AI - Past, Present & Future

Currently Statistical Machines, NOT Cognitive Systems
Machine (Artifical) "Intelligence" $\neq$ Human Intelligence

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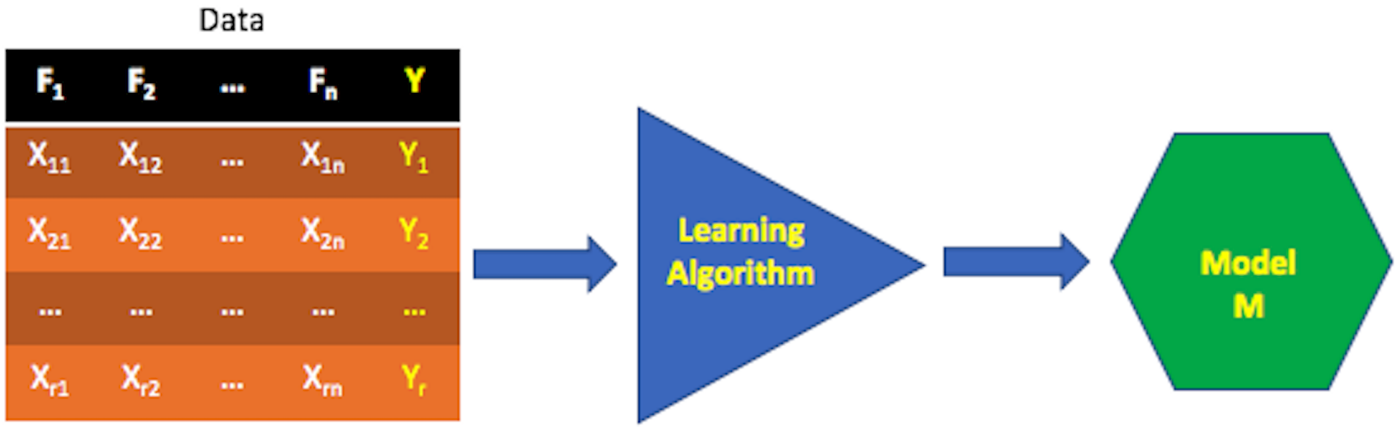
March 31, 2024

Part-1: Knowledge Based Expert Systems (1980-1995)

1. The field of AI was defined as computers performing tasks that were specifically thought of as something only humans can do.
2. In the 1980s, the expert systems were of great interest and focused on knowledge and inference mechanisms. They did a good job in their domains but were narrow in specialization and were difficult to scale.
3. Once these systems worked, they were no longer considered to be AI! For example, today the best chess players are routinely defeated by computers but chess playing is no longer really considered as AI! McCarthy referred to as the "AI effect". IBM's Watson is one such program at a level such as that of a human expert.
4. Fifty years ago Jim Slagle's (MIT) symbolic integration program (MACSYMA) was a tremendous achievement.
5. It is very hard to build a program that has "common sense" and not just narrow domains of knowledge.

Machine Learning - Classification, Classification ...

1. In 1959, Arthur Samuel (MIT), defined ML, a subset of AI, as a *"field of study that gives computers the ability to learn without being explicitly programmed".*



2. ML is effective for complex tasks where deterministic solution don't suffice, e.g., speech recognition, handwriting recognition, spam, fraud detection, etc. These cannot be solved manually in a large scale.

Linear Regression - Elementary Algebra/Calculus

1. Regression is a statistical approach to find the relationship between variables between X_i and Y_i.
2. A common function used to model training data is a linear regression model. The model or the hypothesis is given by:

$$y_i = \theta_0 + \theta_1 x_{i1} + \theta_2 x_{i2} \cdots + \theta_n x_{in} \tag{1}$$

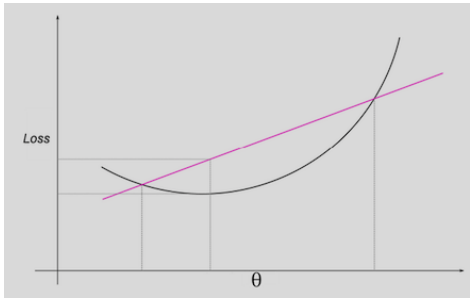
where x_{ij} is the observed value of the feature x_j, y_i is the predicted value of the outcome and θ_i are constants the values of which need to be determined. For now, we limit the the values of the features x_{ij} to numbers, positive or negative. Later on, we will study techniques on how to deal with the situation where the feature value is a string.

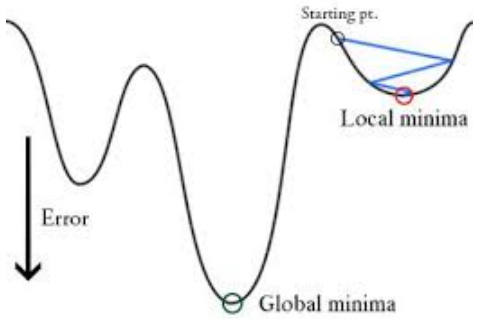
$$\text{Squared Error Loss (L)} = \frac{1}{2} \times \sum_{i=1}^{r} (\hat{y}_i - y_i)^2 \tag{2}$$

This loss function is always positive, there is a minimum, is monotonically increasing from that minimum value in both positive and negative directions. Such a function is called a convex function.

3. We need to minimize some loss function over the training data.

Gradient Descent





1. Minimize by setting the partial derivative of the loss wrt θ_j to zero.

$$\frac{\partial L}{\partial \theta_0} = \sum_{i=1}^{r} (\hat{y}_i - y_i) = 0 \quad \frac{\partial L}{\partial \theta_j} = \sum_{i=1}^{r} (\hat{y}_i - y_i)\, x_{ij} = 0 \tag{3}$$

2. Randomly assigning values to θ_j. For a convex function it does not matter what the initial weights are as it will always converge. $\hat{y}$ and x_{ij} are observed and y_i is computed. This means the slope of the loss function can be readily computed.

Logistic Regression

In many cases the value of y_i need to be bounded between 0 and 1. For logistic regression, Least Squared Error will result in a *non-convex* graph with local minimums and hence is not feasible. In such cases, we use the logistic regression model as given below:

$$y_i = \frac{1}{1 + e^{-z}} \tag{4}$$

$$z_i = \theta_0 + \theta_1 x_1 + \theta_2 x_2 \cdots + \theta_n x_n \tag{5}$$

- for z is large +ve number, $\frac{1}{e^z} = 0$; $y_i = 1$
- for z $= 0$, $y_i = 0.5$
- for z is large -ve number, $y_i = 0$

Hence, the value of y_i is bounded between 0 and 1 for z between -∞ and ∞.

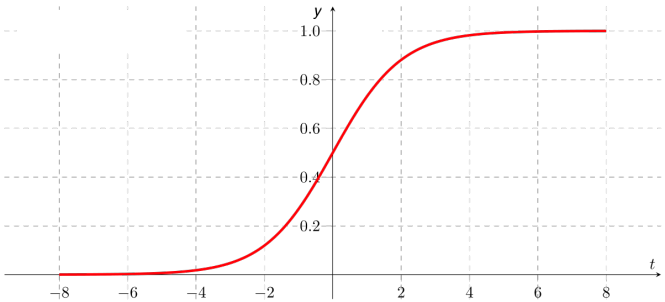
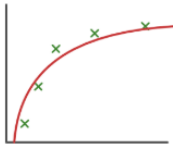
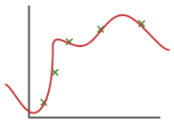


Figure: Sigmoid Curve

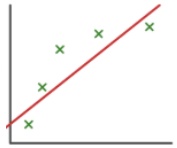
Predictions & Errors



(a) Correct Fit



(b) Over fit



(c) Under fit

Predictions from the model will have differences or errors. Overfitting will occur when an excessive number of features are used than required. Underfitting occurs when an insufficient number of features are used than required.

