture 1:
Introduction to Neural Networks and Deep Learning

MIT MANAGEMENT SLOAN SCHOOL

15.773: Hands-on Deep Learning
Spring 2024
Farias, Ramakrishnan

Prerequisites 👀

- Familiarity with Python at this level
- Familiarity with fundamental machine learning concepts (such as training/validation/testing, overfitting/underfitting, and regularization).
- If you have taken 15.071/15.072(or will be taking it concurrently) OR if you have other relevant coursework or work experience, you should be fine.



Grading

Grading

Your course grade will be based on 2 homework assignments, a final project, and class participation:

Class participation	10%
Homework assignments (25% x 2)	50%
Final project	40%

Rama Ramakrishnan

Professor of the Practice, AI/ML

Education: Ph.D. and M.S. (Operations Research; MIT), B.Tech. (Engineering; Indian Institute of Technology)

Industry Experience

McKinsey followed by 4 data science/machine learning startups (in asset management, transportation, retail and ecommerce). Exits to Oracle, Demandware and Salesforce

Post acquisition, Chief Analytics Officer at Oracle Retail; SVP of Data Science at Salesforce

My most recent startup – CQuotient – is now Salesforce Einstein AI for Commerce and is one of the top personalization engines in the world (live on ~10,000 e-commerce sites worldwide)

Interests: Applying AI/ML to business problems (especially shortest-path-to-human-impact applications e.g., healthcare, drug development)

Outside Activities: Active angel investor, AI advisor to venture firms, several startups and a few large companies

Why HODL?

Why did we create HODL?

- DL is one of the most exciting and profound technology developments of our lifetimes
- It is important for Sloanies to understand how to use DL to transform businesses and create exciting new products/services
- While MIT has other (excellent) DL courses, we wanted one that was a better fit for Sloan

HODL's "philosophy"

- Focus on the key <u>concepts</u> that underlie DL
- Skip the math* (but we are happy to geek out in office hours and/or suggest readings for those who are interested)

*If you are looking for a 'mathy' DL course, this course won't be a good fit and you may want to consider dropping it.

HODL's "philosophy"

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- Skip the math (but we are happy to geek out in office hours and/or suggest readings for those who are interested)
- Focus on coding DL models …
  - It is the only way to develop a visceral (not just intellectual) understanding of how this stuff works
  - Successful new products and services are often inspired by hands-on tinkering

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- Focus on <u>coding</u> DL models …
  - It is the only way to develop a visceral (not just intellectual) understanding of how this stuff works
  - Successful new products and services are often inspired by hands-on tinkering
- … but only up to a point
  - We aren't trying to teach you how to be ML engineers
  - But we want you to be able to build a V1.0 DL model <u>by yourself</u> without looking for a Data Scientist or ML Engineer to help you out

We will start with a very quick introduction to the relationship between

- Artificial Intelligence (AI)
- Machine Learning (ML)
- Deep Learning (DL)
- Generative AI

The field of Artificial Intelligence originated in 1956

In the back row from left to right are Oliver Selfridge, Nathaniel Rochester, Marvin Minsky, and John McCarthy. In front on the left is Ray Solomonoff; on the right, Claude Shannon. The identity of the person between Solomonoff and Shannon remained a mystery for some time. THE MINSKY FAMILY

https://spectrum.ieee.org/dartmouth-ai-workshop

MIT was well-represented 👍

Marvin Minsky

John McCarthy

Claude Shannon

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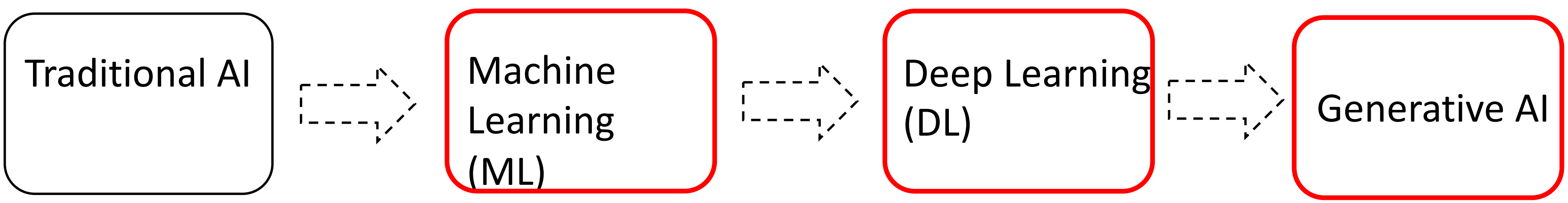
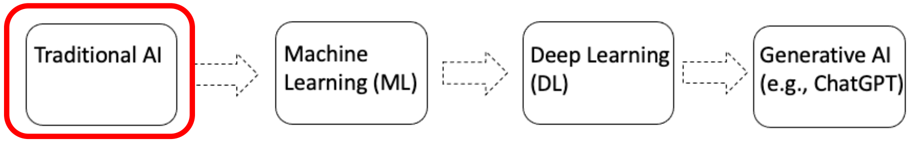
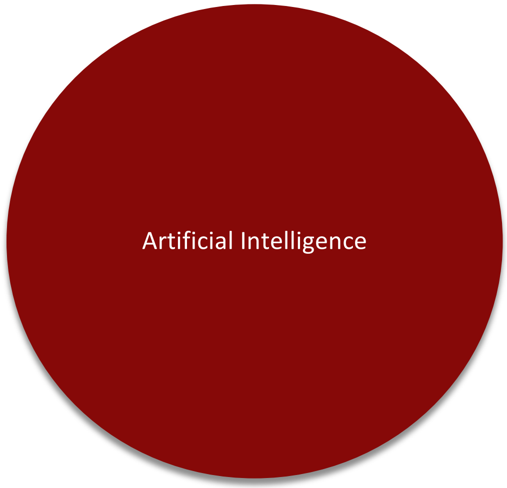
In the decades since its founding, it has gone through several "breakthroughs"



The traditional approach to AI





The Goal: Give computers the ability to do tasks that traditionally only humans have been able to do

Traditional approach:

Ask human experts how they do it, write it down as IF-THEN rules, explicitly program these rules into the computer

Success in only a few areas

Why is this so difficult?

- "We know more than we can tell" (Polanyi's Paradox)
  - We can do lots of things easily but find it very hard to describe how exactly we do them

- We can't write down if-then rules to cover all situations, edge cases etc. (i.e., we can't generalize to new situations)

To address this problem, a different approach was developed

Instead of explicitly telling the computer what to do …

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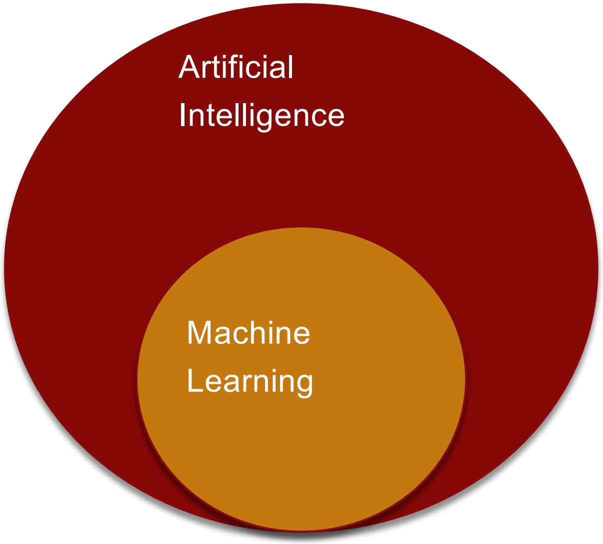
Instead of explicitly telling the computer what to do …

Provide the computer with lots of examples of inputs-and-outputs and use statistical techniques to learn the relationship between inputs and outputs

This is Machine Learning



"learn from input-output examples using statistical techniques*"

There are numerous ways* to create Machine Learning models

Input → **Machine Learning Model** → Output

- Linear Regression
- Logistic Regression
- Classification and Regression Trees
- Support Vector Machines
- Random Forests
- Gradient Boosted Machines
- Neural Networks
- …..

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*Covered in detail in courses like 15.071 The Analytics Edge

Machine Learning has had tremendous impact and is used worldwide across numerous applications (e.g., credit scoring, loan granting, disease prediction, demand forecasting, ….) where the input data is structured

Structured input data = data that can be "numericalized" into a spreadsheet*

INPUT						OUTPUT
Age	**Smoker**	**Exercise**	**Cholesterol**	**Family History**	**Blood Pressure**	**Cardiac Arrest**
30	No	120	190	Yes	120/80	No
45	Yes	30	220	No	130/90	Yes
50	No	60	210	Yes	125/85	No
35	Yes	45	230	No	135/88	Yes
40	No	150	180	Yes	118/78	No
55	Yes	10	240	Yes	140/92	Yes
28	No	180	170	No	115/75	No
60	Yes	20	250	Yes	145/95	Yes
48	No	90	200	No	128/82	No
53	Yes	35	235	Yes	133/89	Yes

*informal definition

But the situation is different for unstructured input data (images, videos, text, audio, ...)

Images

Text

Four score and seven years ago our fathers brought forth, upon this continent, ...

Audio

...

The reason: The “raw form” of unstructured data has no intrinsic meaning

Red

	[,1]	[,2]	[,3]	[,4]	[,5]	[,6]	[,7]	[,8]	[,9]	[,10]
[1,]	147	131	138	144	131	134	144	135	133	145
[2,]	140	131	141	149	138	138	143	132	136	146

Green

	[,1]	[,2]	[,3]	[,4]	[,5]	[,6]	[,7]	[,8]	[,9]	[,10]
[1,]	186	171	179	185	171	172	180	171	168	180
[2,]	177	169	180	188	176	175	178	167	169	180

Blue

	[,1]	[,2]	[,3]	[,4]	[,5]	[,6]	[,7]	[,8]	[,9]	[,10]
[1,]	251	232	233	237	230	243	255	255	250	246
[2,]	248	234	239	245	238	246	255	251	246	243
[3,]	255	241	238	236	229	241	253	249	238	234
[4,]	255	252	243	233	228	237	242	234	218	205
[5,]	255	255	249	231	228	231	224	215	204	166
[6,]	255	255	230	192	189	202	205	205	204	147
[7,]	231	231	188	140	138	152	156	159	177	136
[8,]	155	172	149	114	113	111	93	82	119	115
[9,]	107	130	108	93	113	100	67	66	81	95
[10,]	84	104	90	69	69	61	52	63	59	46

To use ML on unstructured data, we had to manually create a better representation of the data first*

"Unstructured" data

Manual feature extraction →

Datasets in "structured" form like tables

	Beak length	Wing span	Primary color	...
Bird 1	3 cm	43 cm	black	...
Bird 2	0.5 cm	19 cm	yellow	...
Bird 3	5 cm	48 cm	black	...
Bird 4	4 cm	45 cm	black	...
...	...	...	...	...

Figure source: https://magazine.sebastianraschka.com/p/ai-and-open-source-in-2023

*sometimes referred to as feature extraction

Learning effective representations is vital

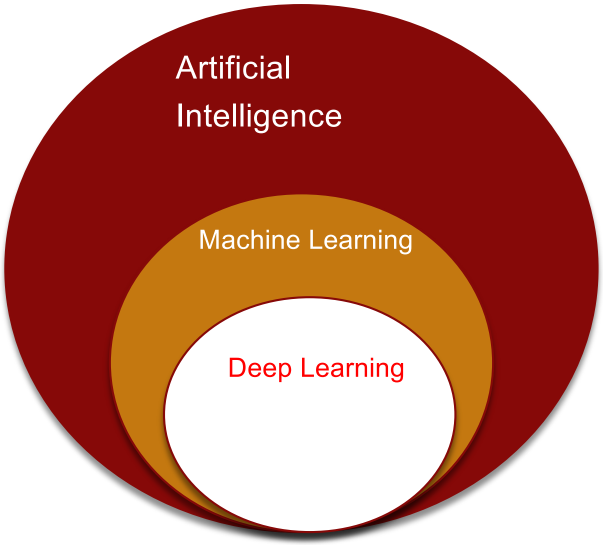
- The raw data has to somehow be transformed into a different representation

- Historically, researchers manually developed these representations and then fed them to traditional machine learning algorithms (often just linear/logistic regression!)

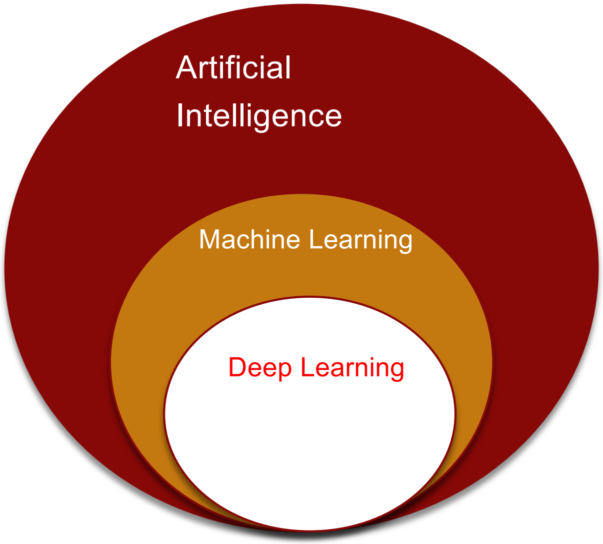
- But this required massive human effort and thus sharply limited the reach of Machine Learning

But developing good representations (before ML could be used) required massive human effort and this “human bottleneck” sharply limited the reach of Machine Learning

To address this problem, a different approach was developed – Deep Learning



Deep Learning can handle unstructured input data without upfront manual preprocessing!!



Structured *and* Unstructured data → Deep Learning → Prediction

0	228	4.81	707	33.82	0	0
0	367	4.51	682	3.51	1	0
0	162	4.93	712	33.67	1	0
0	103	4.91	667	4.74	0	0
0	125	5.17	727	50.81	0	0
1	194	4.65	667	3.84	0	1
1	131	4.78	722	24.22	0	0
0	87	4.95	682	69.91	1	0
0	84	4.43	707	5.63	1	0
0	360	4.53	677	13.85	2	1
0	254	5.14	662	5.12	2	0
0	316	4.75	767	6.07	0	0
0	93	5	747	3.02	0	0

Four score and seven years ago our fathers brought forth, upon this continent, …

What can Deep Learning do that traditional Machine Learning can't?

- It can automatically extract smart representations from raw, unstructured data.

- We can simply feed these smart representations to traditional models like linear regression or logistic regression and achieve amazing performance

This demolishes the “human bottleneck” for using Machine Learning with unstructured data

Deep Learning

The breakthrough came from the confluence of three forces …

- New algorithmic ideas
- Unprecedent amounts of data (due to the digitization of everything)
- Compute power (from the use of powerful Graphics Processing Units (GPUs))

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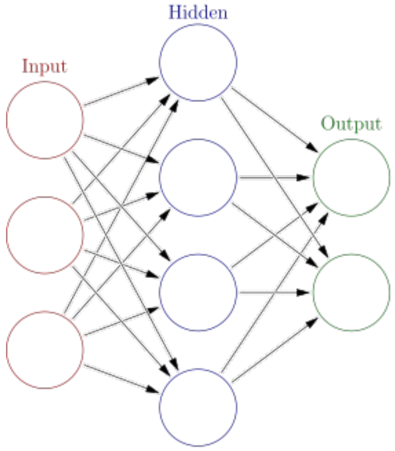
… applied to an old ML idea: Neural Networks

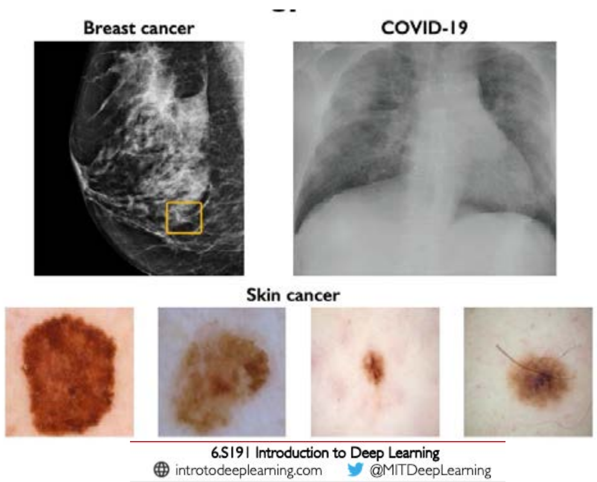


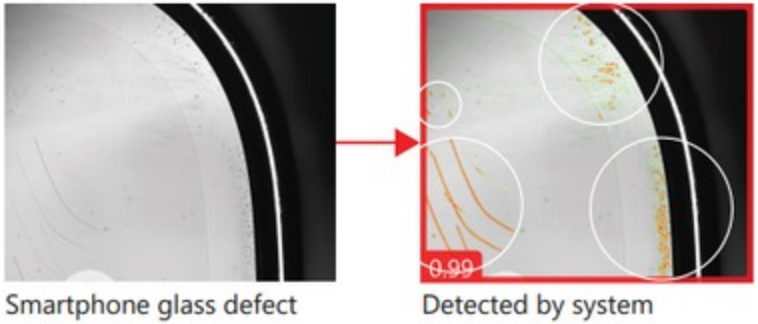
https://en.wikipedia.org/wiki/Artificial_neural_network

What is the ***immediate*** application of Deep Learning?

Every “sensor” can be given the ability to detect, recognize and classify what it is sensing

Examples





https://dwfritz.com/smart-cosmetic-defect-detection-increases-productivity/

Every "sensor" can be given the ability to detect, recognize and classify what it is sensing

You can create dramatically better products and services by "attaching" DL to sensors

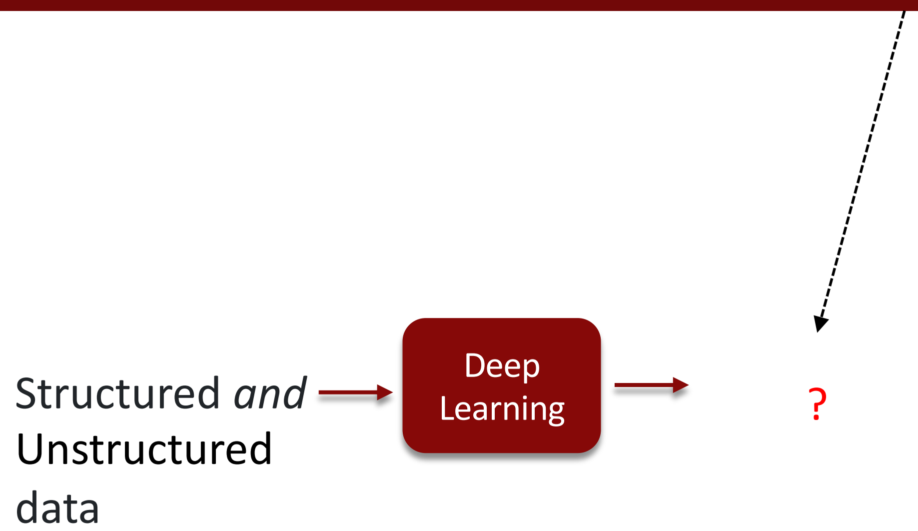
(Spotted last week!) Binoculars + DL = Smart Binoculars

https://www.swarovskioptik.com/us/en/hunting/products/binoculars/ax-visio

+ DL =

https://www.swarovskioptik.com/us/en/hunting/products/binoculars/ax-visio

Now, let’s turn our attention to the output



With Deep Learning, we could predict/generate structured outputs easily

Structured *and* Unstructured data

Examples:

- A single number
  - The probability that a borrower will repay a loan
  - The demand for a product next week
- A few numbers
  - The 4 probabilities that an image contains a chair, stool, table or sofa
  - The two GPS coordinates of a taxi

But we couldn't generate unstructured output very well!