1. Bias is the difference between average model prediction and the true target value and variance is the variation in predictions across different training data samples. Simple models with small number of features have high bias and low variance whereas complex models with large number of features have low bias and high variance.
2. Regularization is a technique used to avoid problem of overfitting. It prevents overfitting in linear models by a penalty term that penalizes large weight values.

Information & Uncertainty

1. In Claude Shannon's (MIT) information theory, one bit of information reduces the uncertainty by 2. Similarly, if 3 bits of information are sent, then the reduction in uncertainly by 2^3, i.e., 8. This is intuitive. With 3 bits, there could be 8 possible values and so if a particular set of bits are transmitted, 8 possibilities are eliminated with 1 certainty.
2. Information Content When the information is probabilistic, the self-information I_x, or Information Content of *measuring a random variable X as outcome x is defined as:*

$$I_x = log\left(\frac{1}{p(x)}\right) = -log(p(x)) \tag{6}$$

where $p(x)$ is probability mass function.

3. Shannon Entropy of the random variable X is defined as:

$$H(X) = \sum_x -p(x)log(p(x)) = E(I_x) \tag{7}$$

It is the *expected information content* of the measurement of X.

Cross Entropy - Kullback–Leibler (KL) divegence

1. Cross-Entropy is defined as:

$$H(p,q) = -\sum_i p(i) log_2 q(i) \tag{8}$$

where p is the true distribution and q is the predicted distribution. If the predictions are perfect, then the cross-entropy is same as the entropy. If the prediction differs, then there is a divergence which is known as *Kullback – Leibler (KL) divergence*. Hence,

$$Cross\ Entropy = Entropy + KL\ Divergence$$

$$KL\ Divergence = H(p,q) - H(p)$$

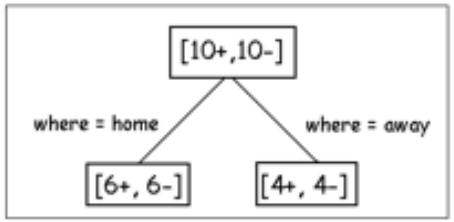
Hence, if the predicted distribution is closer to true distribution when KL divergence is low.

Decision Tree

1. Decision Tree is a supervised machine learning algorithm where You try to separate your data and group the samples together in the classes they belong to. You maximize the purity of the groups as much as possible each time you create a new node of the tree.
2. At each step, each branching, you want to decrease the entropy, so this quantity is computed before the cut and after the cut. If it decreases, the split is validated and we can proceed to the next step, otherwise, we must try to split with another feature or stop this branch.
3. XGBoost is a machine learning algorithm that belongs to the ensemble learning category, specifically the gradient boosting framework. It utilizes decision trees as base learners and employs regularization techniques to enhance model generalization.

Example

Following is a table for win/loss of soccer games at home and away.

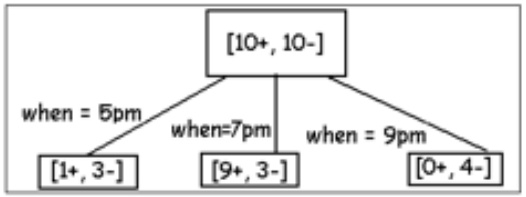


The entropy is:

$$H\left(\frac{6}{12}, \frac{6}{12}\right) = -\frac{6}{12} log_2\left(\frac{6}{12}\right) - \frac{6}{12} log_2\left(\frac{6}{12}\right) = 0.69$$

$$H\left(\frac{4}{8}, \frac{4}{8}\right) = -\frac{4}{8} log_2\left(\frac{4}{8}\right) - \frac{4}{8} log_2\left(\frac{4}{8}\right) = 0.69$$

$$H = -\frac{12}{20} \times H\left(\frac{6}{12}, \frac{6}{12}\right) - \frac{8}{20} H\left(\frac{4}{8}, \frac{4}{8}\right) = 0.69$$

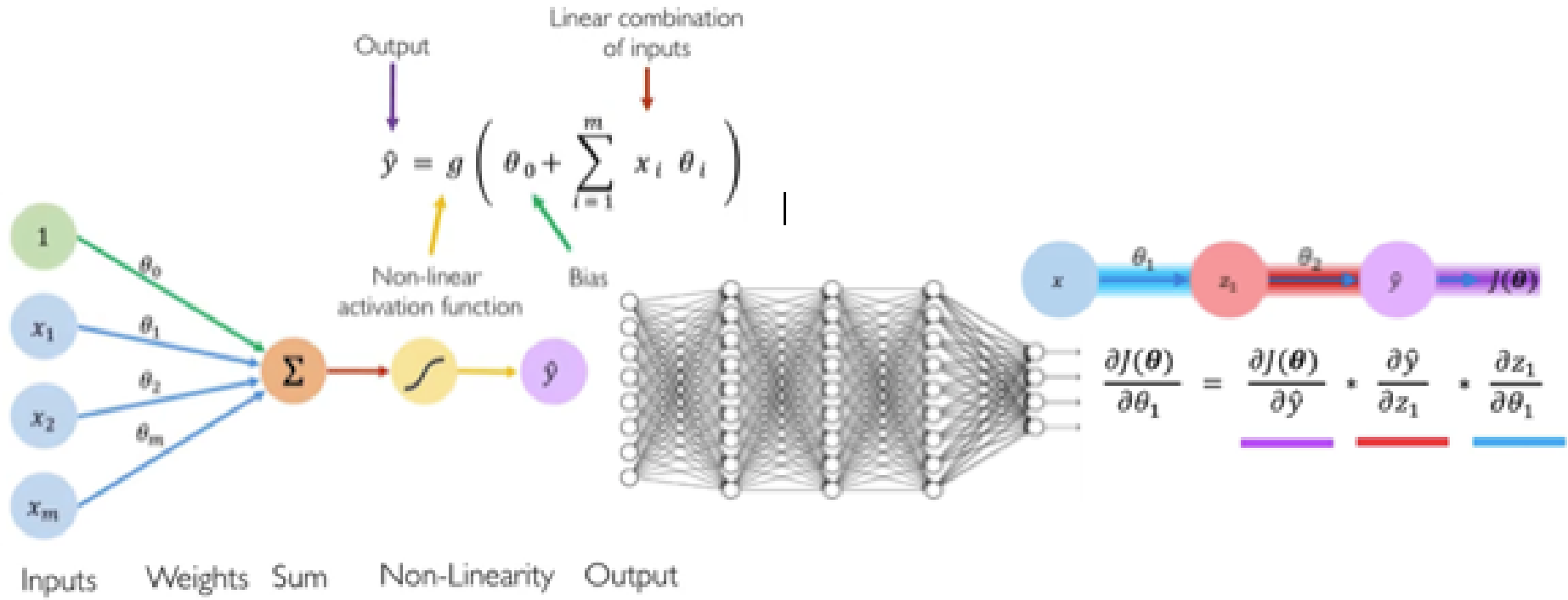


Information gain is 0.69 - 0.45 = 0.24.

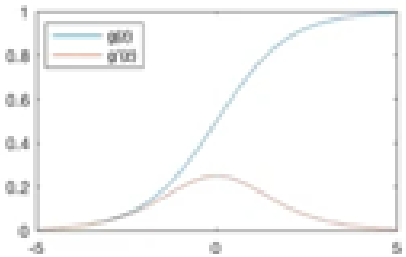
Part-2: From Perceptrons to Deep Learning (1995-2015)

1. Rosenblatt (Cornell) came up with the concept of Perceptrons, "a machine which responds like the human mind" as early as in 1957. In a critical book written in 1969, Marvin Minsky (MIT) & Seymour Papert (MIT) showed that Rosenblatt's original system was blind to simple XOR.
2. In 2006, Hinton developed Deep Learning which extends earlier important work by Yann LeCun (New York Univ). In ImageNet 2012, Hinton achieved the best accuracy in image recognition over $> 10\%$.
3. Deep Learning Success Stories - Image Recognition, Speech Comprehension, Chatbot. DNNs are suitable where the raw underlying features are not individually interpretable. This success is attributed to their ability to learn hierarchical representations, unlike traditional methods that rely upon hand-engineered features.
4. DL's innovation is to have models learn categories incrementally, attempting to nail down lower-level categories (like letters) before attempting to acquire higher-level categories (like words).

Deep Neural Net



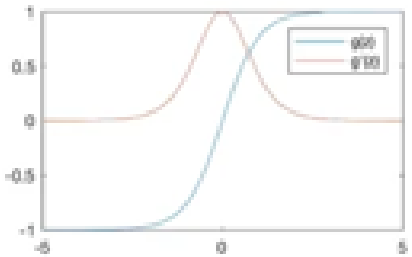
Sigmoid Function



$$g(z) = \frac{1}{1+e^{-z}}$$

$$g'(z) = g(z)(1-g(z))$$

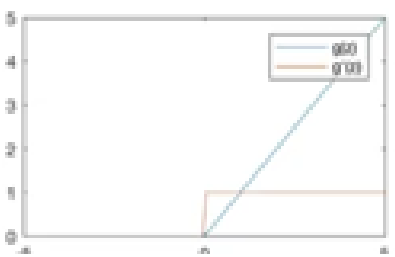
Hyperbolic Tangent



$$g(z) = \frac{e^{z}-e^{-z}}{e^{z}+e^{-z}}$$

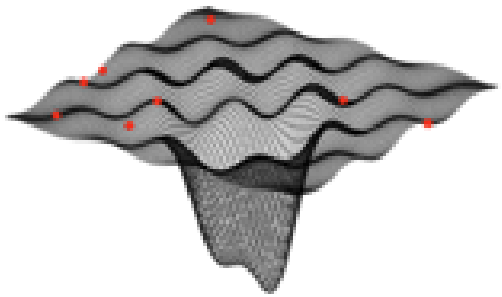
$$g'(z) = 1-g(z)^2$$

Rectified Linear Unit (ReLU)



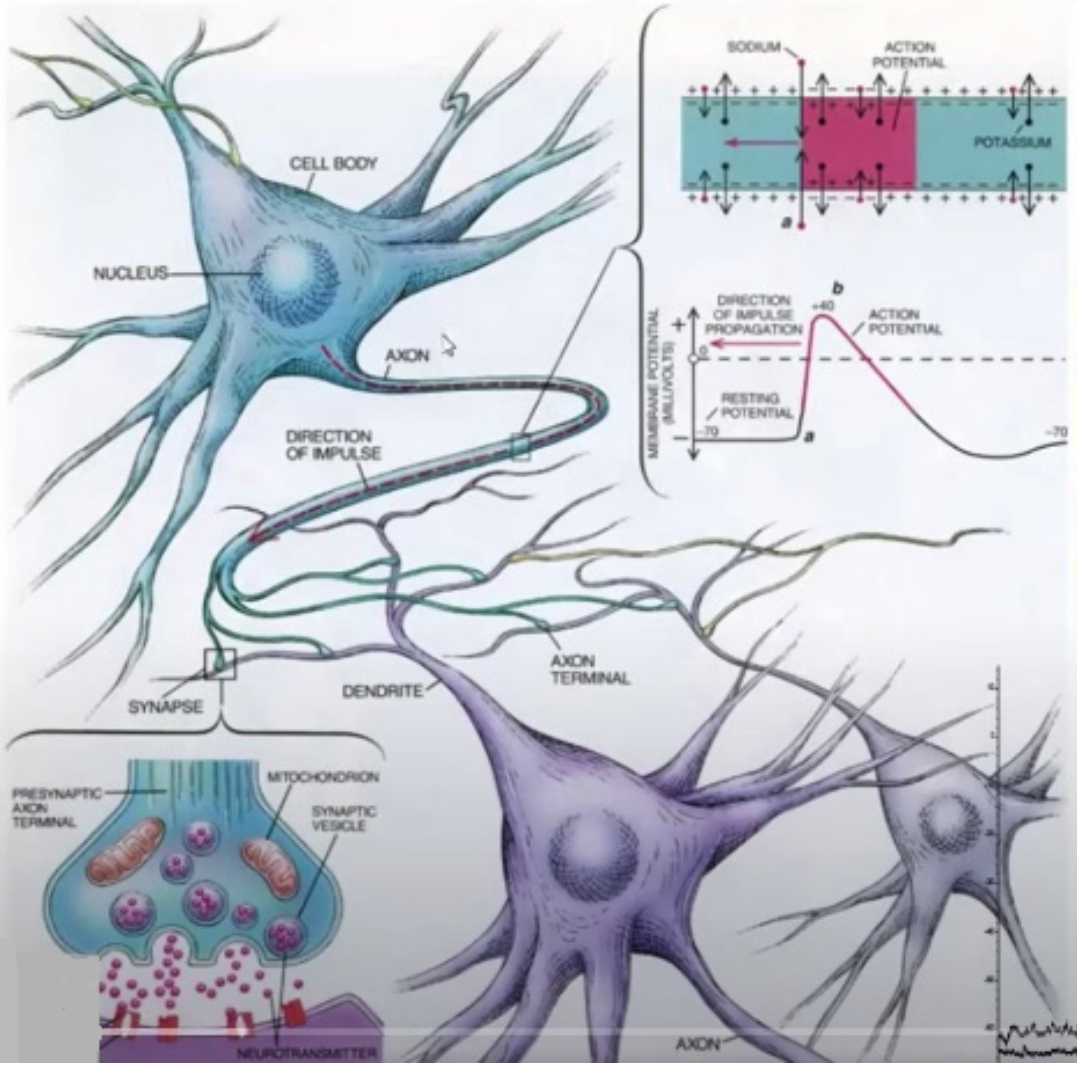
$$g(z) = \max(0, z)$$

$$g'(z) = \begin{cases} 1, & z > 0 \\ 0, & \text{otherwise} \end{cases}$$



Neurons & Synapses

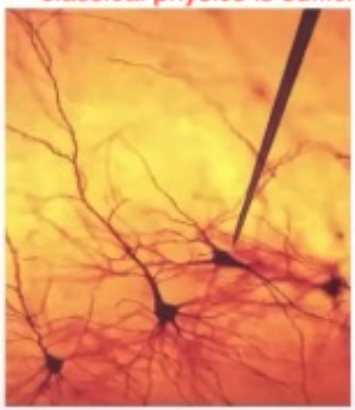
Neurons transmit information via electrical spikes and make synapses with other neurons to form networks

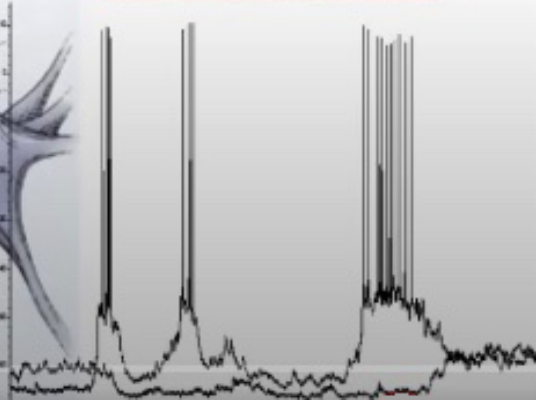


Sir Alan LLoyd Hodgkin, Nobel Prize 1963

Roger Penrose - Orchestrated Objective Reduction - quantum processes within brain's microtubules?