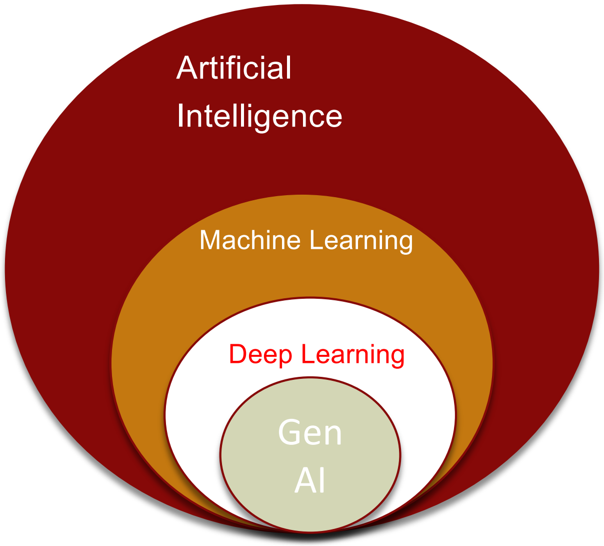
Structured *and* Unstructured data → **Deep Learning** →

Images

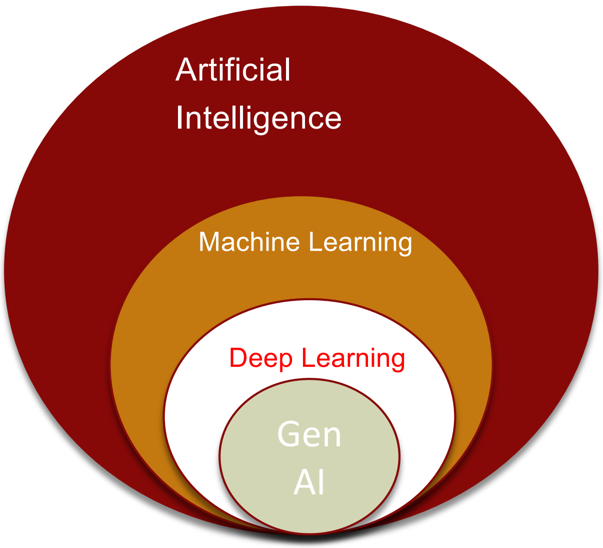
Text *Four score and seven years ago our fathers brought forth, upon this continent, …*

Audio …

And then Generative AI happened



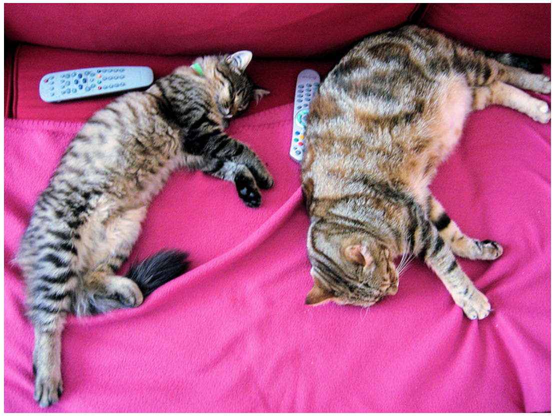
Gen AI can produce unstructured outputs



Unstructured input → Gen AI → Unstructured output

"generate a picture of a cute labrador retriever puppy"

Image-to-text



Gen AI

two cats laying on a pink blanket with remotes

https://huggingface.co/spaces/nielsr/comparing-captioning-models

Text-to-image

temple in ruins, forest, stairs, columns, cinematic, detailed, atmospheric, epic, concept art, Matte painting, background, mist, photo-realistic, concept art, volumetric light, cinematic epic + rule of thirds octane render, 8k, corona render, movie concept art, octane render, cinematic, trending on artstation, movie concept art, cinematic composition , ultra-detailed, realistic , hyper-realistic , volumetric lighting, 8k –ar 2:3 –test –uplight

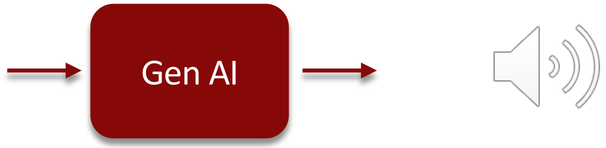
→ Gen AI →

Image generated using Stable Diffusion AI from prompt quoted above.

https://mpost.io/best-100-stable-diffusion-prompts-the-most-beautiful-ai-text-to-image-prompts/

Text-to-music

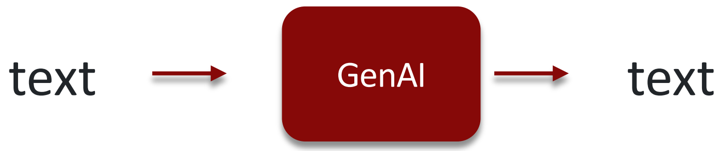
The main soundtrack of an arcade game. It is fast-paced and upbeat, with a catchy electric guitar riff. The music is repetitive and easy to remember, but with unexpected sounds, like cymbal crashes or drum rolls.



https://google-research.github.io/seanet/musiclm/examples/

Audio generated using MusicLM from prompt the main soundtrack of an arcade game. It is fast-paced and upbeat, with a catchy electric guitar riff. The music is repetitive and easy to remember, but with unexpected sounds, like cymbal crashes or drum rolls.

Text-to-text



Multi-modal

[text, image] → GenAI → text

A fun multi-modal example

[text, image] → ChatGPT →

https://twitter.com/petergyang/status/1707169696049668472

A fun multi-modal example

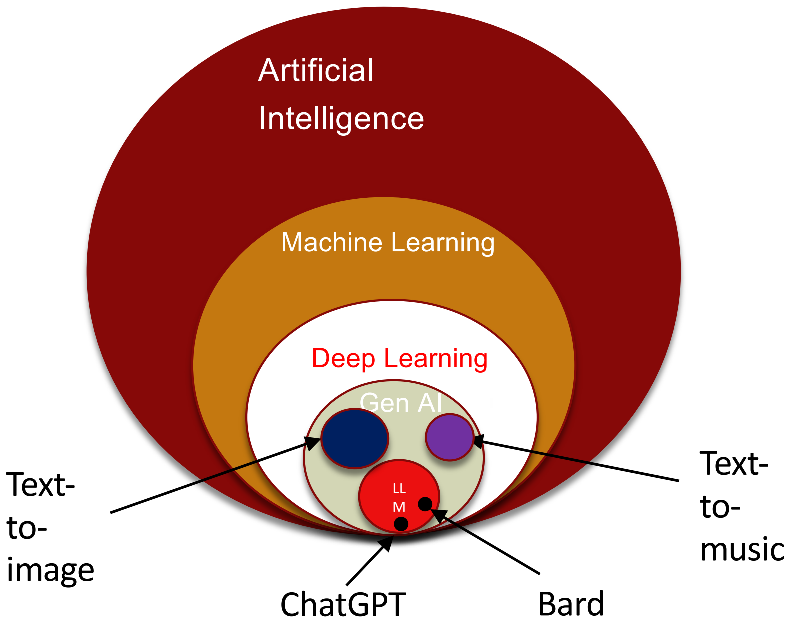
[text, image] → ChatGPT → text

It's Wednesday at 4 pm. Can I park at this spot right now? Tell me in 1 line.

Yes, you can park for up to 1 hour starting at 4 pm.

https://twitter.com/petergyang/status/1707169696049668472

The landscape

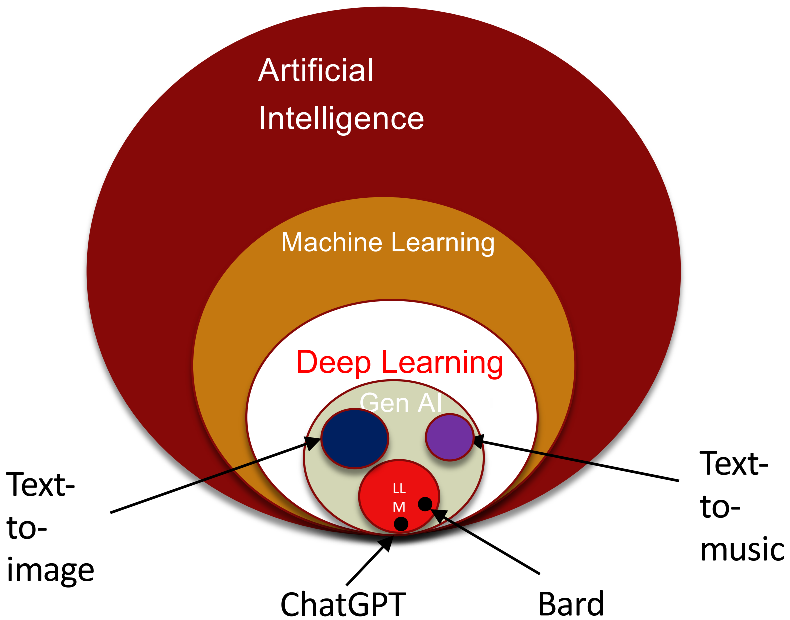


… and the circles inside GenAI are merging!

Summary: X-to-Y

X and Y can be *anything* *<u>and</u>* *it can be multi-modal!*

Note that ALL the AI excitement is due to the success of Deep Learning



If you understand Deep Learning, everything becomes possible! 🙂

OK, let's start at the beginning. What's a Neural Network?

Recall Logistic Regression

$[x_1, x_2, x_3, \ldots, x_n]$ → Logistic Regression → probability

$$Pr(Y=1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n)}}$$

Recall Logistic Regression

$$Pr(Y=1) = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+\cdots+\beta_n x_n)}}$$

Let us look at it through the lens of a “network” of mathematical operations.

We will work with this simple classification example

- Given independent variables …
  - GPA
  - Experience
- … predict who will be called for a job interview

	Interview	GPA	Experience
1	0	3.27	1.93
2	0	3.37	0.07
3	0	3.57	1.91
4	0	3.91	4.35
5	0	3.20	1.70
6	1	3.90	2.41
7	1	3.94	3.00
8	0	3.66	2.47
9	0	3.63	0.93
10	0	3.06	4.14
11	0	3.21	3.34
12	0	3.18	3.97
13	0	3.69	0.54
14	0	3.38	3.62
15	1	3.77	2.06
16	0	3.50	4.10
...	...	...	...
25	1	3.31	3.46
26	0	3.78	0.29
27	0	3.87	1.21
28	0	4.00	0.49
29	1	3.87	2.11

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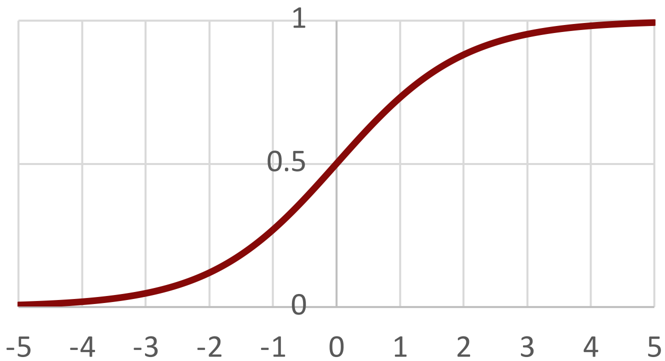
28	0	4.00	0.49
29	1	3.87	2.11

We can estimate this logistic regression model and find values for the coefficients:

$$P(Y=1) = \frac{1}{1+e^{-(0.4+0.2\cdot\mathrm{GPA}+0.5\cdot\mathrm{Experience})}}$$



We can re-write this formula as a network with input data flowing through two functions that have been connected

Model equation: $$P(Y=1) = \frac{1}{1 + e^{-(0.4 + 0.2 \cdot \text{GPA} + 0.5 \cdot \text{Experience})}}$$

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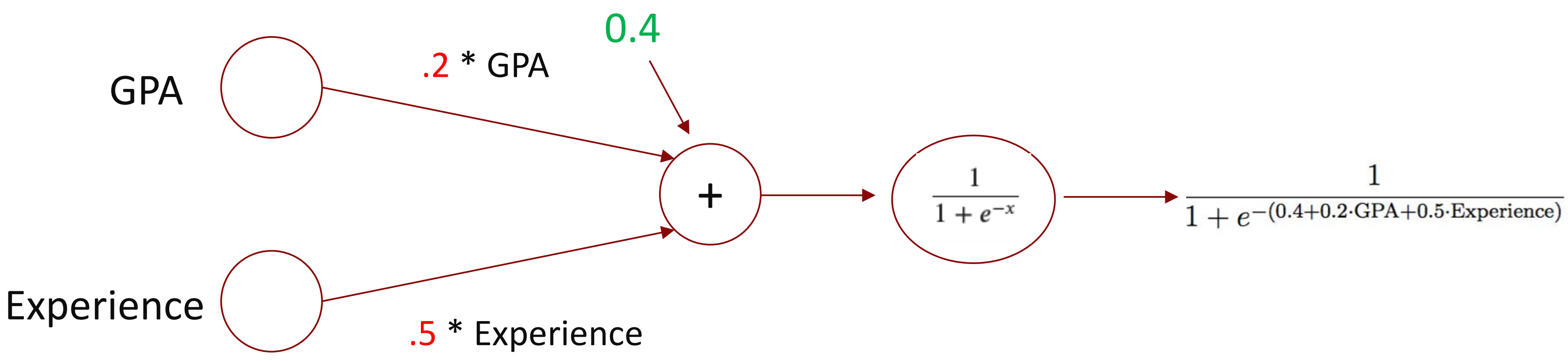
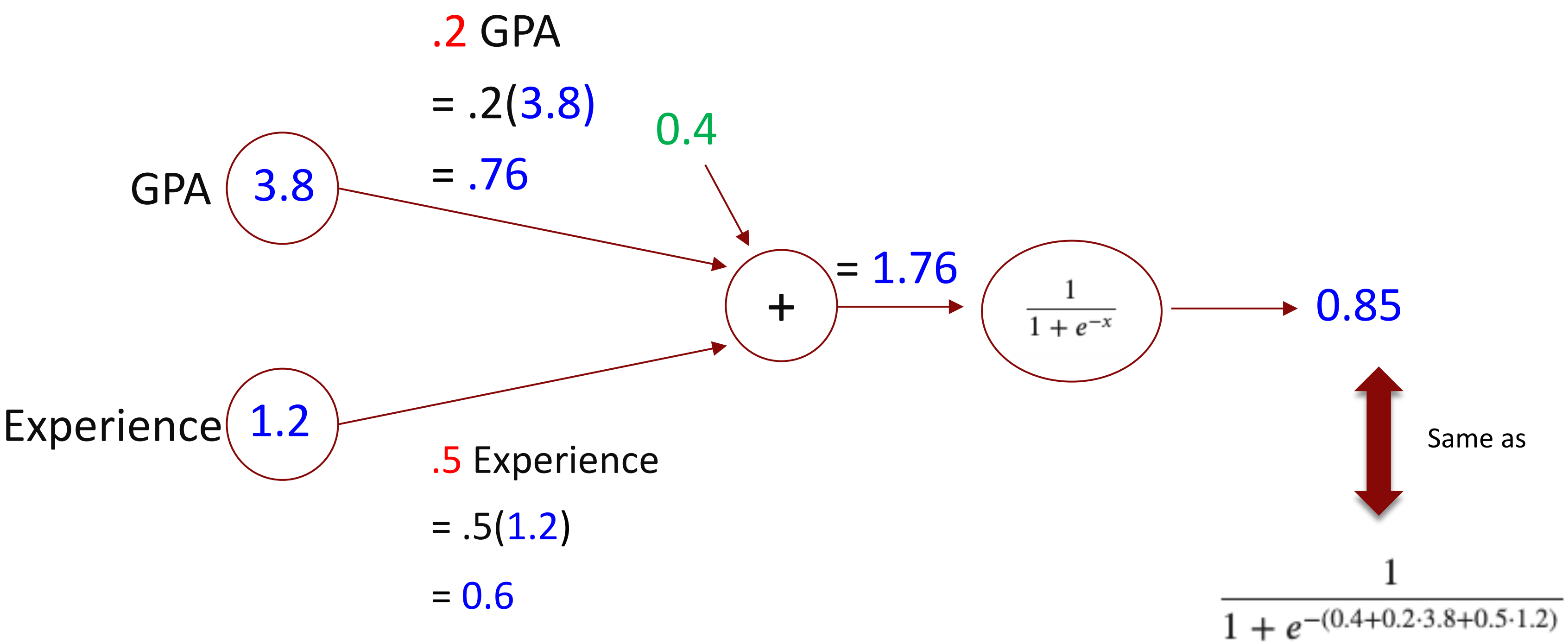


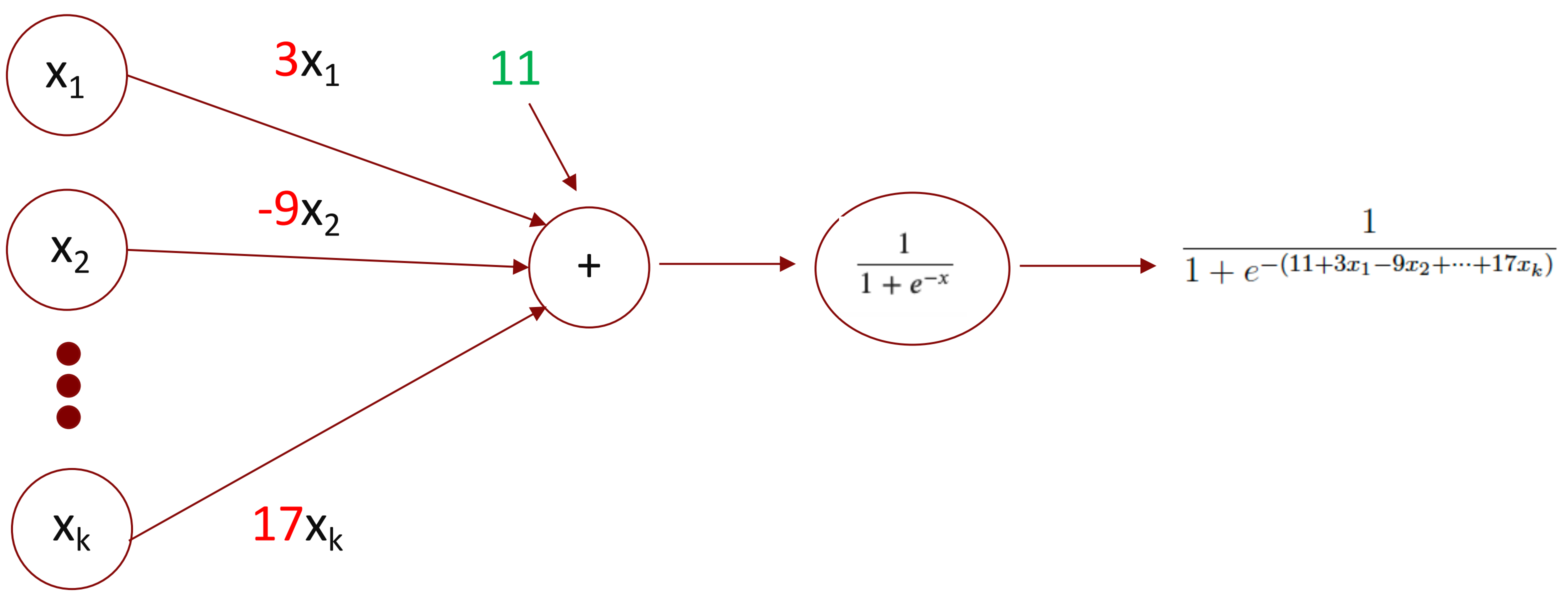
Let's make a prediction with this "network"

Consider a job applicant with a GPA of 3.8 and 1.2 years of experience.