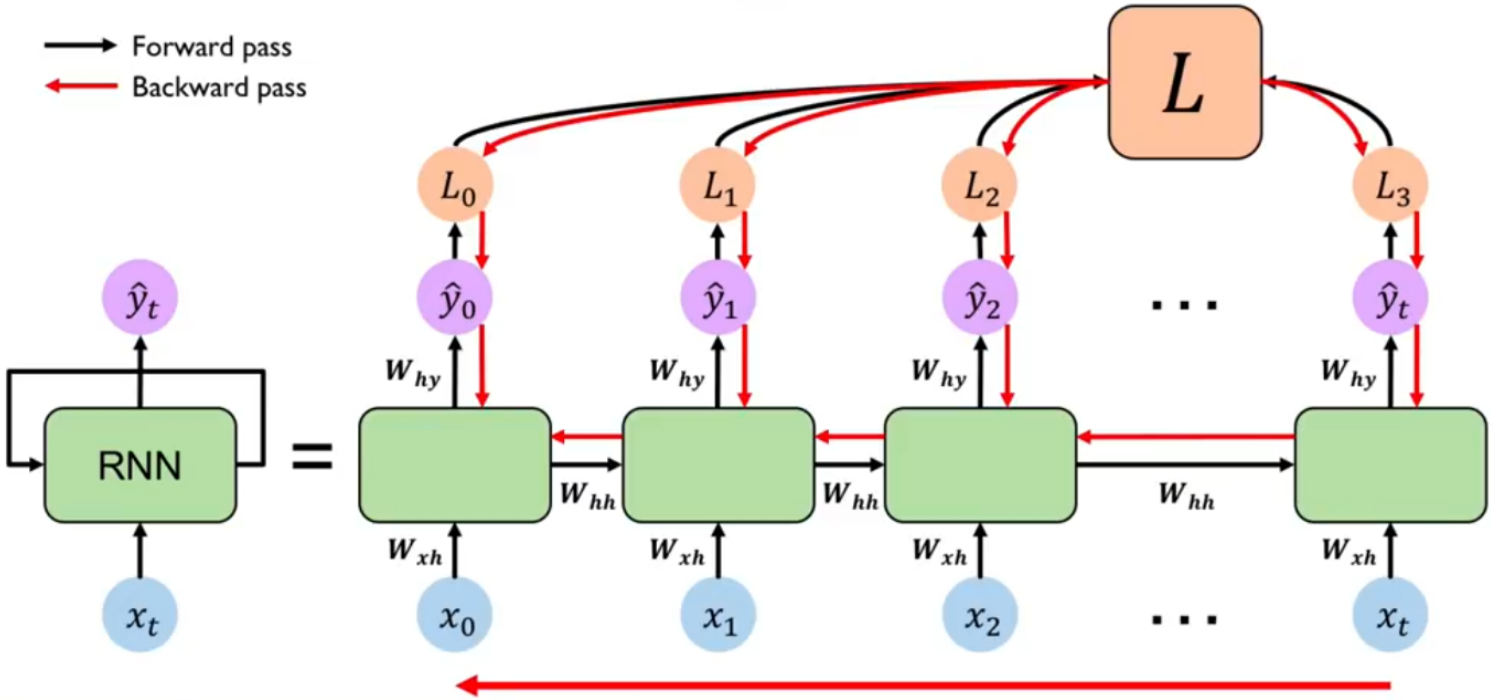
Max Tegmark (MIT) - classical physics is sufficient?





RNN

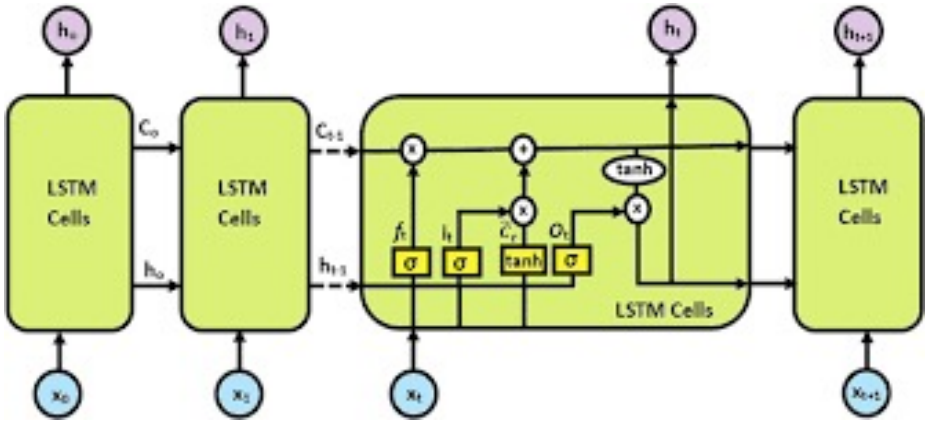
RNNs are connectionist models with the ability to selectively pass information across sequence steps while processing sequential data one element at a time.



But problems of vanishing and exploding gradients occur when backpropagating errors across many time steps.

Long Short Term Memory - Hochreiter & Schmidhuber, RL

Can handle vanishing gradient problem faced by RNN. A separate cell state - the horizontal line running through the top of the LSTM unit allowing information to flow unchanged across many time steps. **Forget Gate**: Determines which information from the previous cell state should be forgotten. **Input Gate**: Controls the update of the cell state by selectively adding new information to it. **Output Gate**: Decides what information should be output from the cell state based on the current input and the previous cell state. Backpropagation does not require matrix multiplication



Reinforcement Learning - Agent learns to make decisions by interacting with the environment to achieve the goal through reward & punishment.

Part-3: Generalised Pretrained Transformer (2017-now)

Attention Is All You Need

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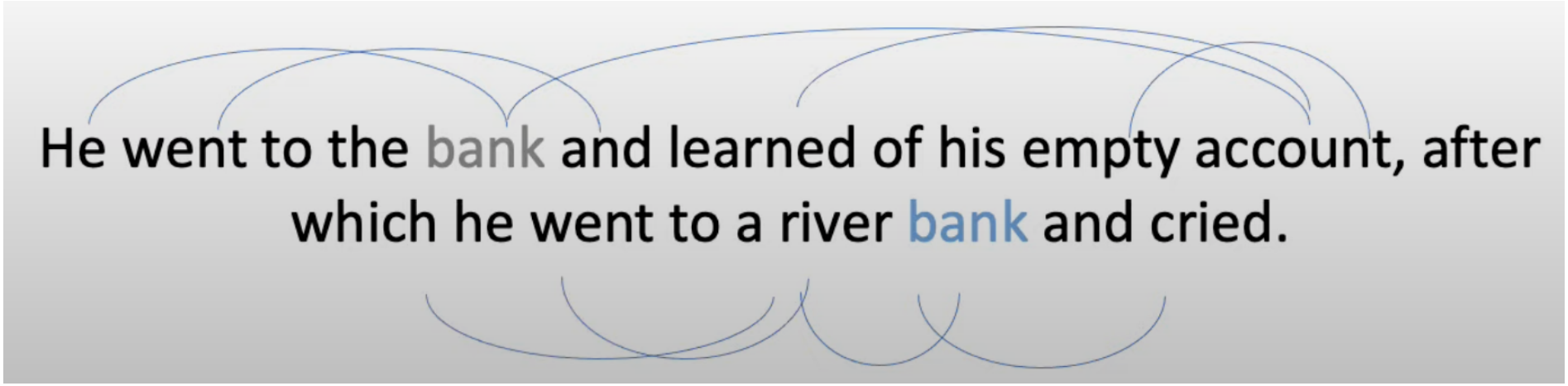
"Neural Machine Translation by Jointly Learning to Align and Translate" by Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio, 2014. Introduced concept of attention mechanism and laid the foundation for subsequent developments in NLP and DL, including the transformer architecture introduced in "Attention Is All You Need."

Attention



1. Attention mechanism has an infinite reference window
2. In contrast, Recurring Neural Network (RNN) has a short reference window, Long Short Term Memory (LSTM) has a longer window. RNN does not work, LSTM has limited capability.

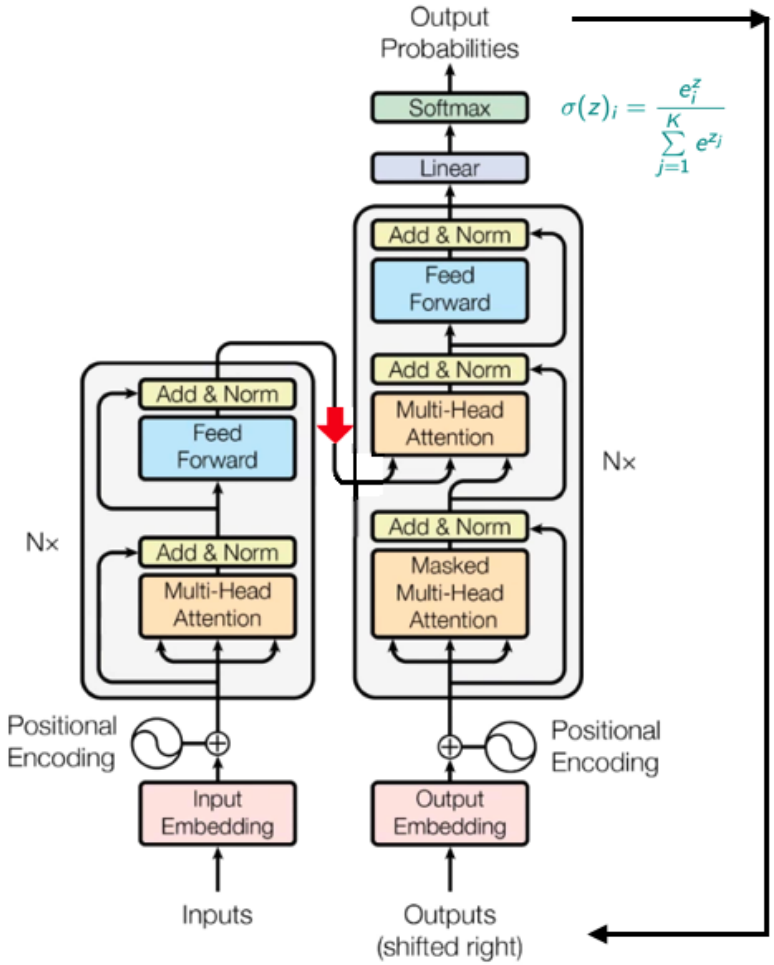
Key Concepts

1. Encode, Positional encoding

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{\text{model}}})$$

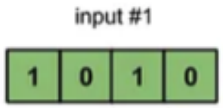
$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{\text{model}}})$$

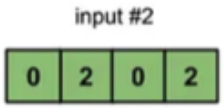
2. Key, Query and Value $\rightarrow$ Attention Filter
3. Multi Head Attention
4. Information preservation, normalisation
5. Decode, Masked Attention

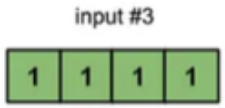


Decoders are autoregressive models; They are trained to predict the next token after reading the preceding ones

Query, Key & Value







Because every input has a dimension of 4, each set of the weights must have a shape of 4×3.
Weights are initialised randomly, it is done once before training.

Weights for **key**

```
[[0, 0, 1],
 [1, 1, 0],
 [0, 1, 0],
 [1, 1, 0]]
```

Weights for **query**

```
[[1, 0, 1],
 [1, 0, 0],
 [0, 0, 1],
 [0, 1, 1]]
```

Weights for **value**

```
[[0, 2, 0],
 [0, 3, 0],
 [1, 0, 3],
 [1, 1, 0]]
```

Key representation for input 1:

```
                [0, 0, 1]
[1, 0, 1, 0] x  [1, 1, 0] = [0, 1, 1]
                [0, 1, 0]
                [1, 1, 0]
```

Key representation for input 2:

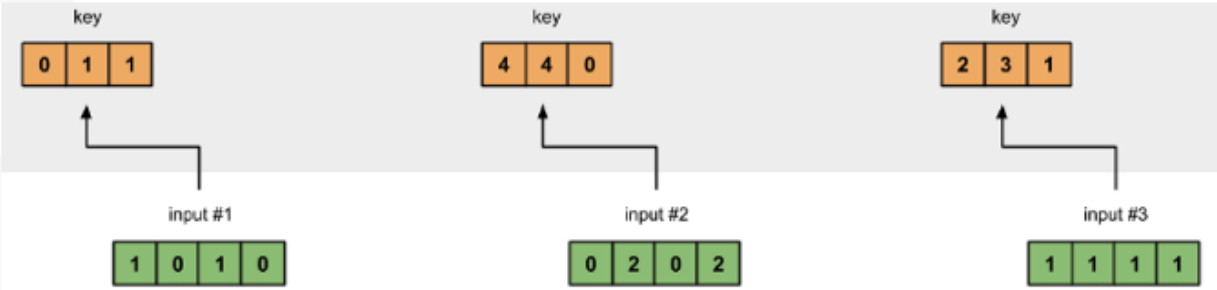
```
                [0, 0, 1]
[0, 2, 0, 2] x  [1, 1, 0] = [4, 4, 0]
                [0, 1, 0]
                [1, 1, 0]
```

Key representation for input 3:

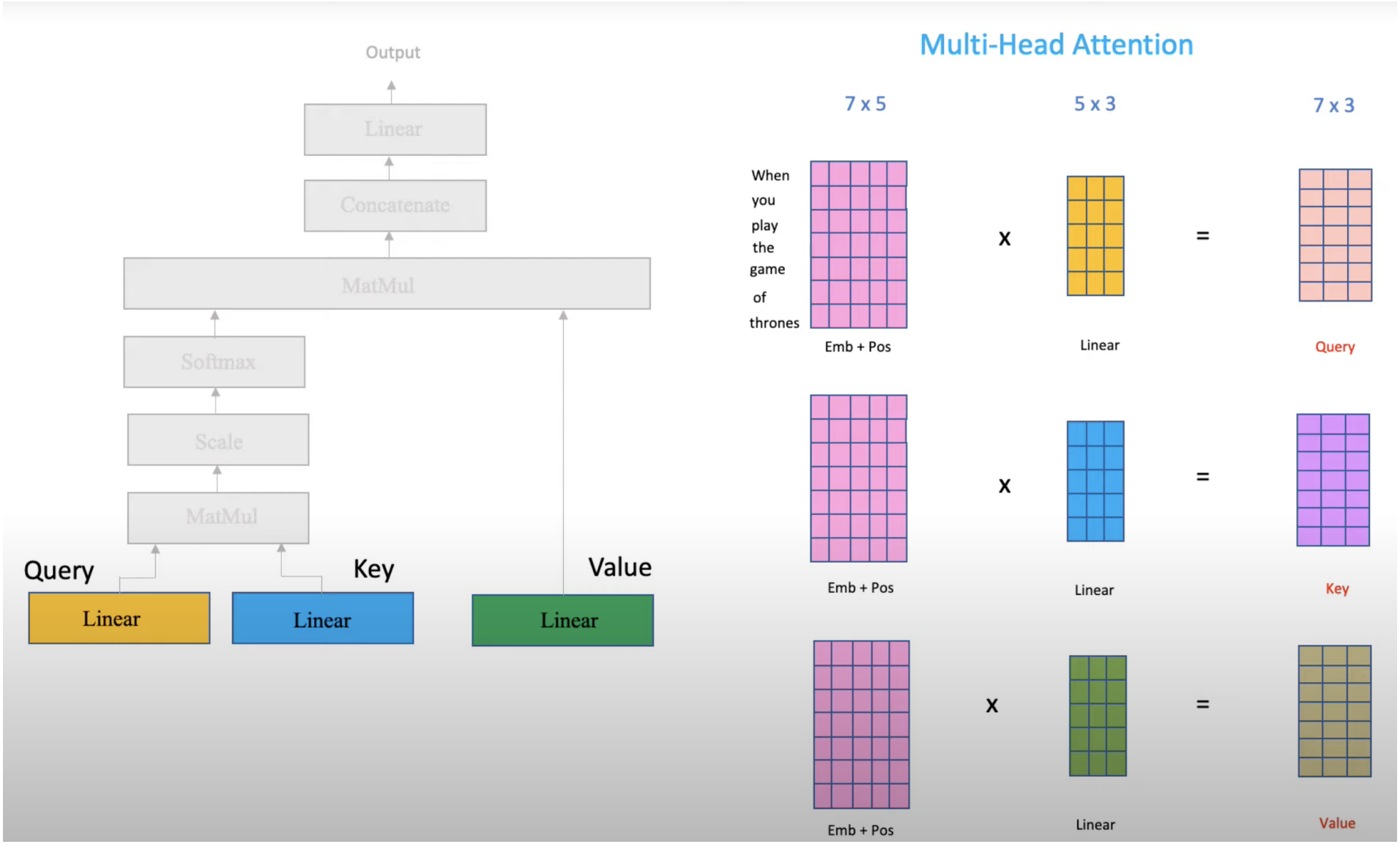
```
                [0, 0, 1]
[1, 1, 1, 1] x  [1, 1, 0] = [2, 3, 1]
                [0, 1, 0]
                [1, 1, 0]
```