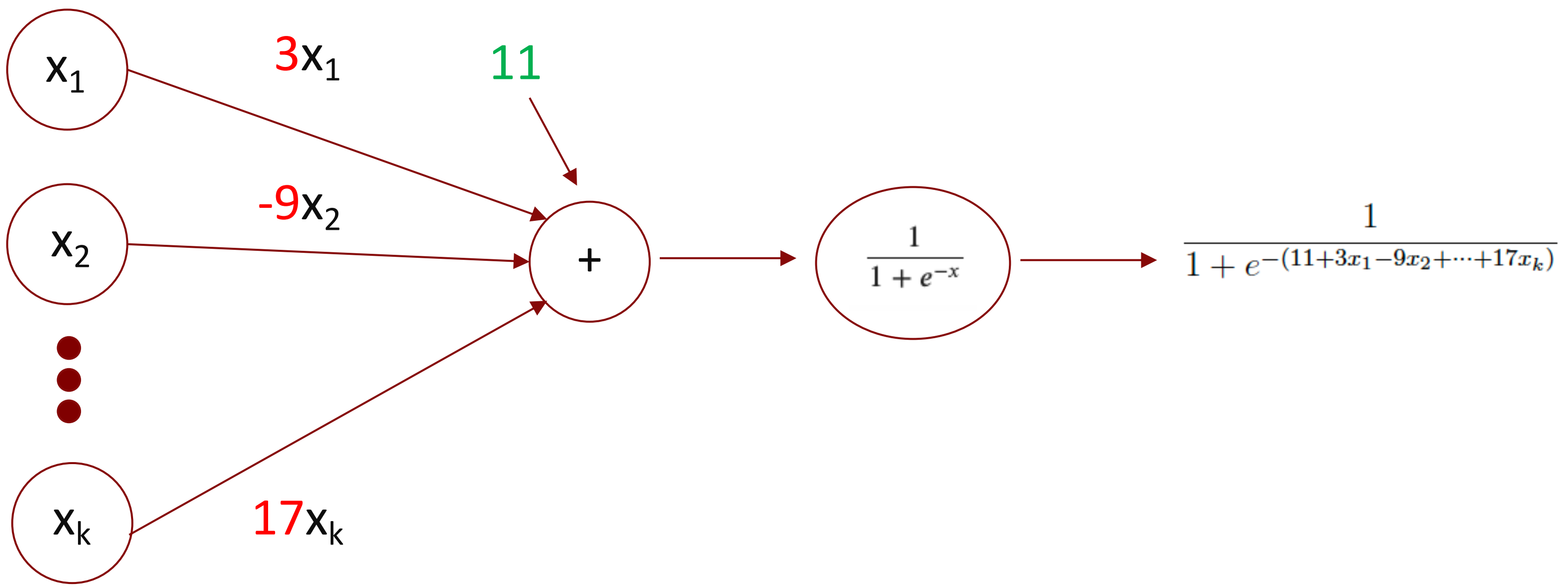
The general logistic regression model viewed through a network lens

Model equation: $$P(Y=1) = \frac{1}{1+e^{-(11+3x_1-9x_2+\cdots+17x_k)}}$$



Notice how the data flows through the network from left to right

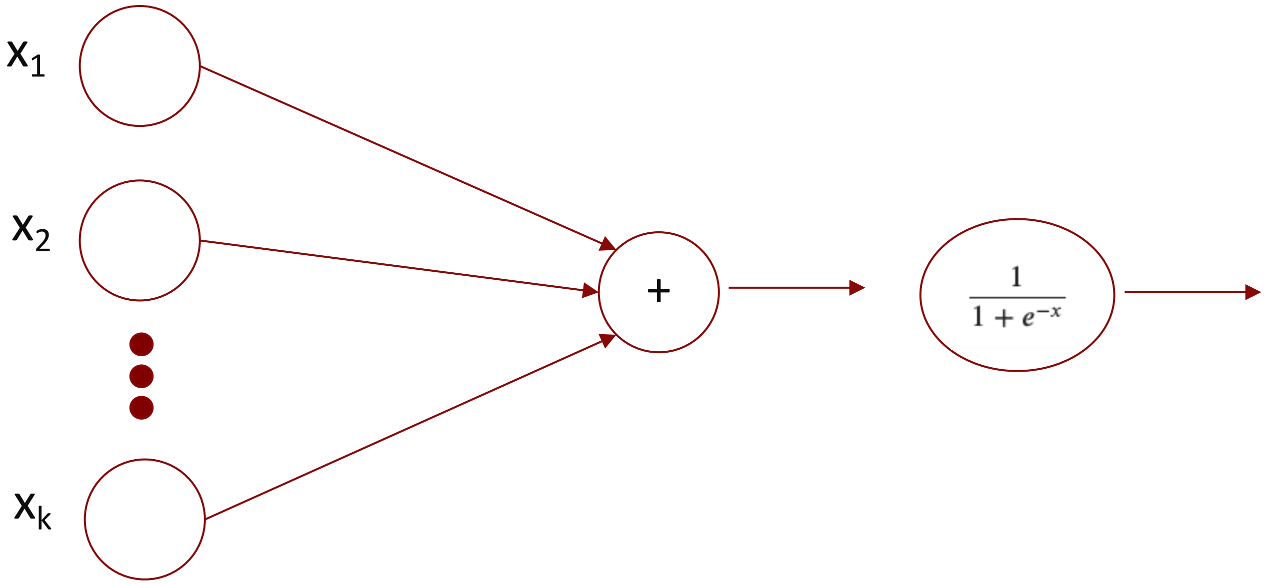
Terminology



- Multipliers on values from each node = coefficients = weights
- Intercept = bias

What’s the advantage of viewing through a network “lens”?

Recall the notion of learning smart representations of the input data



*I am not showing the weights and biases to avoid clutter

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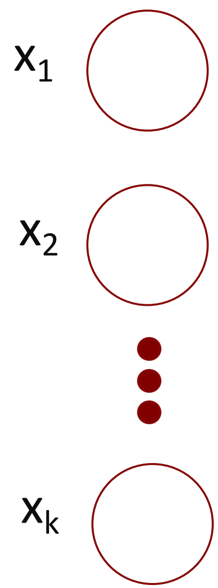
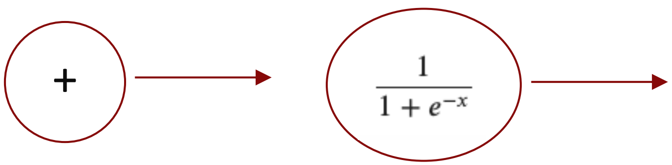


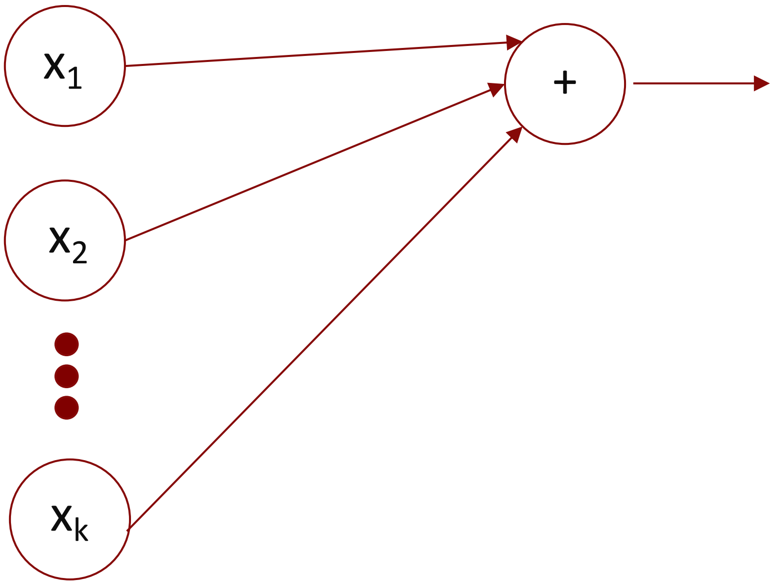
What is the simplest thing we can do here?

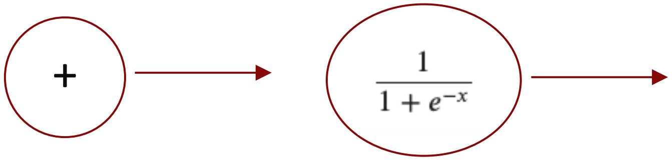
We can insert linear functions



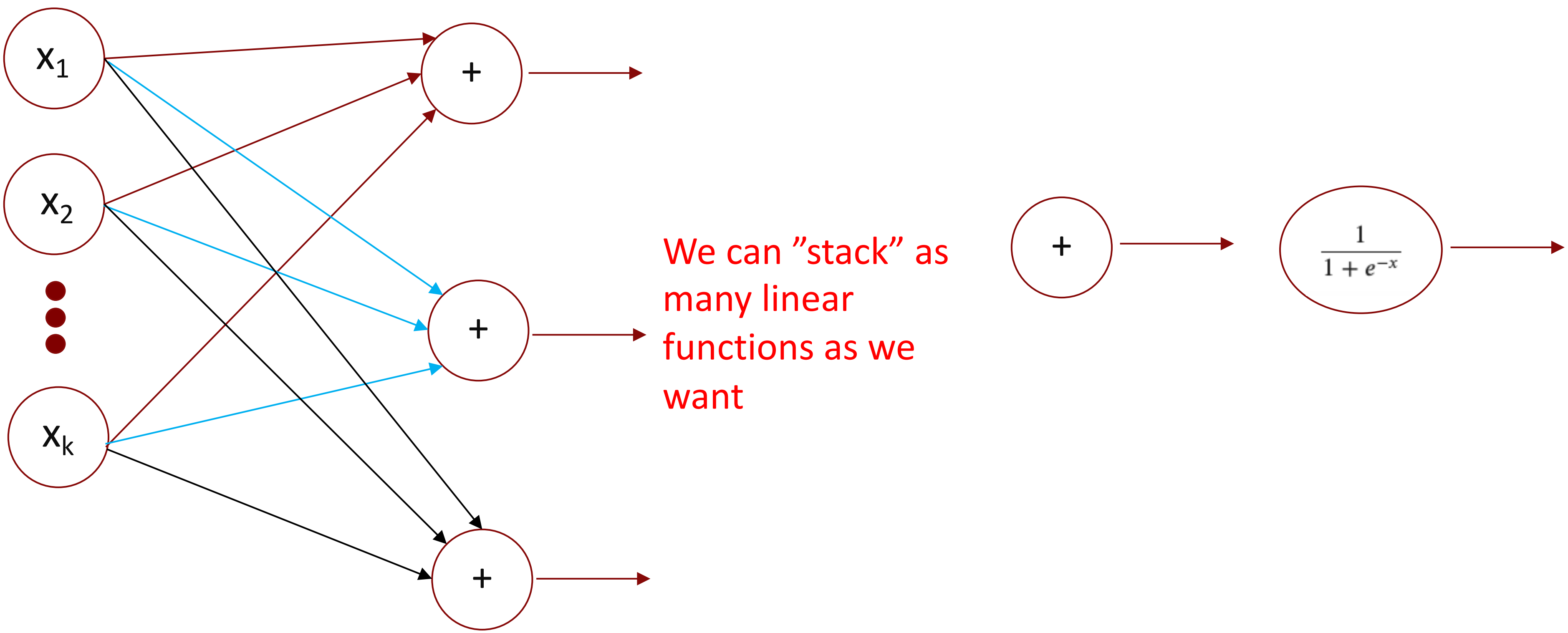
To learn smart representations, we would like to transform the inputs one or more times before we do the prediction

A linear function



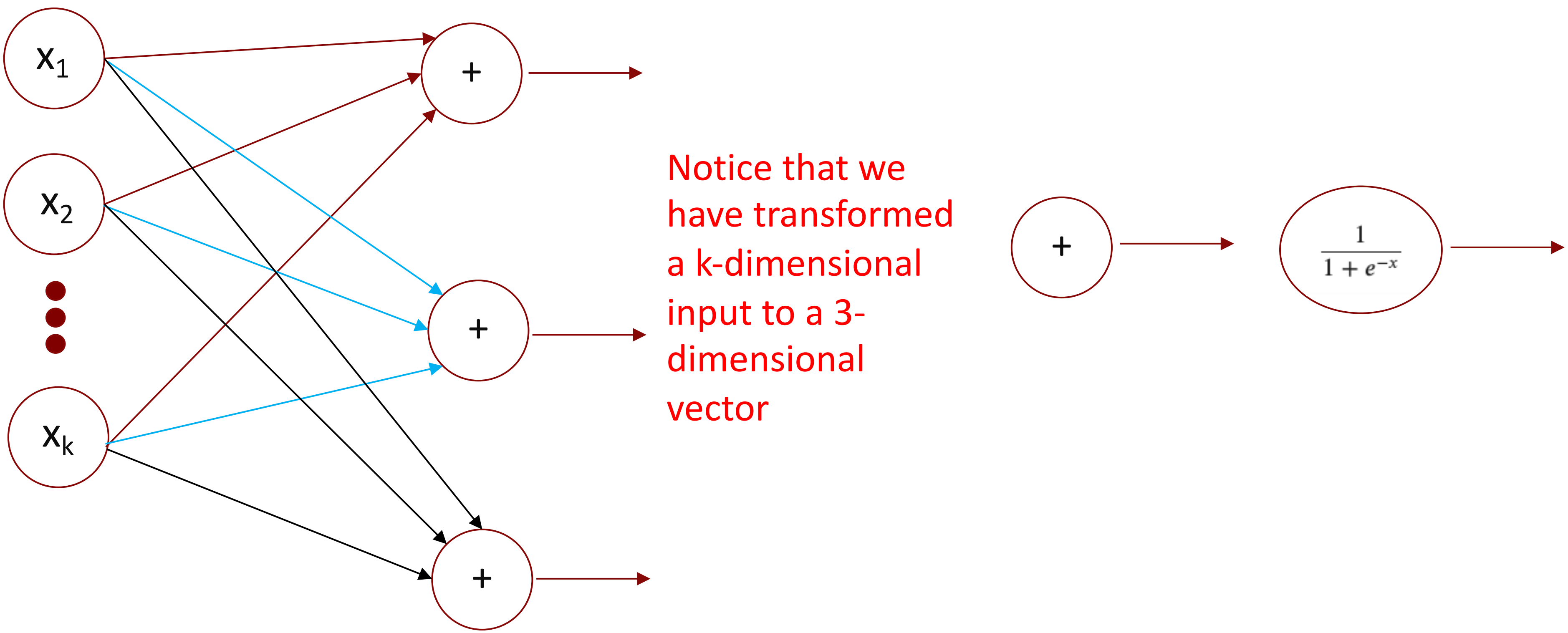


To learn smart representations, we would like to transform the inputs one or more times before we do the prediction



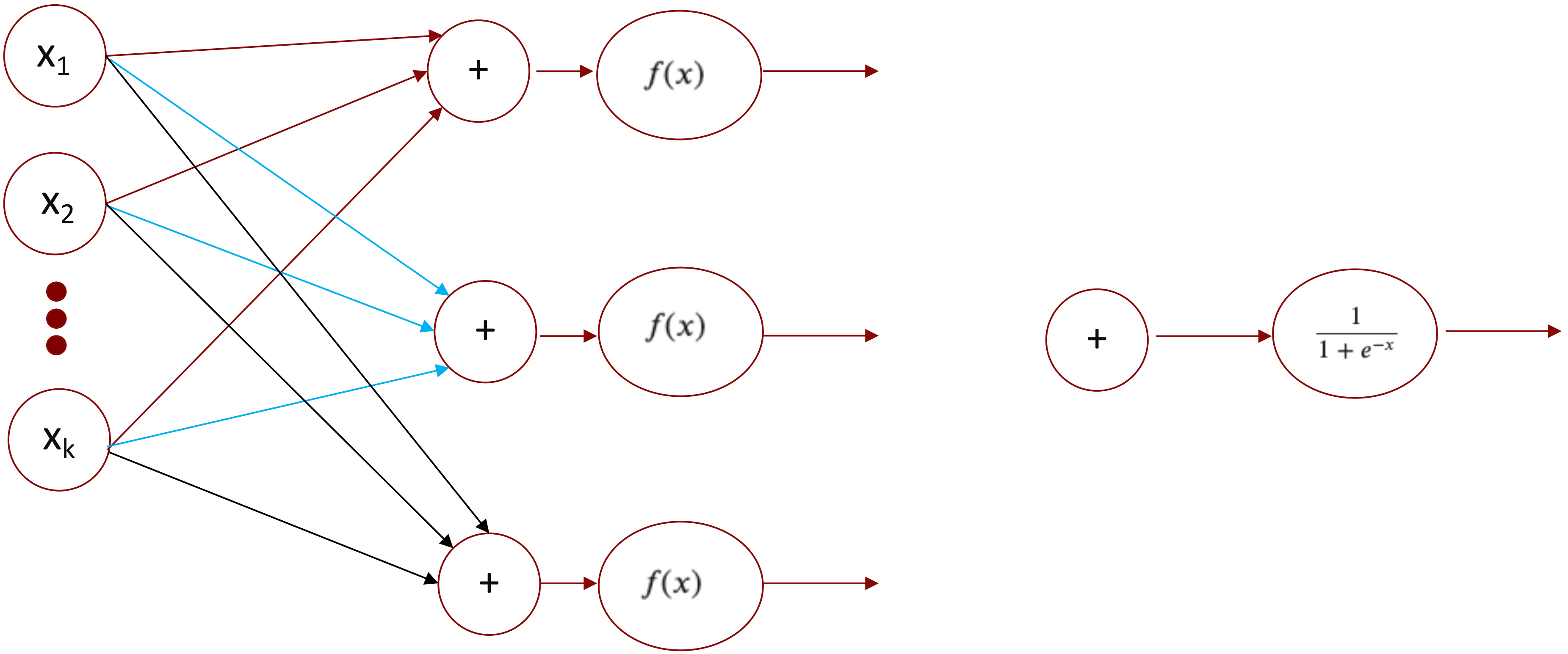
We can "stack" as many linear functions as we want

To learn smart representations, we would like to transform the inputs one or more times before we do the prediction