Key representation: (Vectorise)

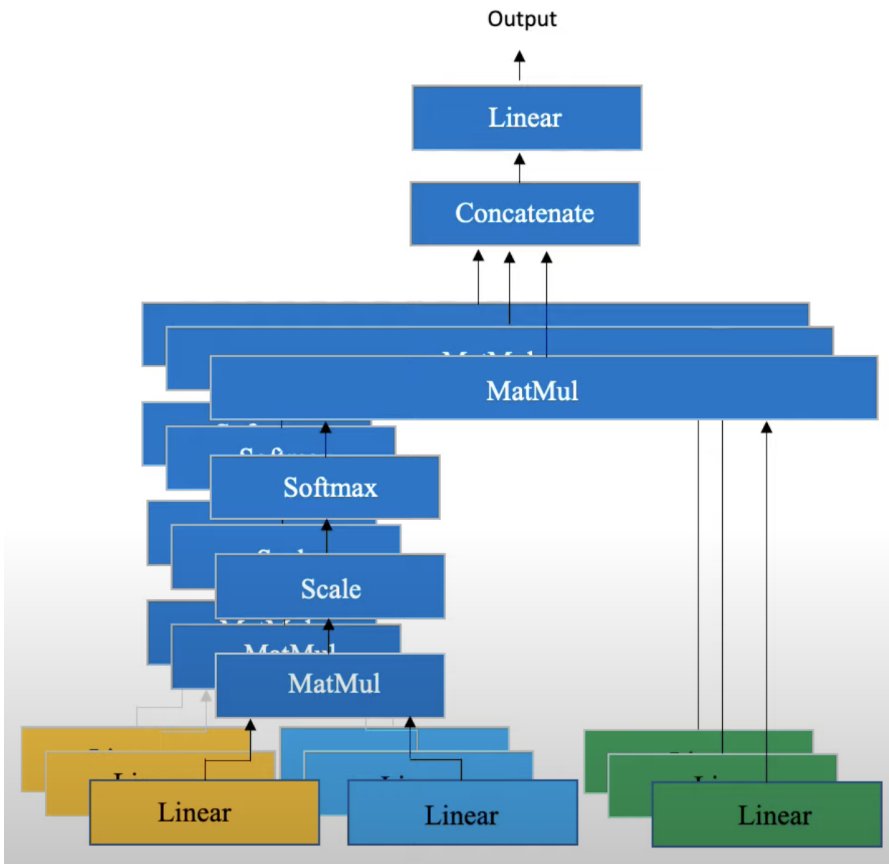
```
                [0, 0, 1]
[1, 0, 1, 0]    [1, 1, 0]   [0, 1, 1]
[0, 2, 0, 2] x  [0, 1, 0] = [4, 4, 0]
[1, 1, 1, 1]    [1, 1, 0]   [2, 3, 1]
```

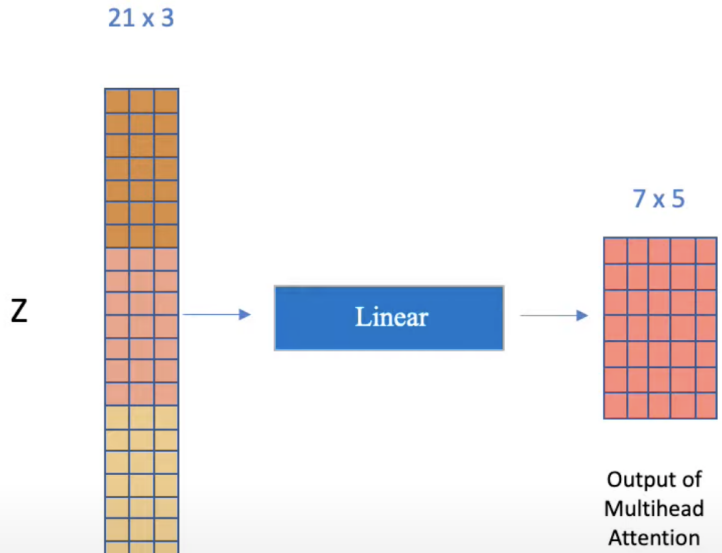


Multi Head Attention

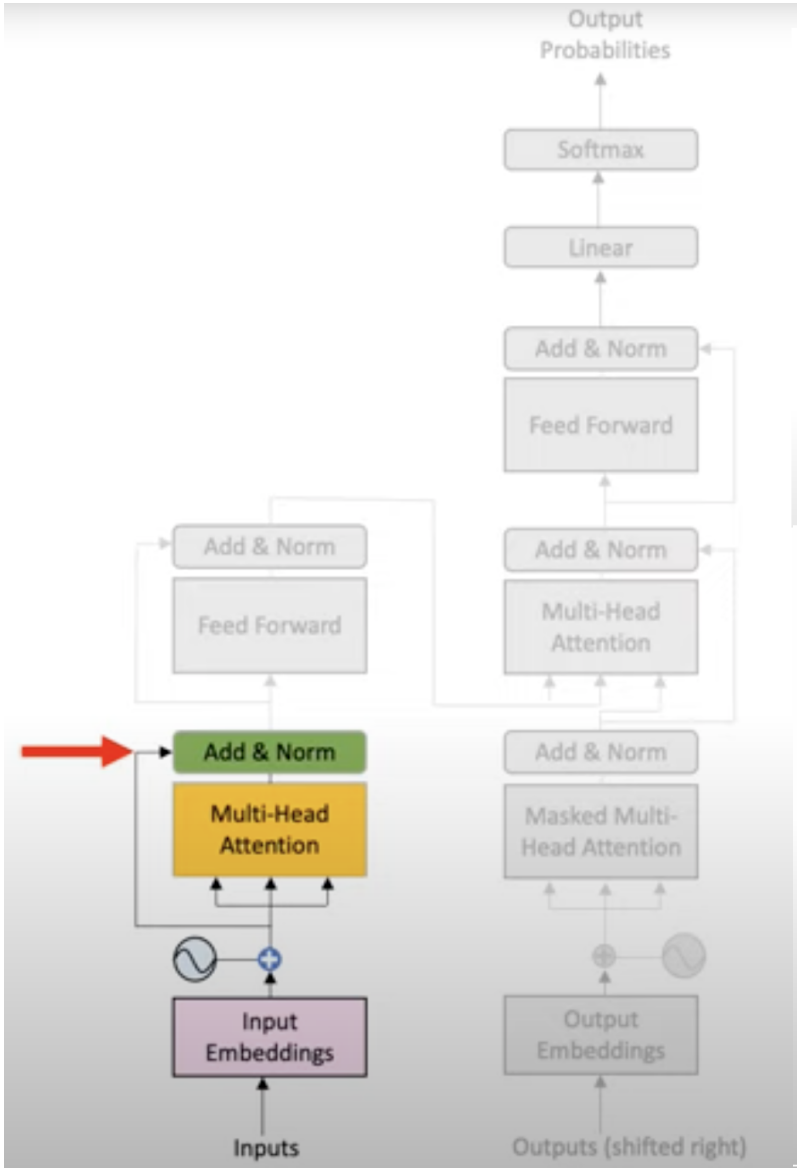


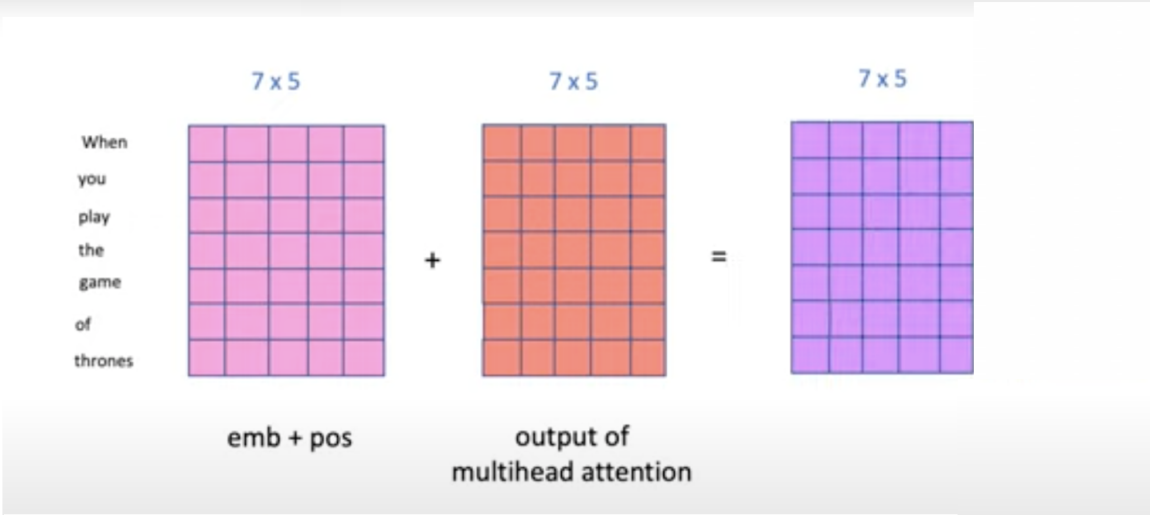
Multi Head Attention - Concatenation





Add (Preserve Information) & Normalisation



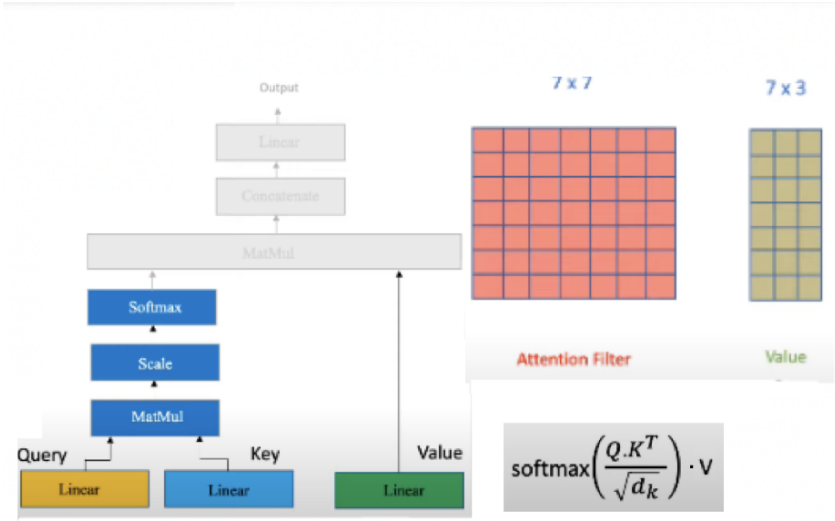


7 x 3

						mean (μ)	std (σ)
x_0 = When	0.98	1.28	0.41	0.27	0.41	0.67	0.44
x_1 = you	0.52	0.01	2.06	0.27	0.33	0.64	0.82
x_2 = play	2.22	0.27	0.10	0.41	2.06	1.01	1.04
x_3 = the	0.99	1.00	0.11	0.27	0.33	0.54	0.42
x_4 = game	0.52	0.01	0.33	2.06	0.52	0.69	0.79
x_5 = of	0.10	2.06	0.73	0.27	0.41	0.71	0.79
x_6 = thrones	0.33	0.01	0.13	0.27	1.28	0.40	0.51
	f_0	f_1	f_2	f_3	f_4		

$$x_0 = \frac{0.98 - 0.67}{\sqrt{0.44^2 + 0.0001}}$$

Attention Filter - filter out unnecessary information (noise)



$$\text{softmax}\left(\frac{Q.K^T}{\sqrt{d_k}}\right) \cdot V$$

7 x 7

	When	you	play	the	game	of	thrones
When	89	20	41	10	55	10	59
you	20	90	81	22	70	15	72
play	41	81	95	10	90	30	92
the	10	22	10	92	88	40	89
game	55	70	90	88	98	44	87
of	10	15	30	40	44	85	59
thrones	59	72	92	90	95	59	99

Then Divide by $\sqrt{d_k}$

Softmax

7 x 7

	When	you	play	the	game	of	thrones
When	33.6	7.6	15.5	3.8	20.8	3.8	22.3
you	7.6	34.0	30.6	8.3	26.5	5.7	27.2
play	15.5	30.6	35.9	3.8	34.0	11.3	34.8
the	3.8	8.3	3.8	34.8	33.3	15.1	33.6
game	20.8	26.5	34.0	33.3	37.0	16.6	35.9
of	3.8	5.7	11.3	15.1	16.6	32.1	22.3
thrones	22.3	27.2	34.8	34.0	35.9	22.3	37.4