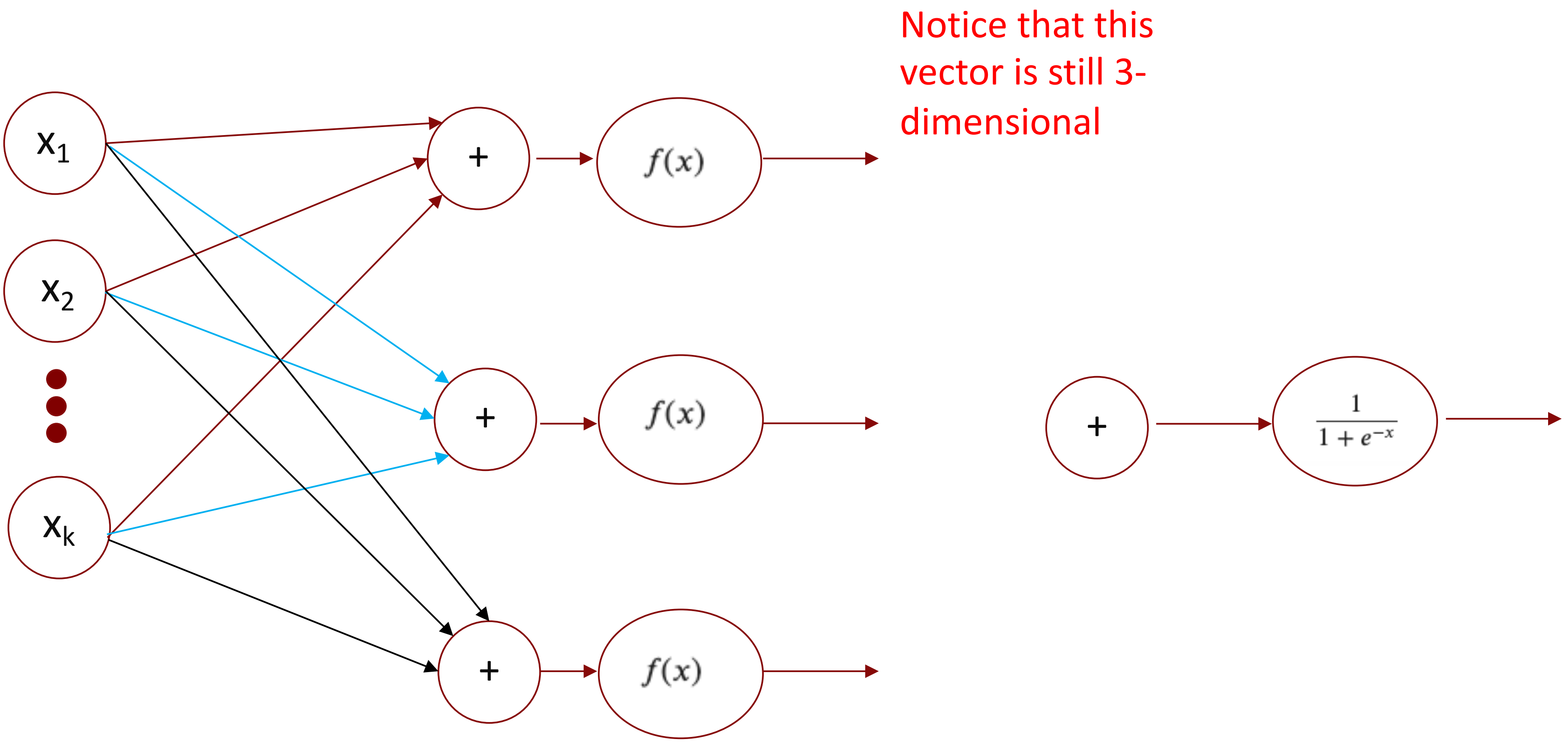


To learn smart representations, we would like to transform the inputs one or more times before we do the prediction

We can "flow" this 3-dimensional vector through another function

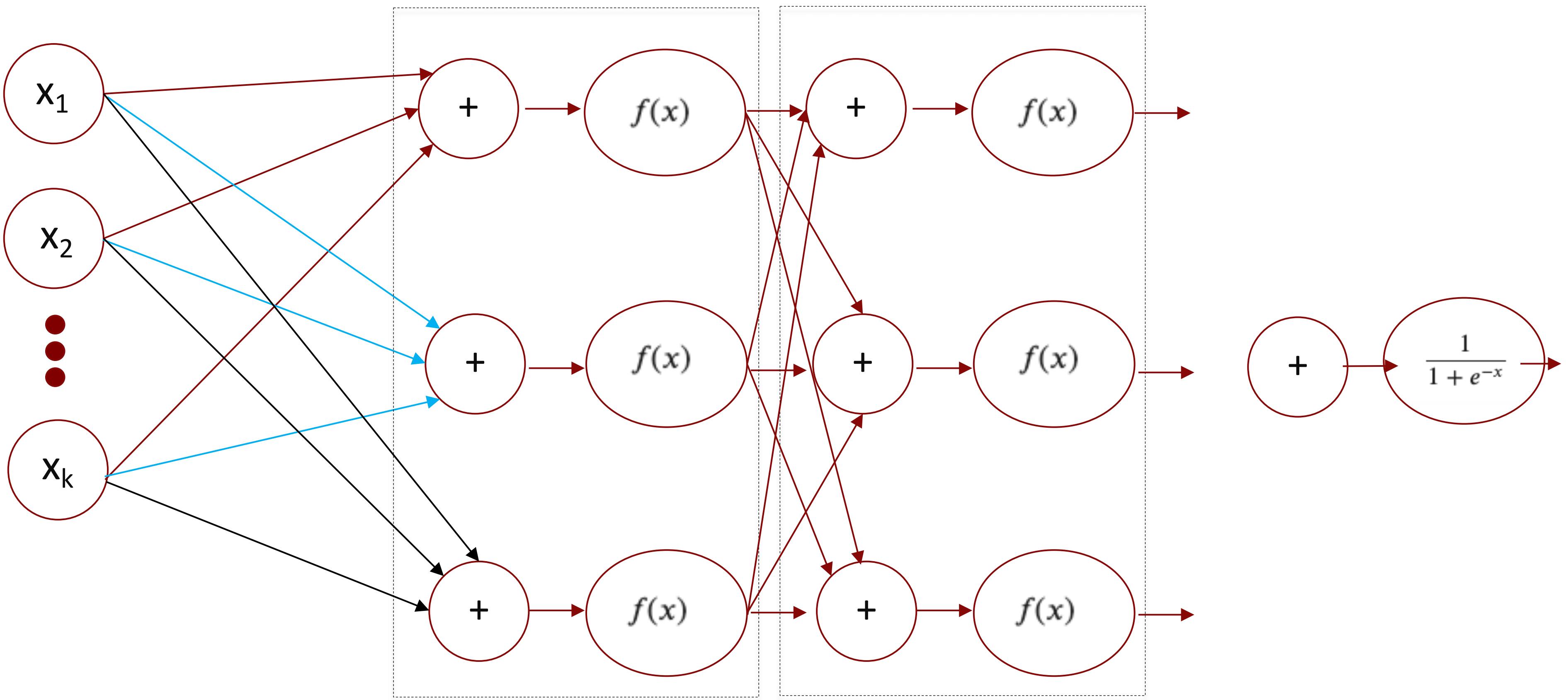


To learn smart representations, we would like to transform the inputs one or more times before we do the prediction

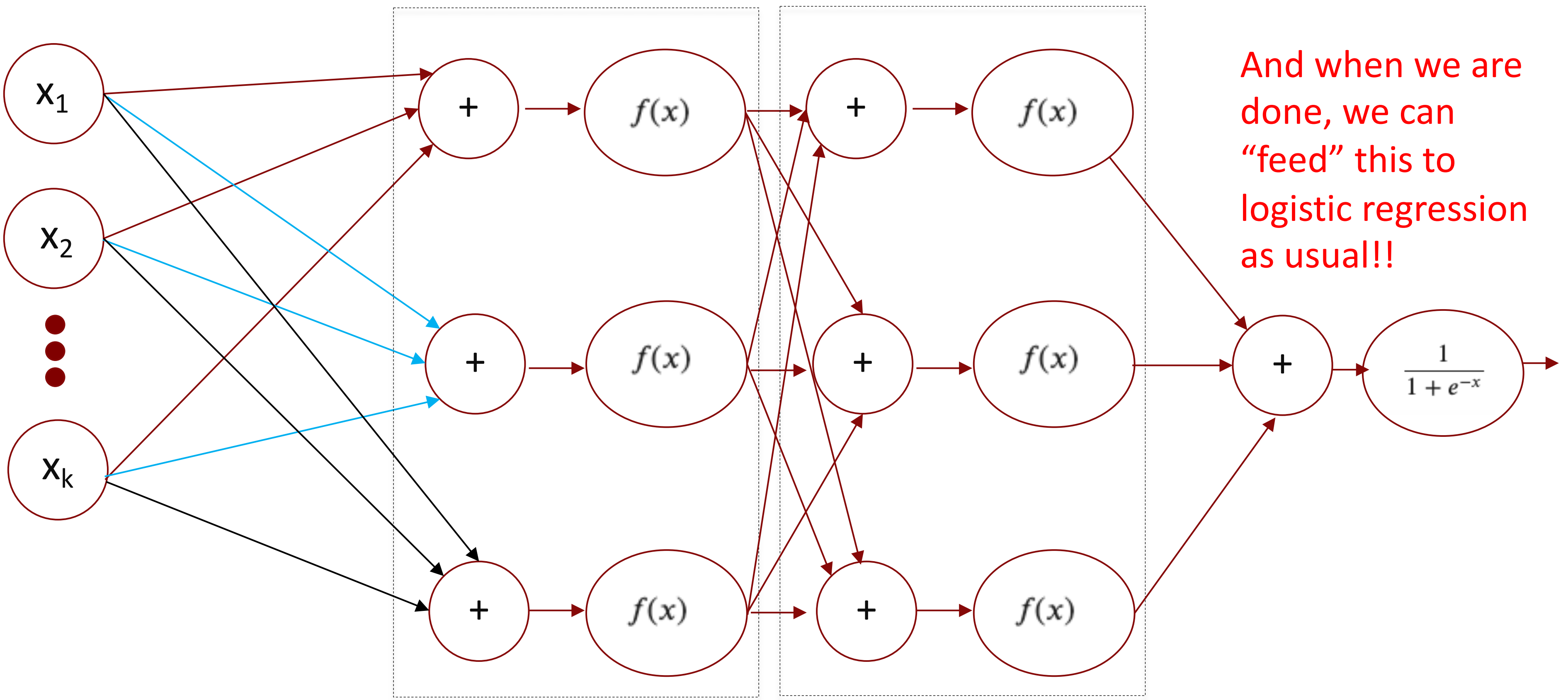


To learn smart representations, we would like to transform the inputs one or more times before we do the prediction

We can do this repeatedly



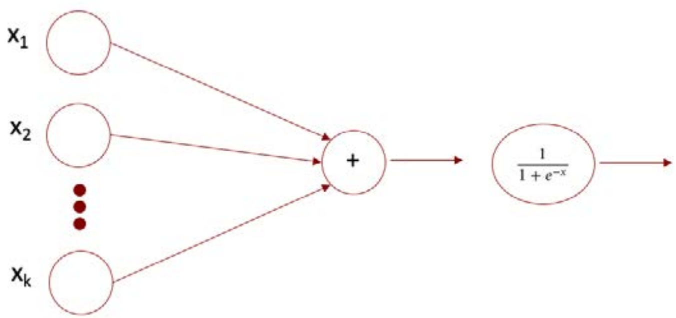
To learn smart representations, we would like to transform the inputs one or more times before we do the prediction



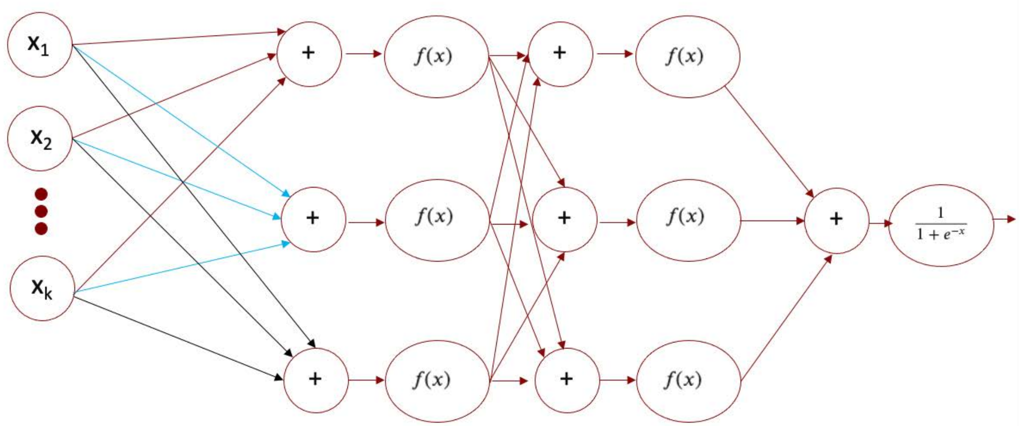
And when we are done, we can "feed" this to logistic regression as usual!!

Key Takeaway: Instead of feeding the ”raw” input to logistic regression, we feed a repeatedly transformed input

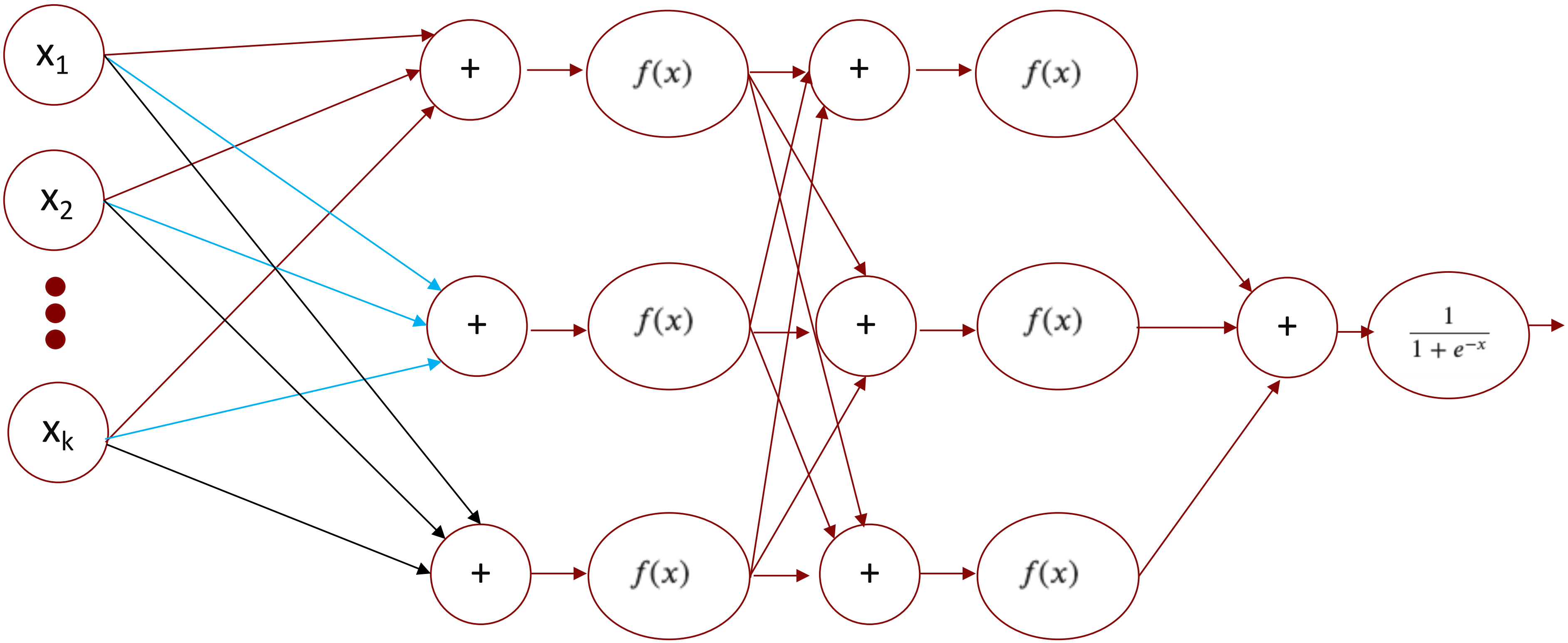
Before



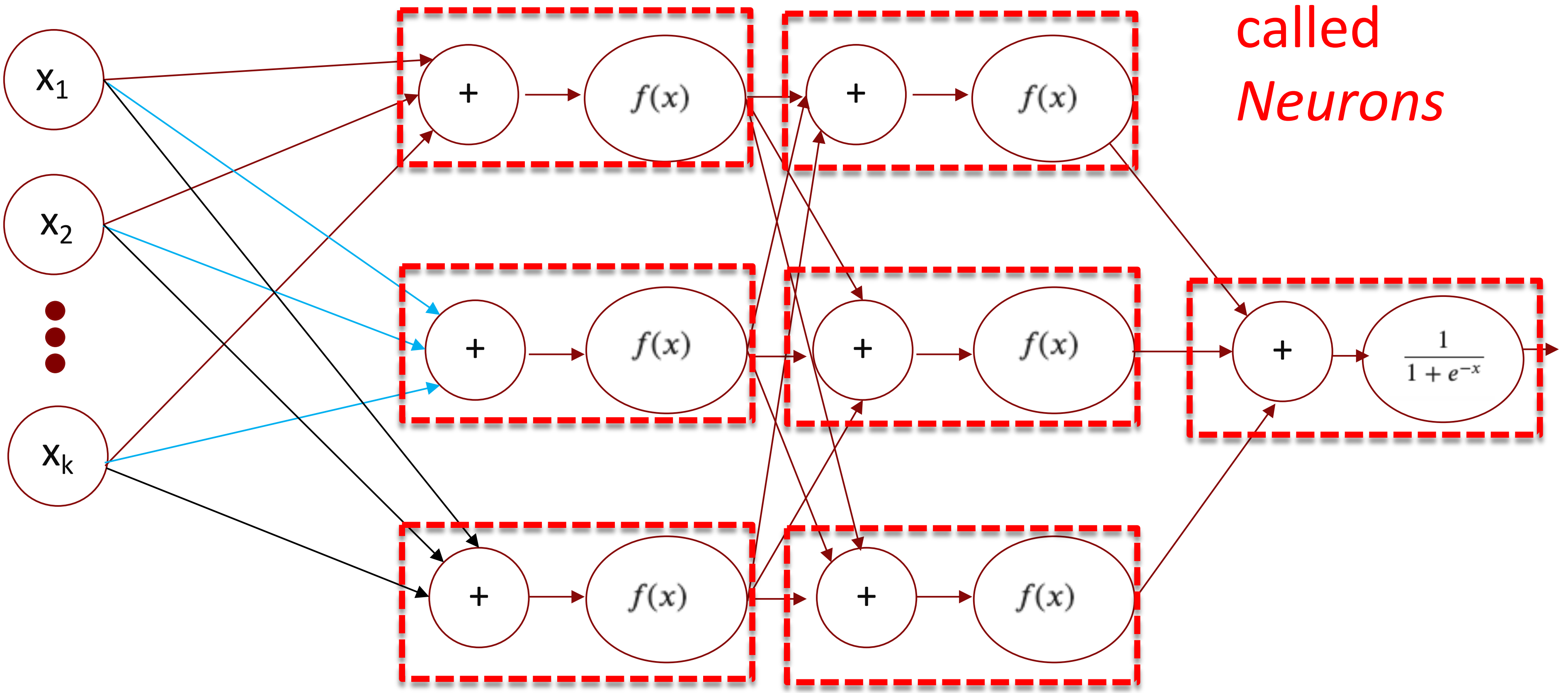
After



This is a Neural Network!

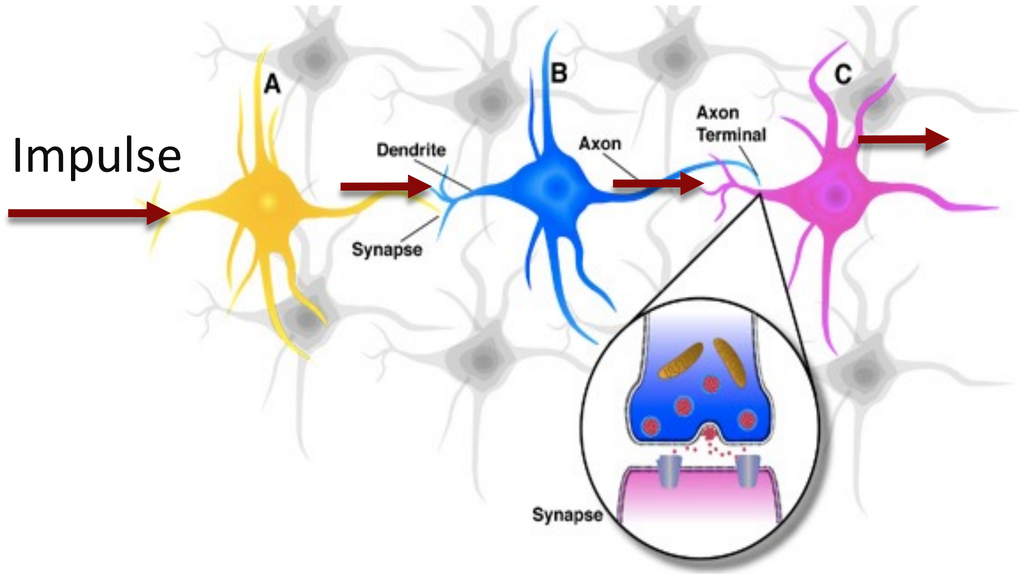


Terminology



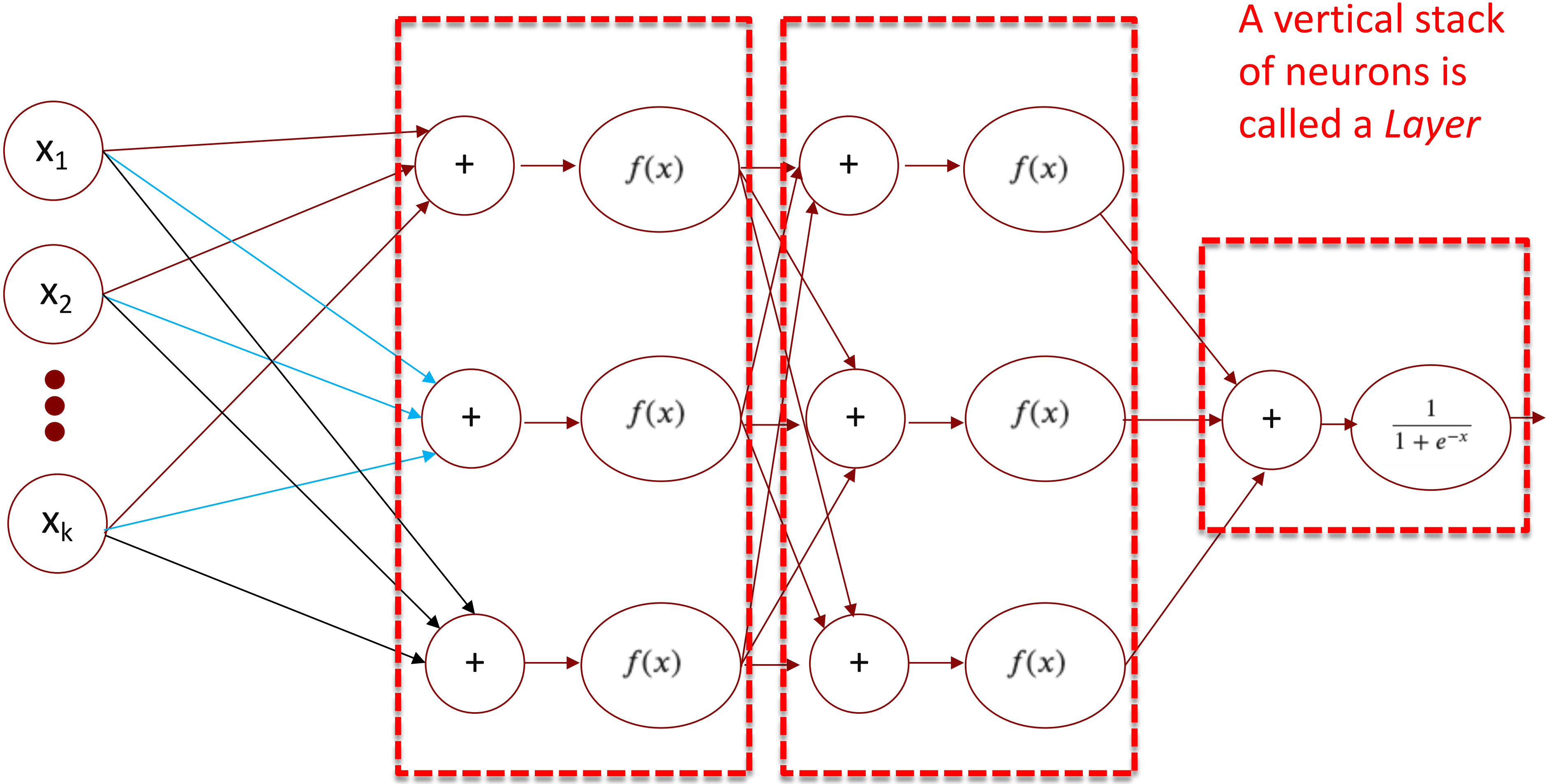
These are called *Neurons*

Aside: The “neural” connection



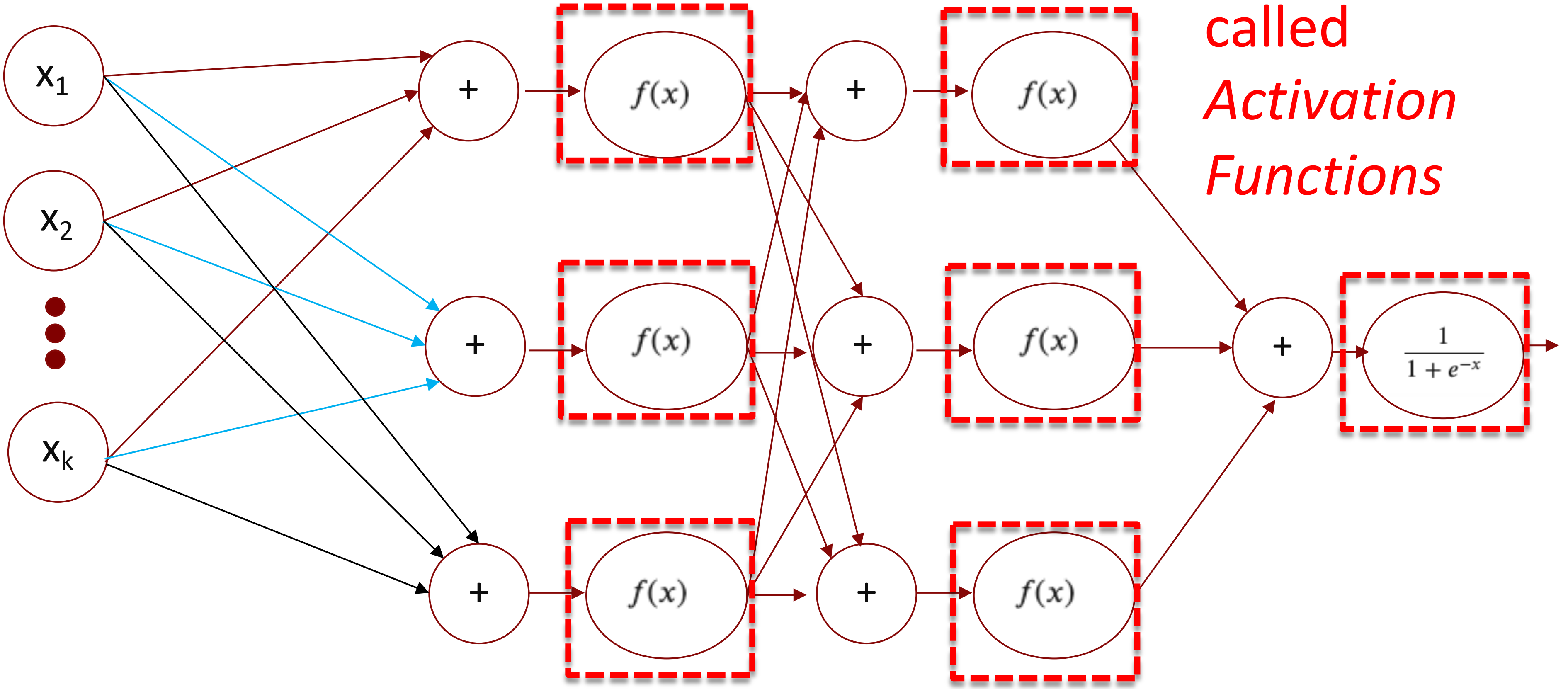
In the brain, the dendrites of one neuron connect to the axons of others at synapses, forming a <u>network</u>

Terminology



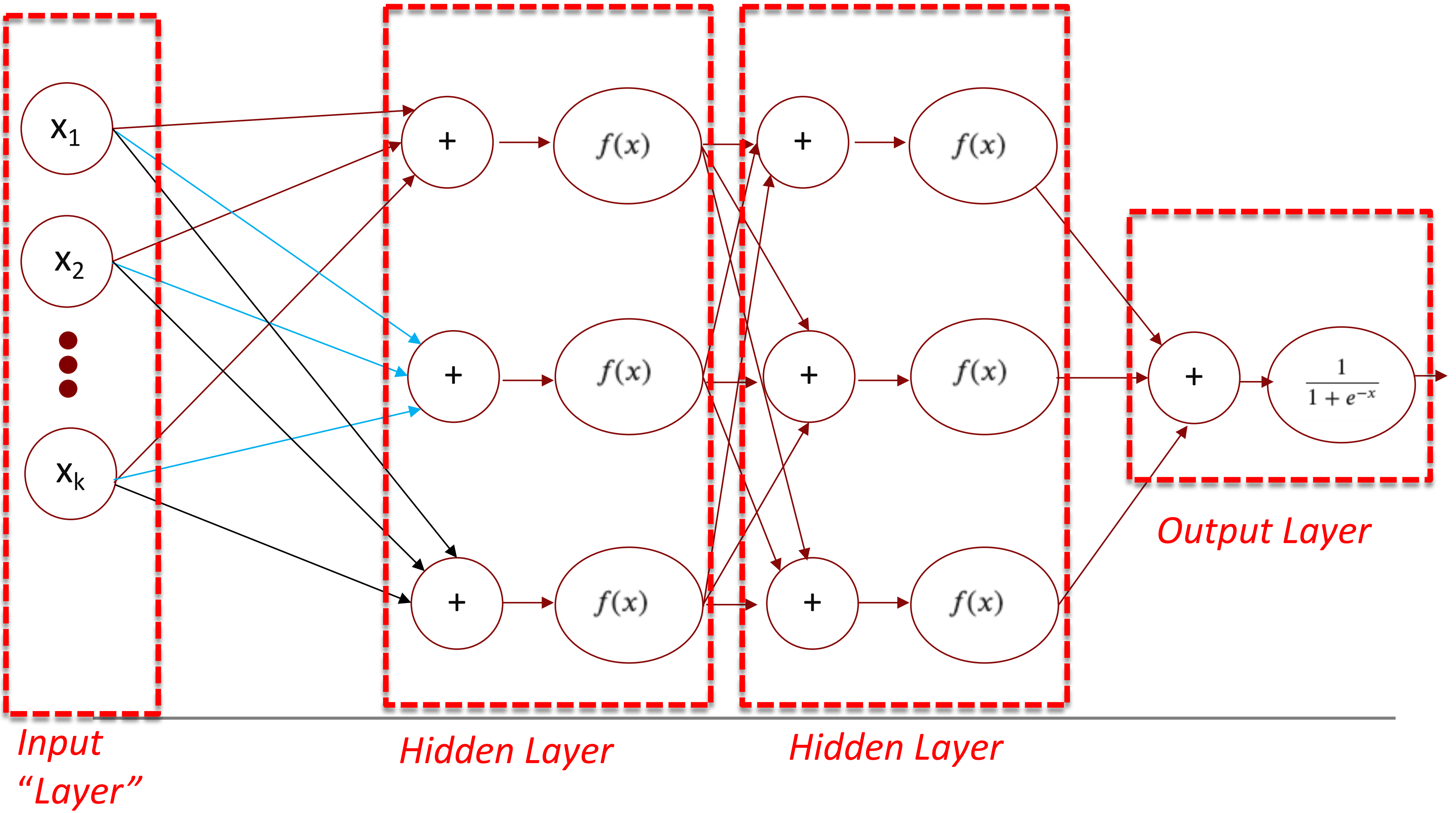
A vertical stack of neurons is called a *Layer*

Terminology

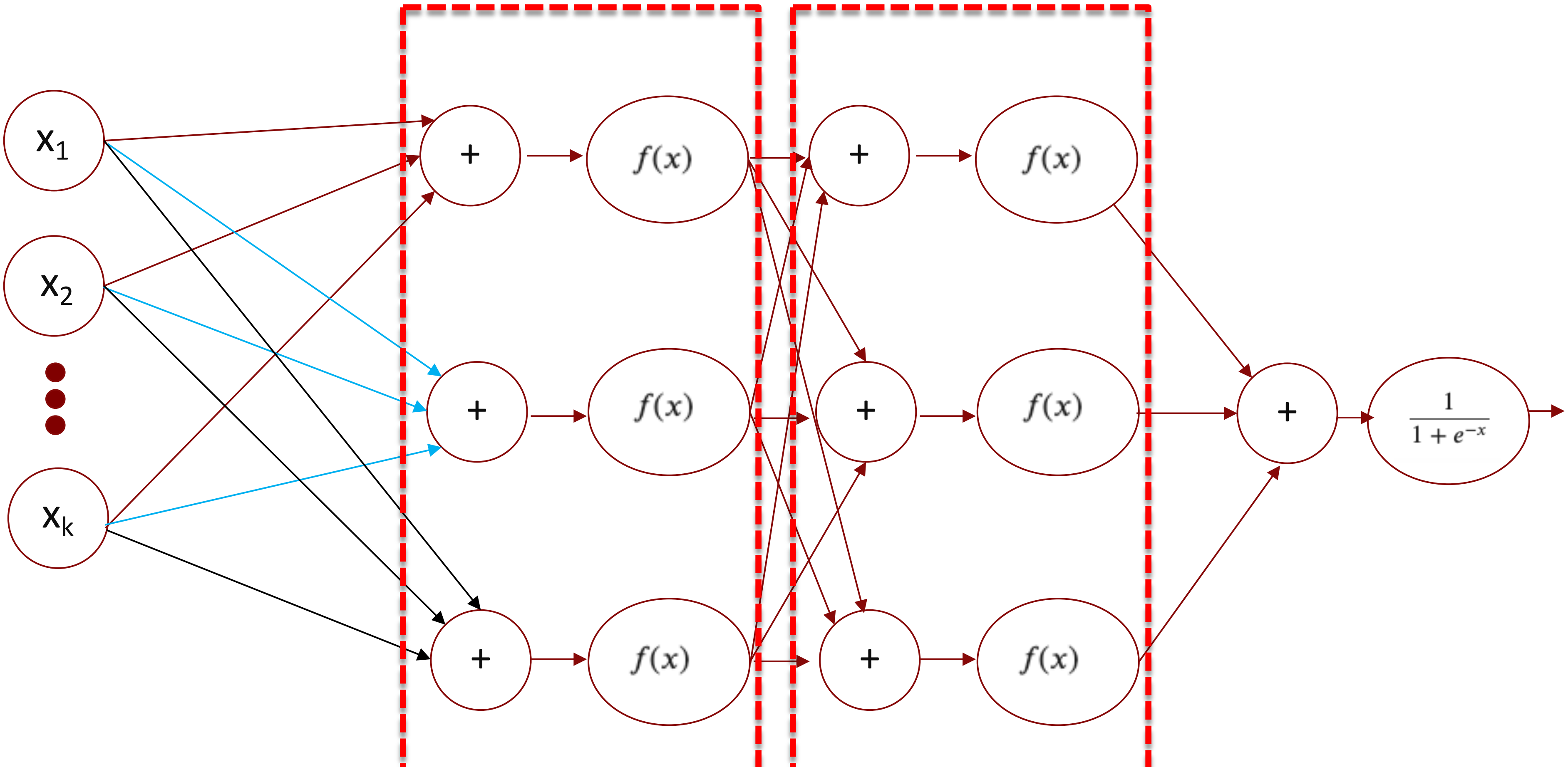


These are called *Activation Functions*

Terminology



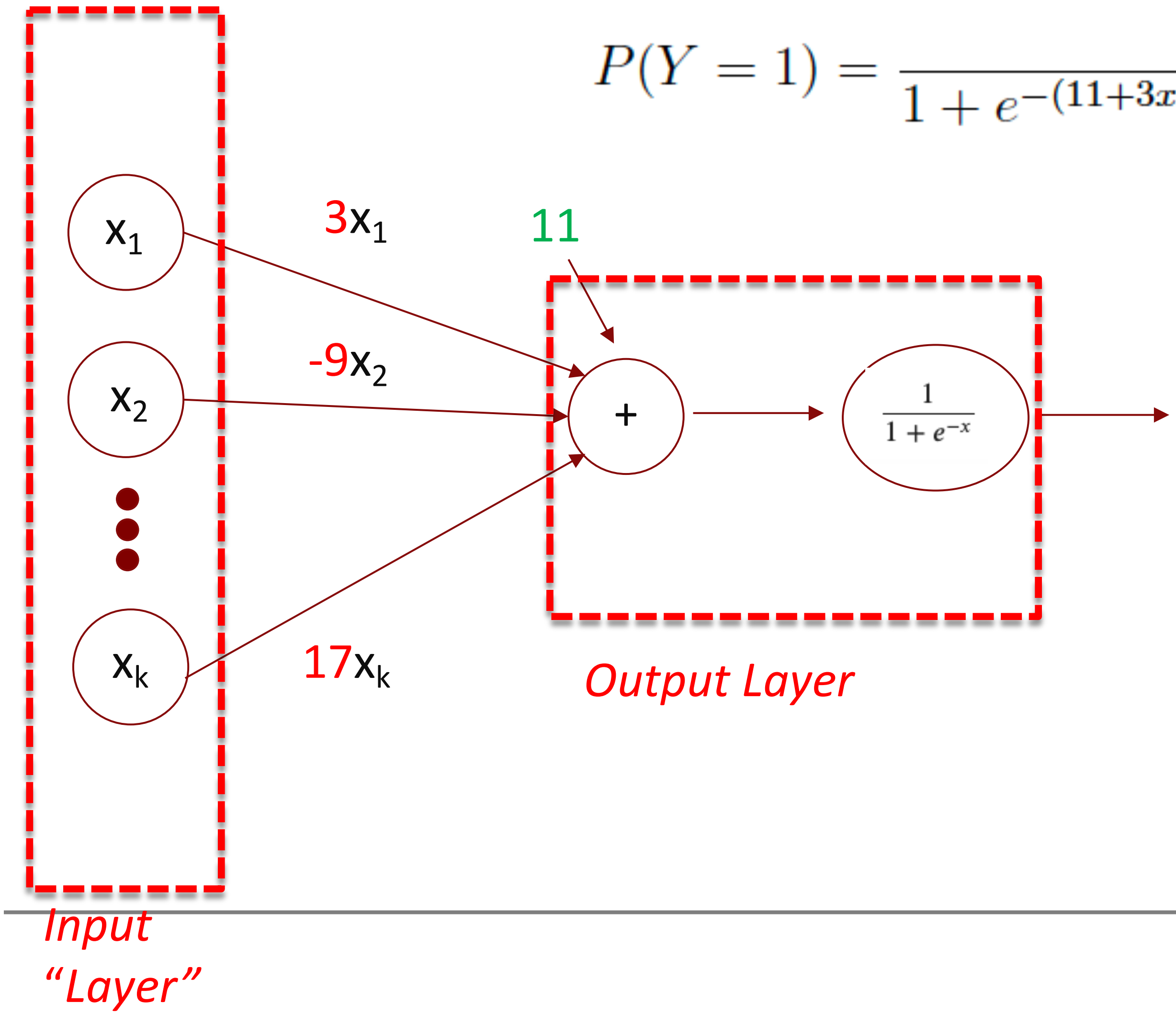
Terminology



When every neuron in a layer is connected to every neuron in the next layer, it is called Dense or Fully Connected