$$\text{softmax}\,(x_i) = \frac{\exp(x_i)}{\sum_i \exp(x_i)}$$

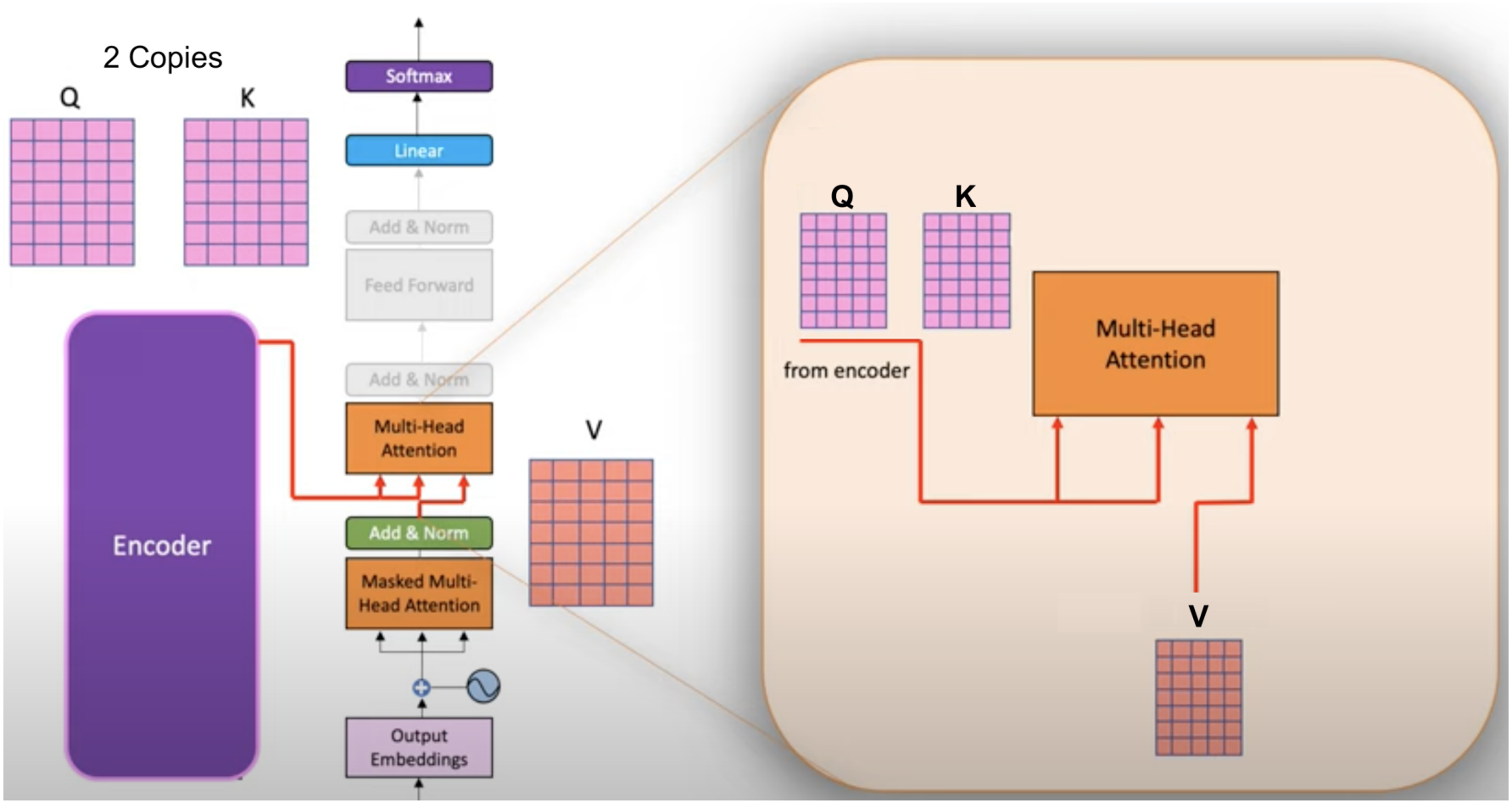
=

7 x 7

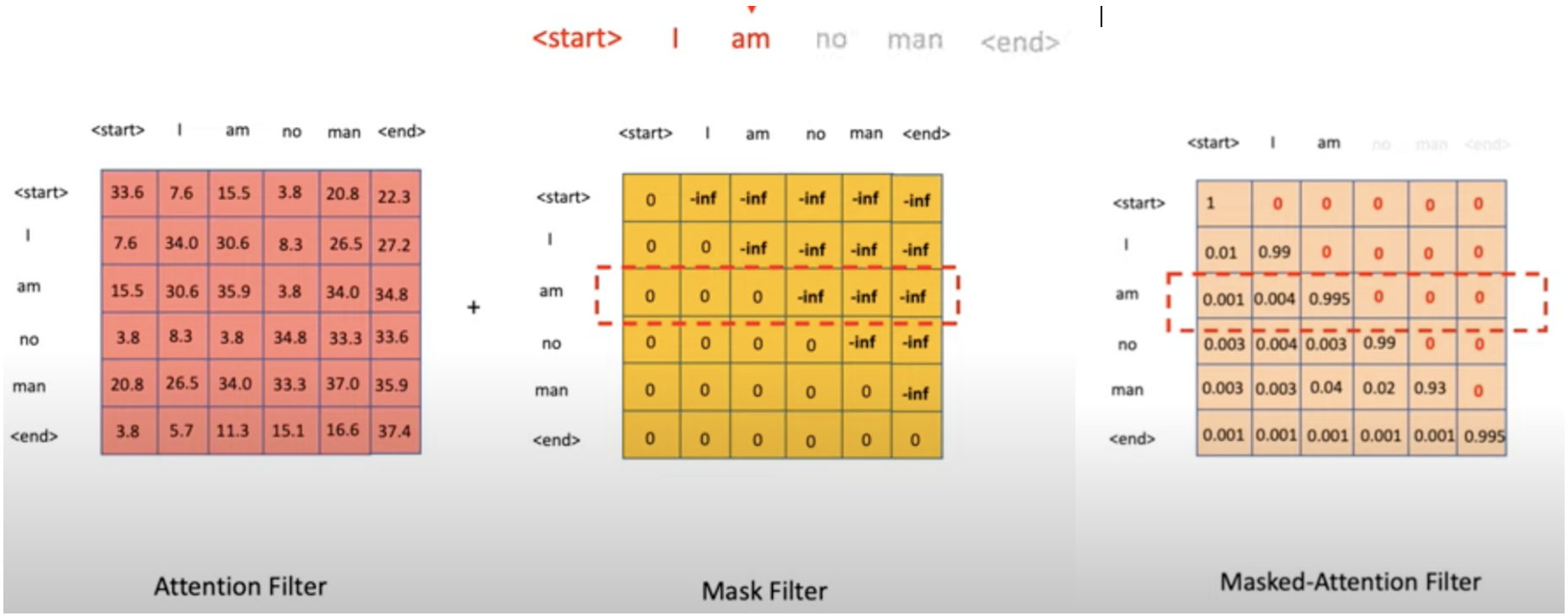
	When	you	play	the	game	of	thrones
When	1.00	0.00	0.00	0.00	0.00	0.00	0.00
you	0.00	0.97	0.03	0.00	0.00	0.00	0.00
play	0.00	0.00	0.68	0.00	0.10	0.00	0.22
the	0.00	0.00	0.00	0.65	0.14	0.00	0.21
game	0.00	0.00	0.03	0.02	0.72	0.00	0.23
of	0.00	0.00	0.00	0.00	0.00	1.00	0.00
thrones	0.00	0.00	0.05	0.03	0.17	0.00	0.75

Attention Filter

Decoder Layer



Masking


<start> I am no man <end>
<start> I am no man <end>
<start> 33.6 7.6 15.5 3.8 20.8 22.3
I 7.6 34.0 30.6 8.3 26.5 27.2
am 15.5 30.6 35.9 3.8 34.0 34.8
no 3.8 8.3 3.8 34.8 33.3 33.6
man 20.8 26.5 34.0 33.3 37.0 35.9
<end> 3.8 5.7 11.3 15.1 16.6 37.4
+
<start> I am no man <end>
<start> 0 -inf -inf -inf -inf -inf
I 0 0 -inf -inf -inf -inf
am 0 0 0 -inf -inf -inf
no 0 0 0 0 -inf -inf
man 0 0 0 0 0 -inf
<end> 0 0 0 0 0 0
<start> I am no man <end>
<start> 1 0 0 0 0 0
I 0.01 0.99 0 0 0 0
am 0.001 0.004 0.995 0 0 0
no 0.003 0.004 0.003 0.99 0 0
man 0.003 0.003 0.04 0.02 0.93 0
<end> 0.001 0.001 0.001 0.001 0.001 0.995
Attention Filter
Mask Filter
Masked-Attention Filter

LLM - Summary

1. GPT does not replicate human writing or speaking processes. Although they imitate human writing, any apparent cleverness primarily arises from our inclination to attribute human characteristics to non-human entities (anthropomorphization).
2. LLMs are essentially establishing statistical connections among vectors representing words and more extended grammatical structures. Each word within a sentence is linked to the subsequent word in the sequence with an associated probability.
3. This diverges significantly from human cognitive processes, where we employ word meanings to construct intricate and precise structures of "meanings" and definitions. For LLMs, definitions are confined to statistical interrelations among intricate vectors encompassing words, sentences, and more extensive grammatical constructs.
4. LLMs cannot innovate, not just yet. But the results are often stunning! LLMs do have massive use cases.

LLM pitfalls?

1. LLMs can do jaw-dropping things. But nobody knows exactly why.
2. Figuring it out is one of the biggest scientific puzzles of our time and a crucial step towards controlling more powerful future models.
3. Burda and Edwards teamed up with colleagues at OpenAI to study the phenomenon. They found that in certain cases, models could seemingly fail to learn a task and then all of a sudden just get it, as if a lightbulb had switched on. This wasn't how deep learning was supposed to work. They called the behavior "grokking".
4. According to classical statistics, the bigger a model gets, the more prone it is to overfitting.
5. Double descent - performance of thea model initially decreases, then increases, and finally decreases again as the model complexity or dataset size increases. Contradicts the traditional bias-variance tradeoff.
6. This behavior, dubbed benign overfitting, is not fully understood. Raises basic questions about how models should be trained.

Questions?

Thank You!