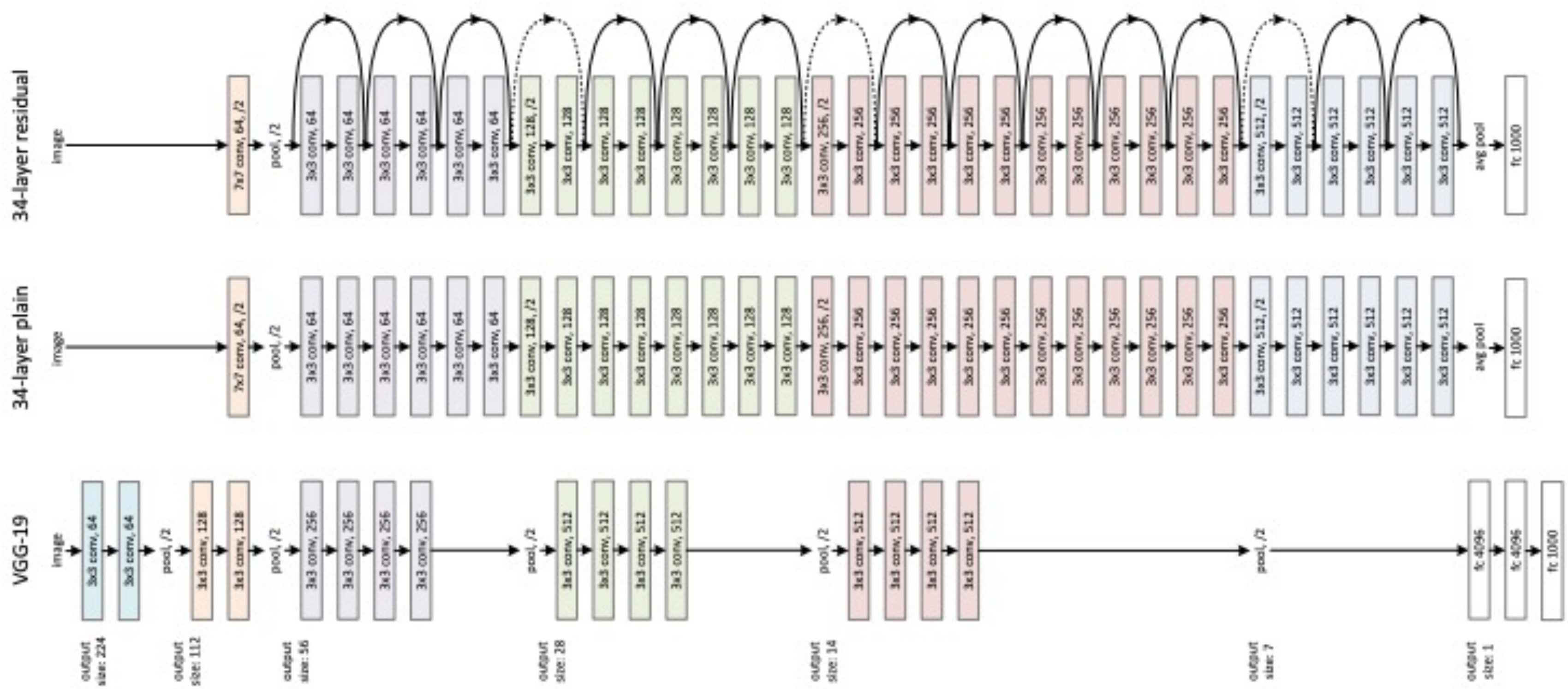
The general logistic regression model is an NN but a simple one since it has no hidden layers

$$P(Y=1) = \frac{1}{1+e^{-(11+3x_1-9x_2+\cdots+17x_k)}}$$



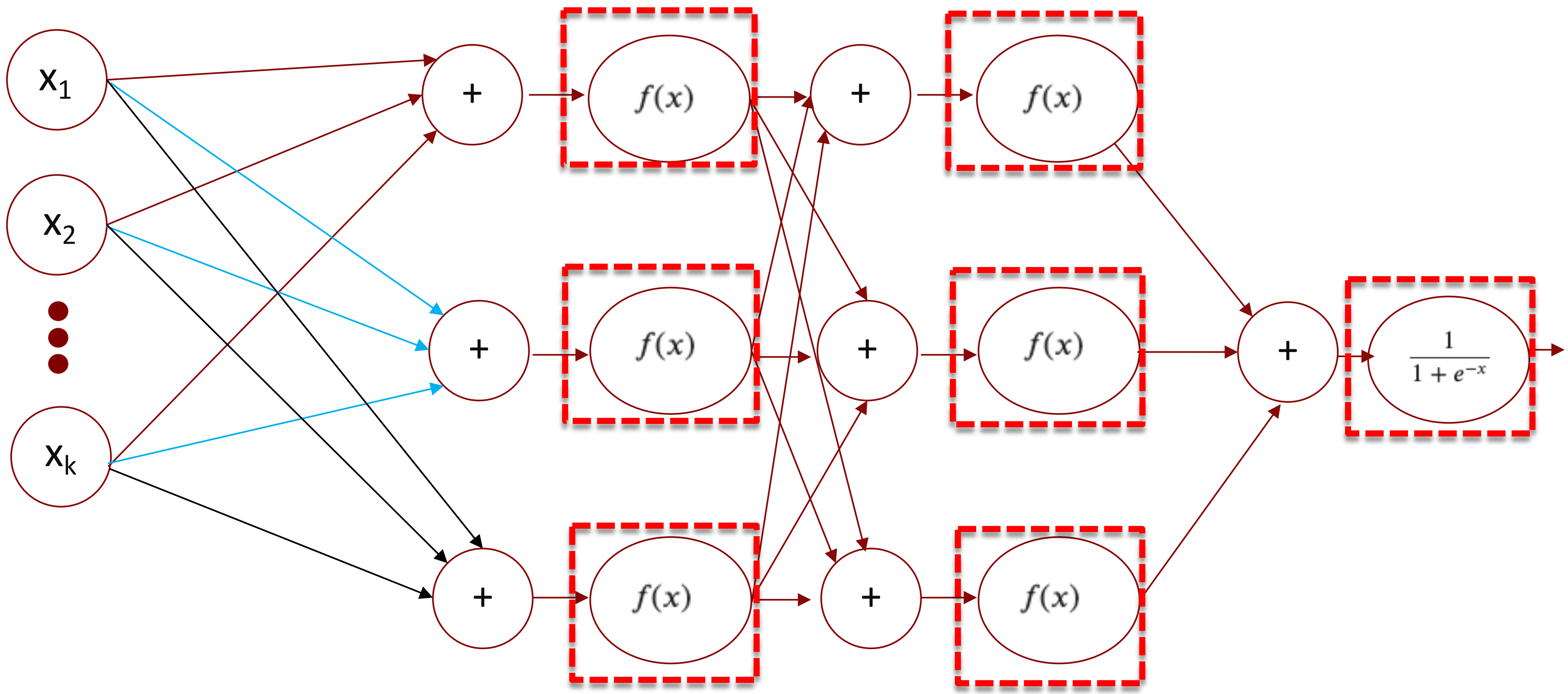
Deep Learning is *just* neural networks with lots and lots of …

Deep Learning is *just* neural networks with lots and lots of hidden layers



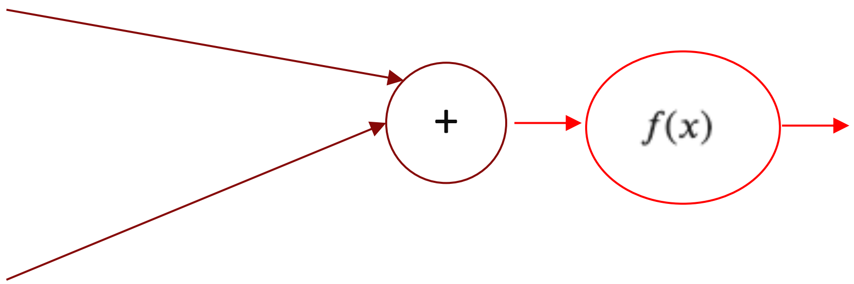
https://arxiv.org/pdf/1512.03385.pdf

Let's now turn to Activation Functions



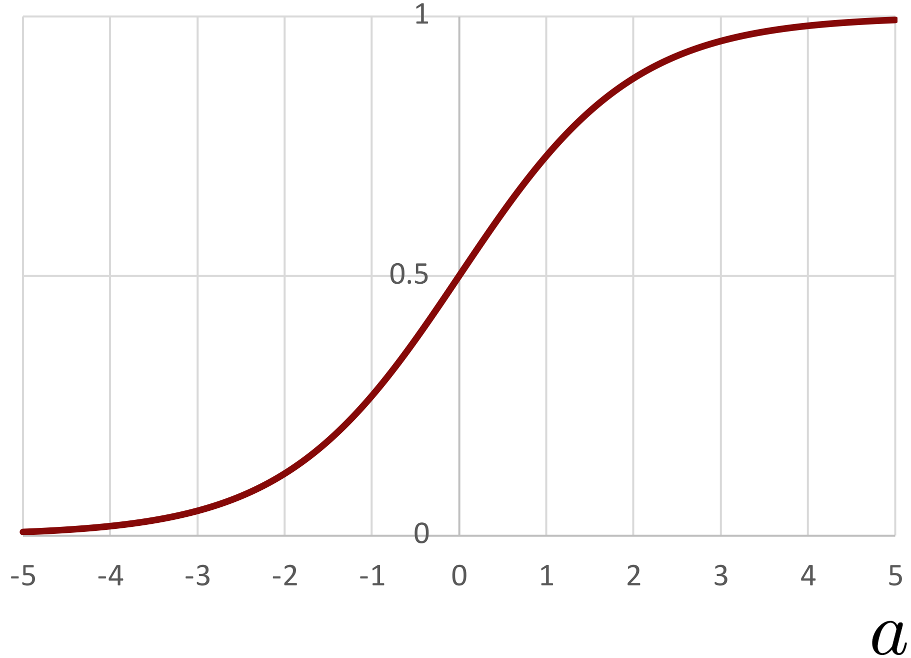
Activation functions

The activation function of a node is just a function that receives a single number and outputs a single number (i.e., scalar in -> scalar out)



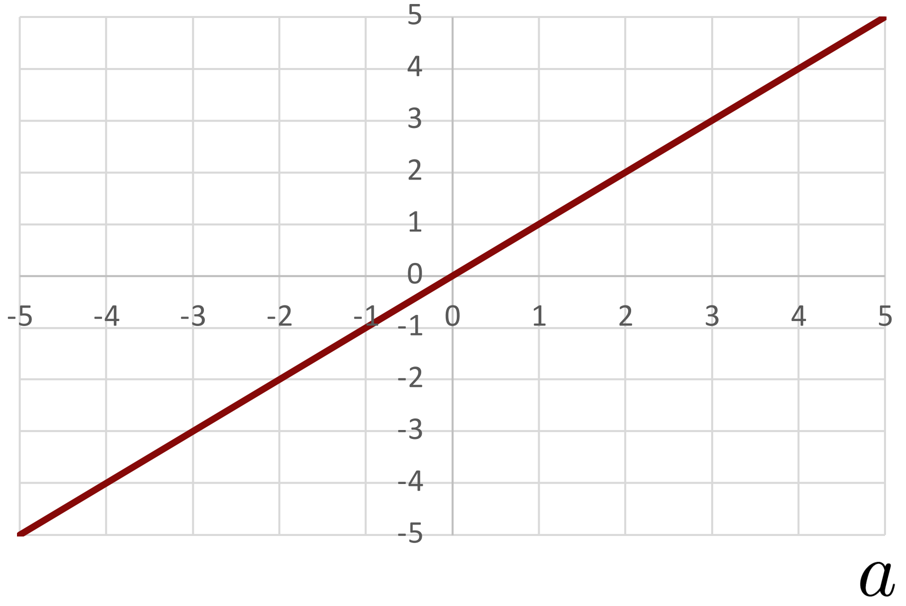
Common Activation Functions

Sigmoid activation function: $$\sigma(a) = \frac{1}{1 + e^{-a}}$$



Common Activation Functions

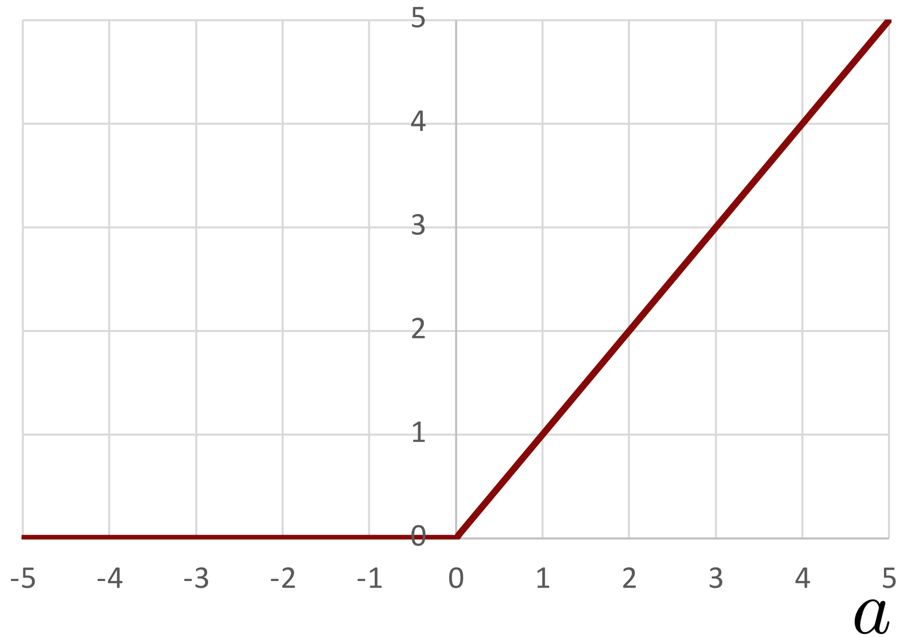
Linear activation function: $f(a) = a$



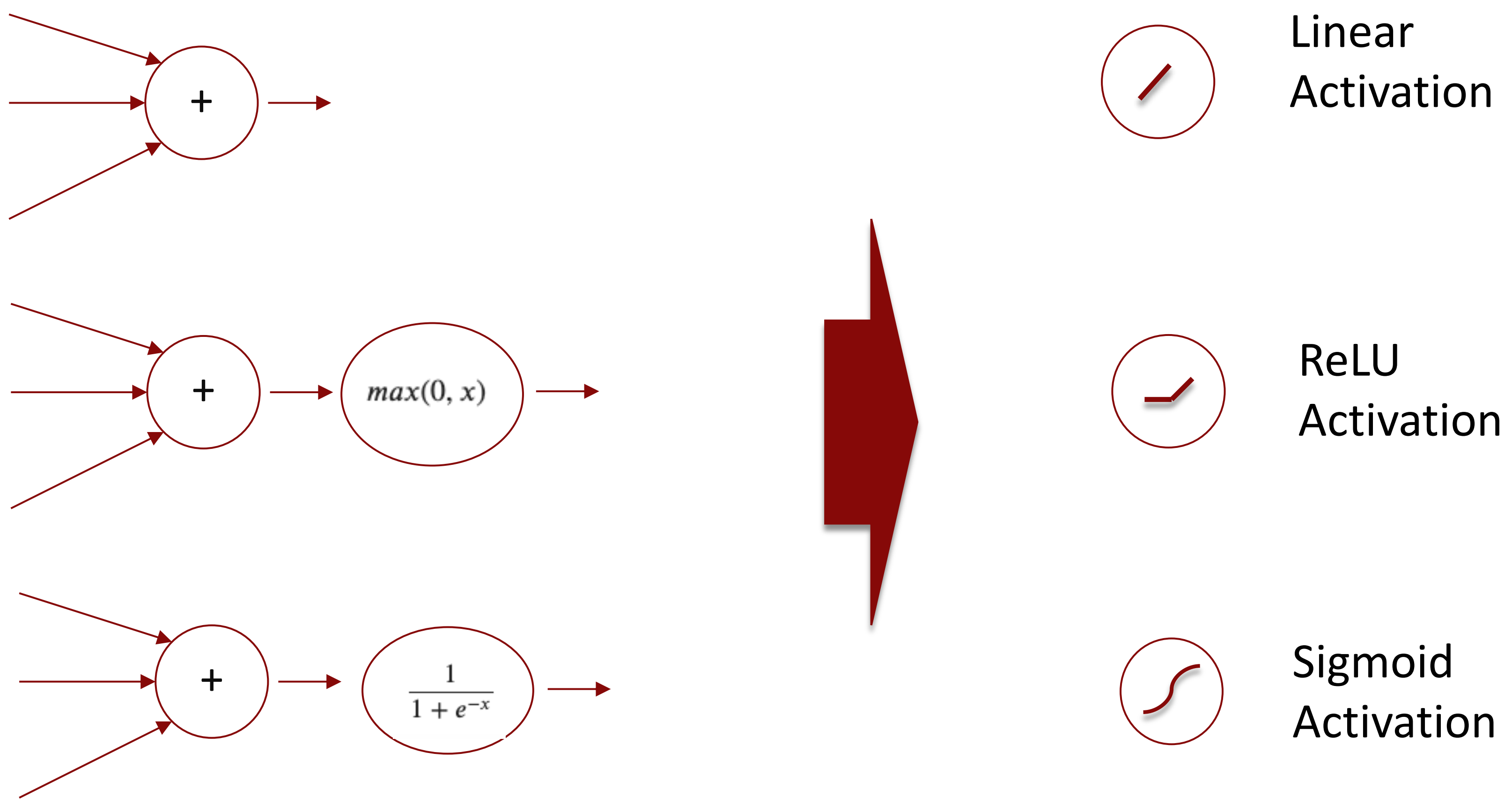
Common Activation Functions

ReLU: $$g(a) = \max(0, a)$$

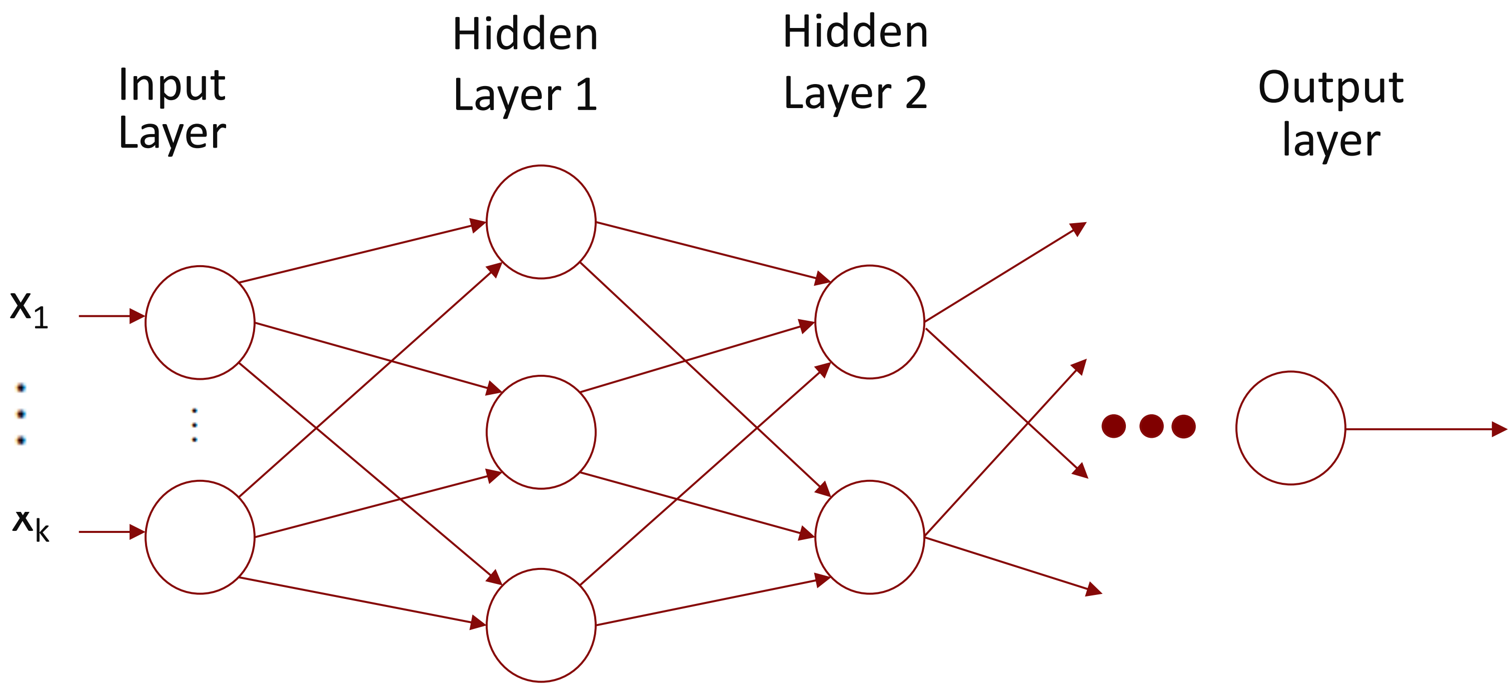
(“**Re**ctified **L**inear **U**nit”)



We will use this "visual shorthand" from now on



Recap: Designing a DNN



*<u>User</u> chooses the **# of hidden layers**, **# units in each layer**, the **activation function(s)** for the hidden layers and for the output layer*

Let's use a DNN for our interview classifier

- Recall the problem:
  - Two input variables (i.e., GPA and experience)
  - An output variable that should be between 0 and 1

*User chooses the **# of hidden layers**, **# units in each layer**, the **activation function(s)** for the hidden layers and for the output layer*

Let's use a DNN for our interview classifier

- Recall the problem:
  - Two input variables (i.e., GPA and experience)
  - An output variable that should be between 0 and 1
- Design choices
  - We will use **one hidden layer** with **3 neurons** **(ReLU)**
  - Since the output is constrained to be in (0,1), we will use the **sigmoid for the output layer**

*User chooses the **# of hidden layers**, **# units in each layer**, the **activation function(s)** for the hidden layers and for the output layer*

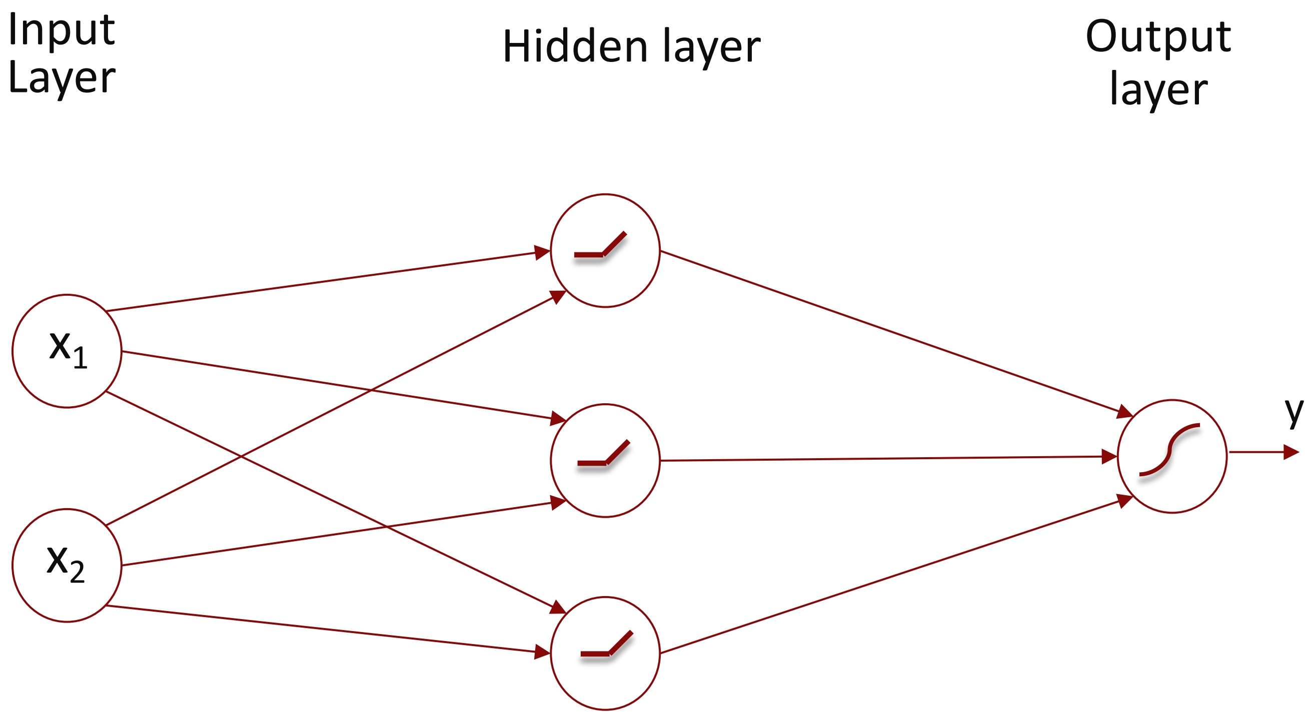
Let's practice setting up a simple NN

Input Layer

Hidden layer

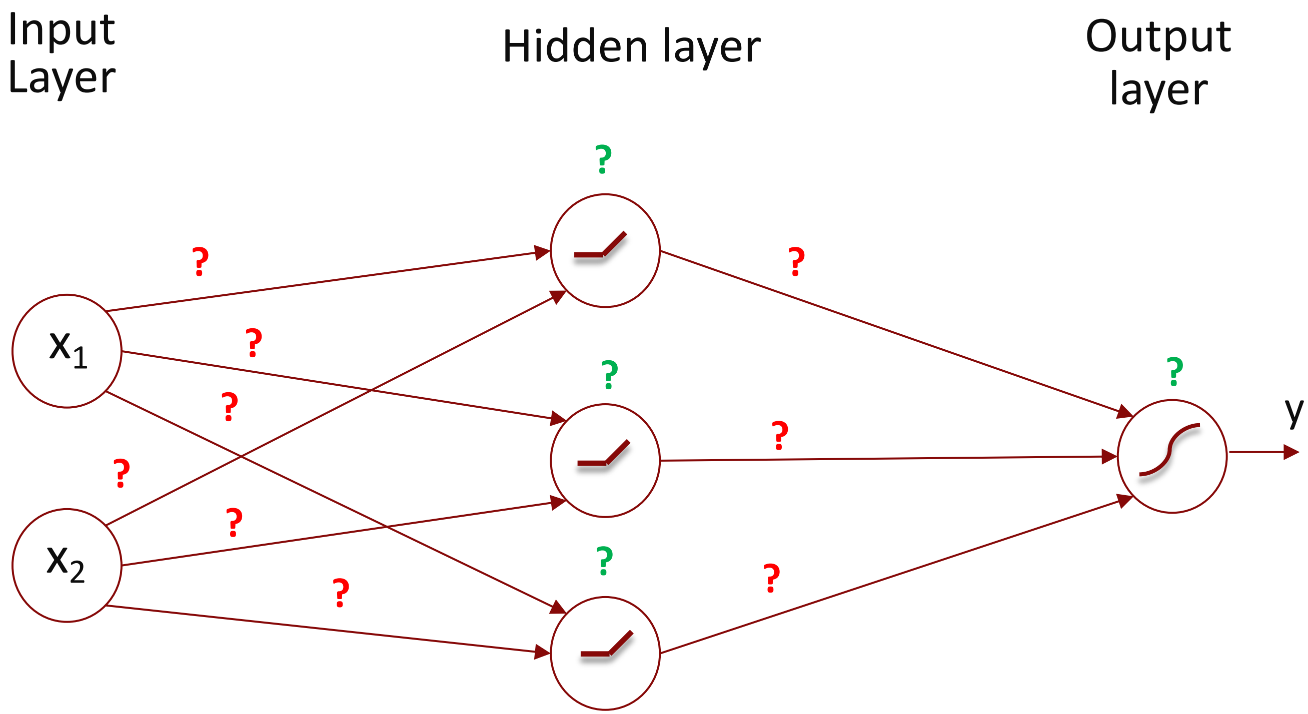
Output layer

Let's practice setting up a simple NN



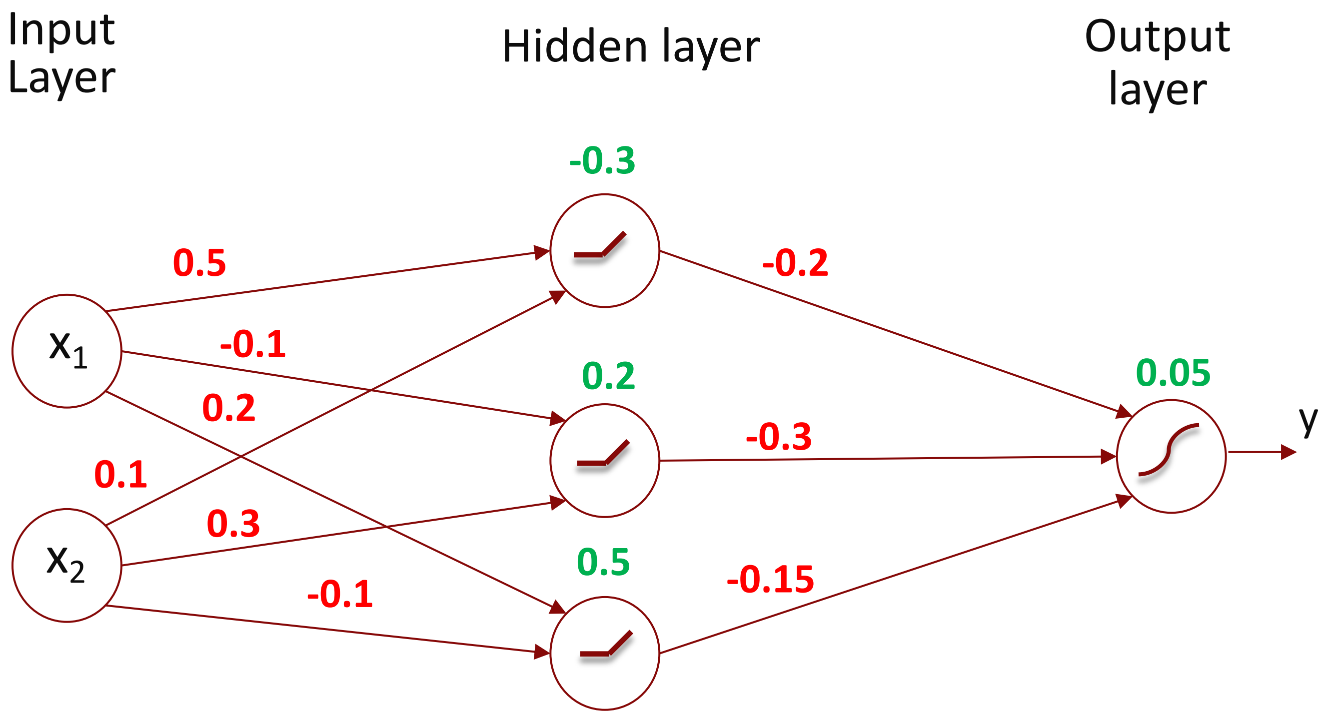
How many parameters (i.e., weights and biases) does this network have?

Let’s practice setting up a simple NN



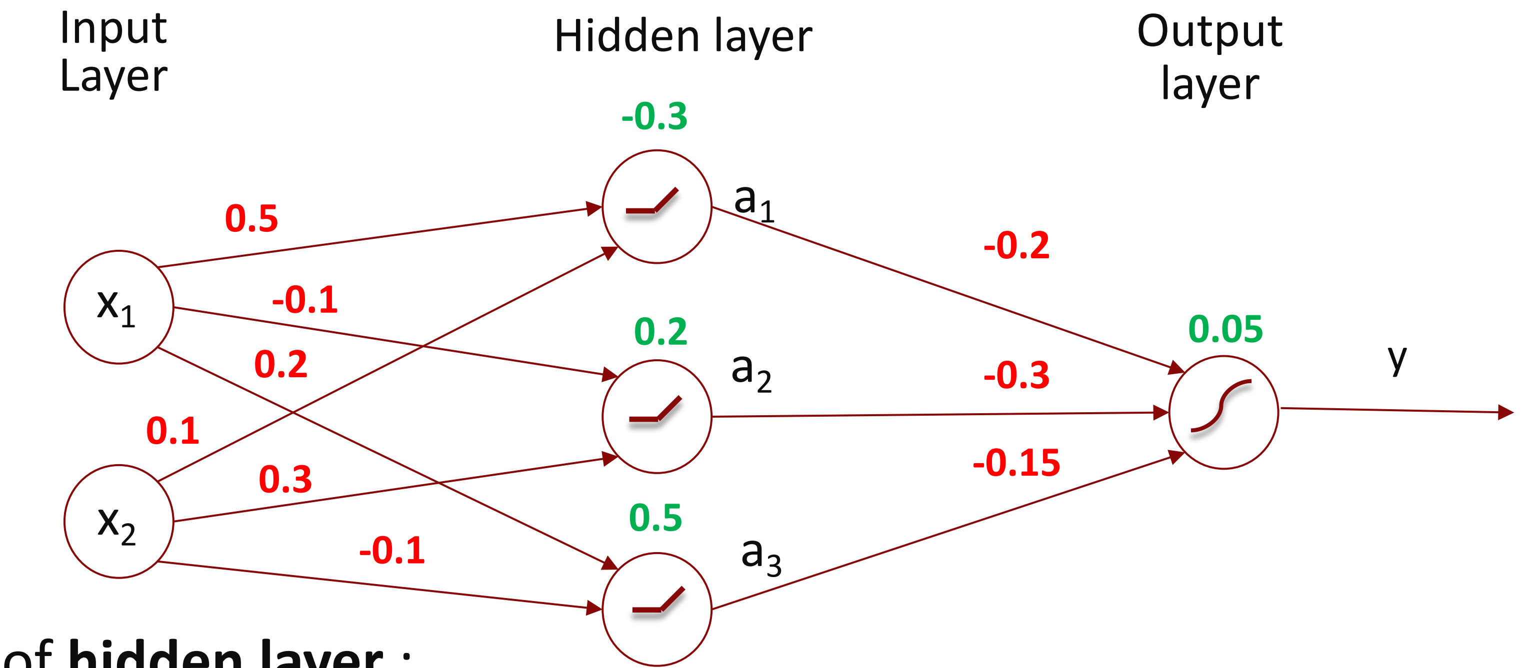
How many parameters (i.e., weights and biases) does this network have? 13

Let's assume that we have trained* this network on data and have found these values for the parameters



*details in the next class

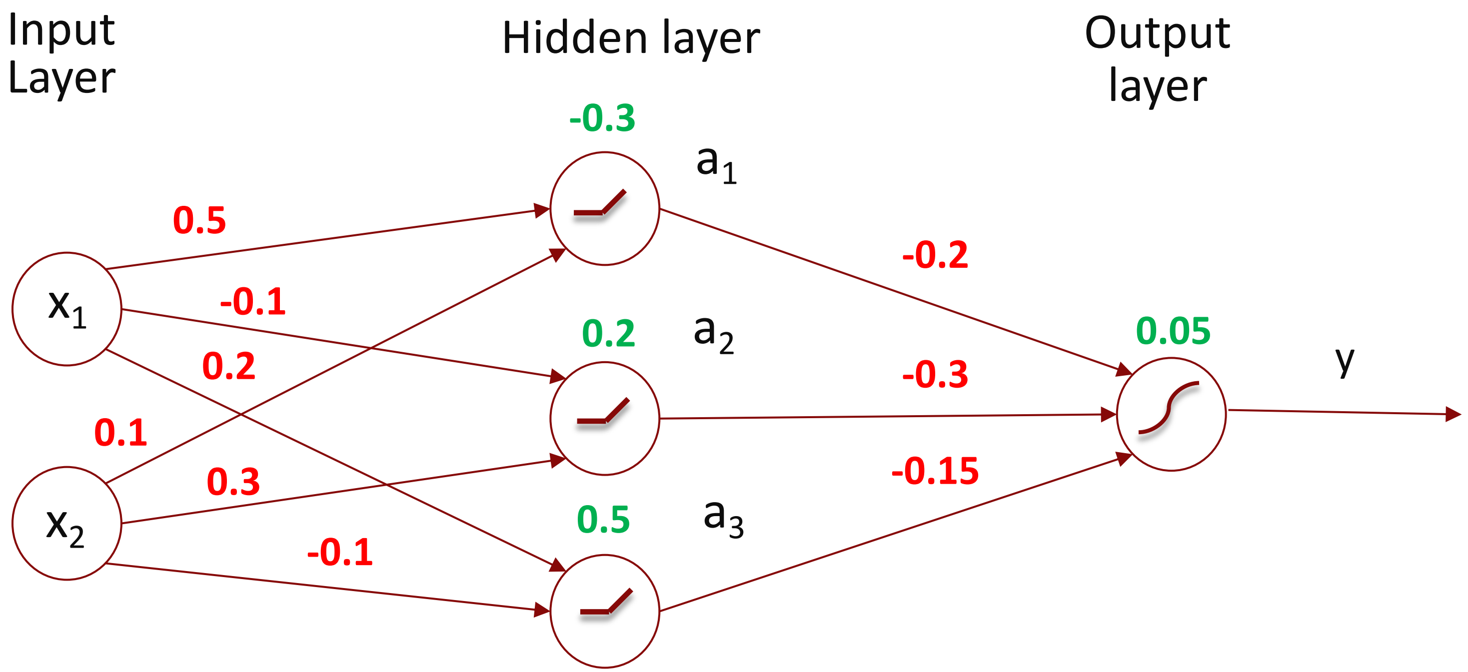
Predicting with the NN



Output of **hidden layer** :

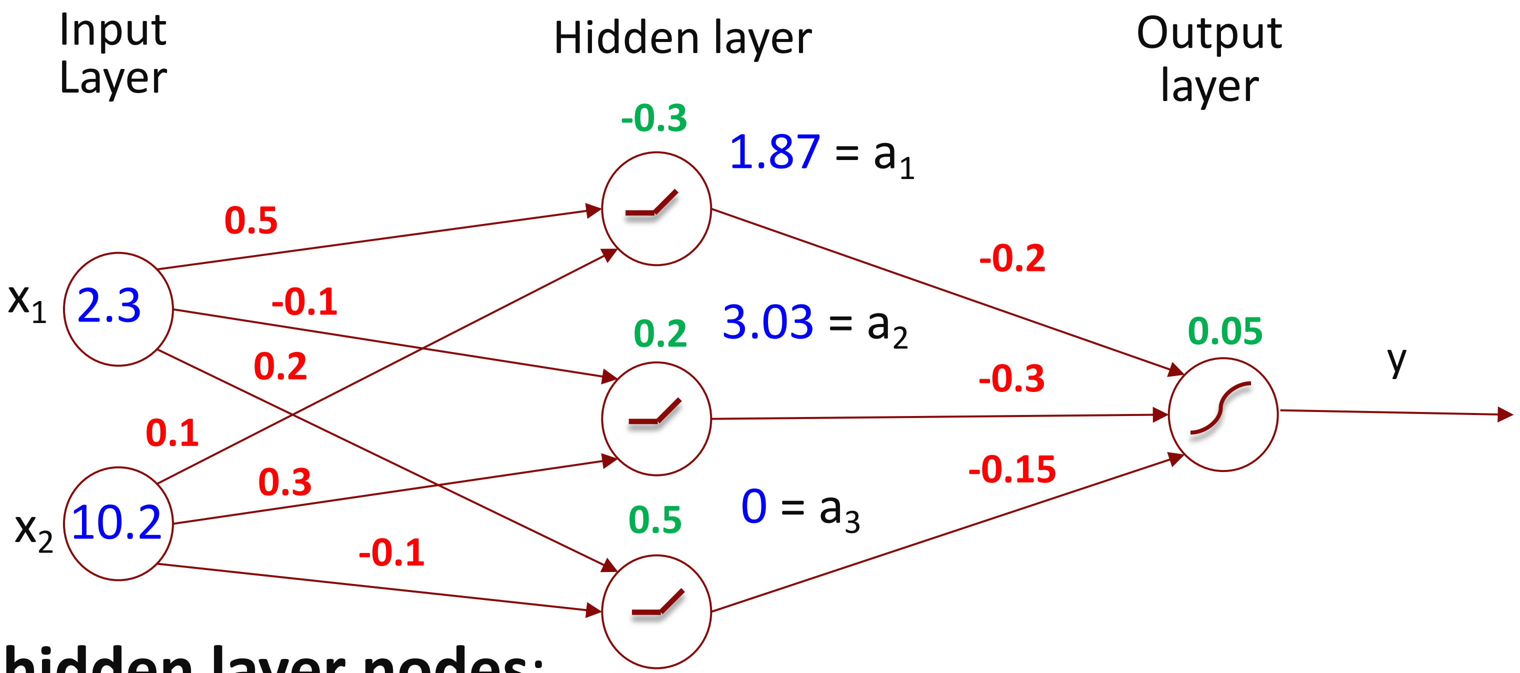
- Top node: $\max(0, -0.3 + 0.5x_1 + 0.1x_2) = a_1$
- Middle node: $\max(0, 0.2 - 0.1x_1 + 0.3x_2) = a_2$
- Bottom node: $\max(0, 0.5 + 0.2x_1 - 0.1x_2) = a_3$

Predicting with the NN



- Recall a_1, a_2, and a_3 are the output of the hidden layer nodes
- Output of **output layer node**: $$\frac{1}{1+e^{-(0.05-0.2a_1-0.3a_2-0.15a_3)}}$$

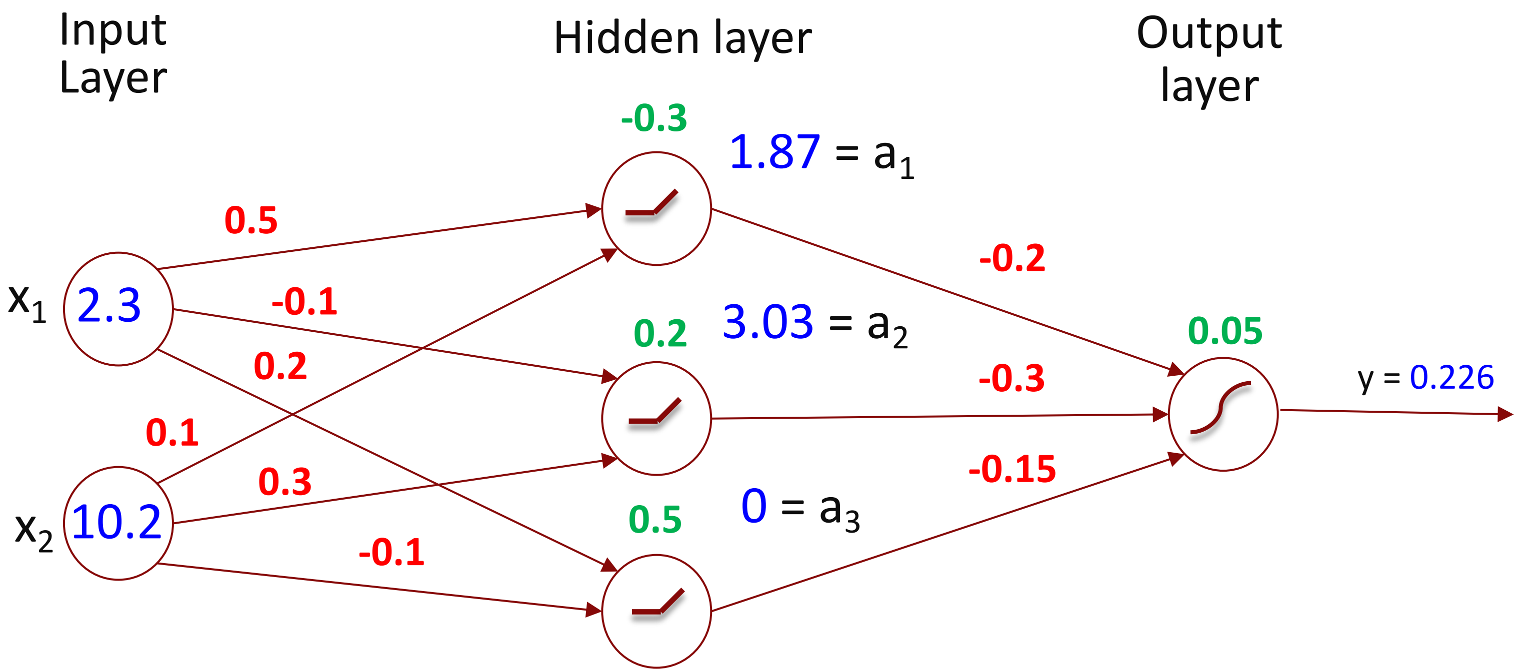
Predicting with the NN



Output of **hidden layer nodes**:

- Top node: max(0, -0.3 + 0.5*2.3 + 0.1*10.2) = 1.87 = a_1
- Middle node: max(0, 0.2 – 0.1*2.3 + 0.3*10.2) = 3.03 = a_2
- Bottom node: max(0, 0.5 + 0.2*2.3 - 0.1*10.2) = 0 = a_3

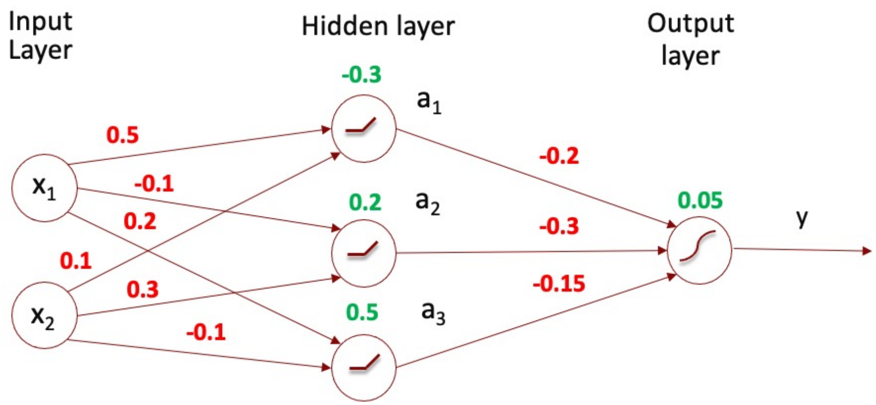
Predicting with the NN



Output of **output layer node**:

$$\frac{1}{1+e^{-(0.05-0.2*1.87-0.3*3.03-0.15*0)}} = 0.226$$

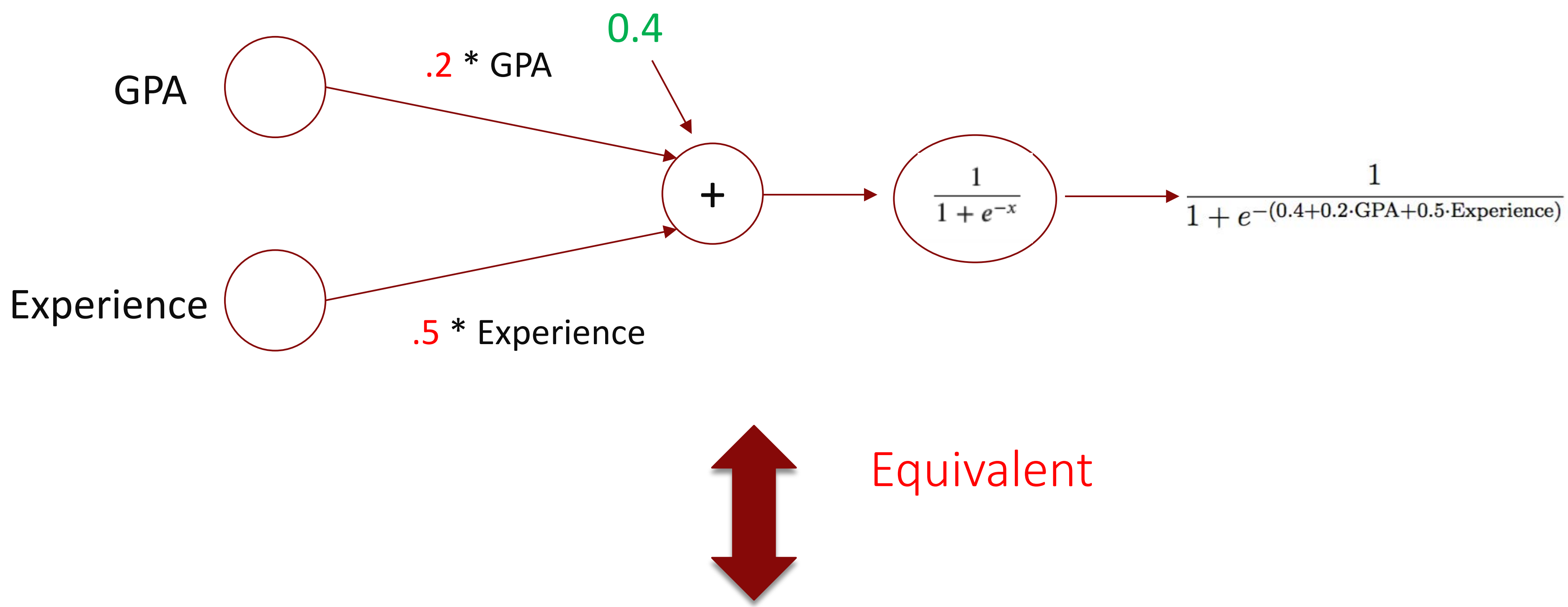
The Network can be written as this function



Equivalent

$$y = \frac{1}{1 + e^{-(.05-0.2(max(0,-0.3+0.5x_1+0.1x_2))-0.3(max(0,0.2-0.1x_1+0.3x_2)-0.15(max(0.5+0.2x_1-0.1x_2))}}$$

Contrast with the Logistic Regression model from before



$$P(Y=1) = \frac{1}{1+e^{-(0.4+0.2 \cdot \text{GPA}+0.5 \cdot \text{Experience})}}$$

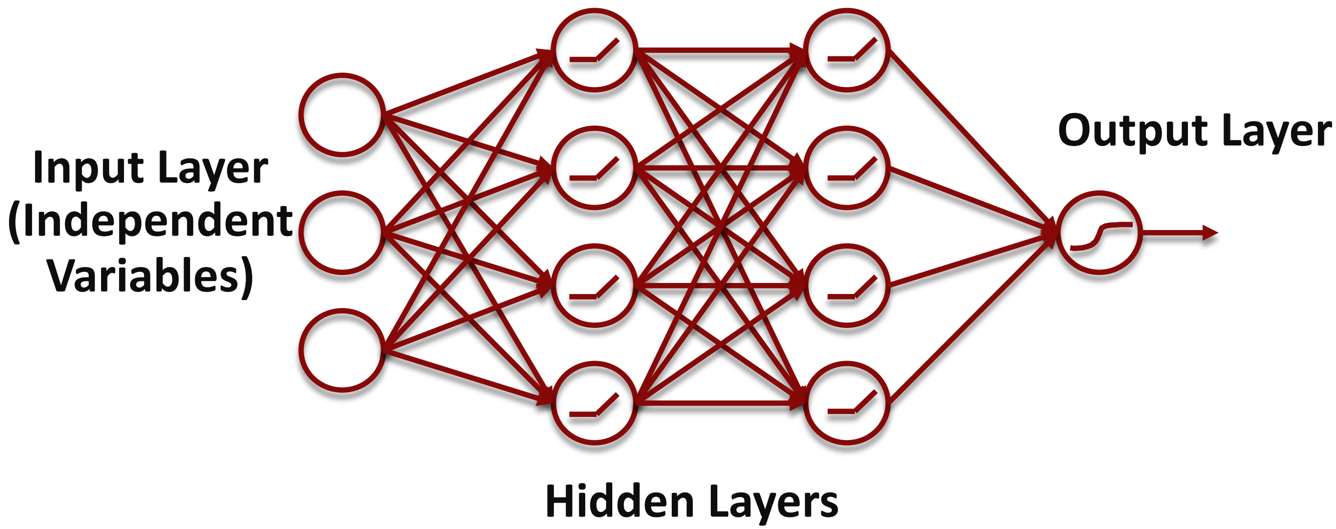
Note the complexity of even this simple network compared to the logistic regression model

$$y = \frac{1}{1 + e^{-(.05-0.2(max(0,-0.3+0.5x_1+0.1x_2))-0.3(max(0,0.2-0.1x_1+0.3x_2)-0.15(max(0.5+0.2x_1-0.1x_2))}}$$

$$y = \frac{1}{1 + e^{-(0.4+0.2x_1+0.5x_2)}}$$

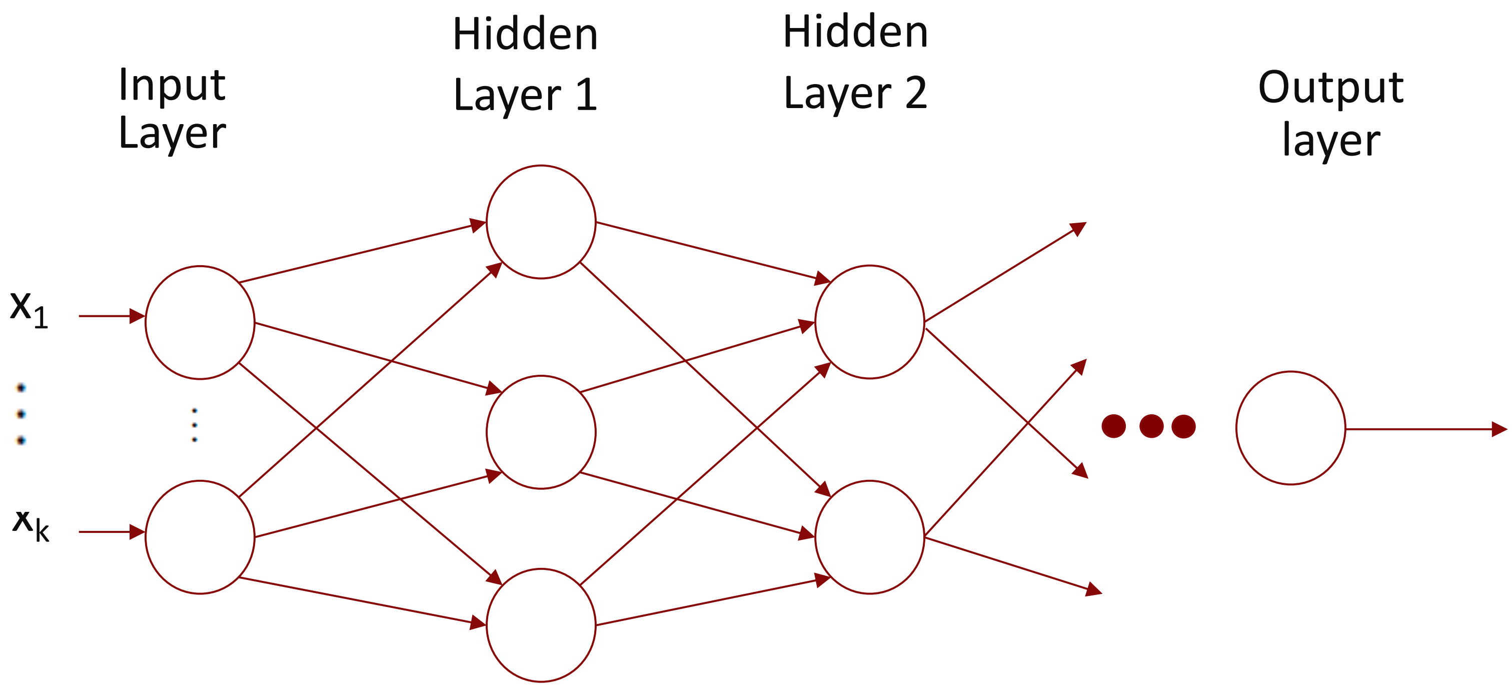
y is a much more complex function of its inputs x_1 and x_2 compared to (say) $\frac{1}{1 + e^{-(0.4+0.2 \cdot \text{GPA}+0.5 \cdot \text{Experience})}}$ and it can capture more complex relationships between *x* and *y*.

Summary: A Deep Neural Network



- This is a **feedforward** (or **vanilla**) neural network
- In general, the arrangement of neurons into layers, the activation functions, and the connections between layers are referred to as the network's **architecture**

Summary: Designing a DNN



<u>User</u> chooses the ***# of hidden layers****,* ***# units in each layer****, the* ***activation function(s)*** *for the hidden layers and for the output layer*

15.773 Hands-on Deep Learning

Spring 2024