

# Fundamentals of Machine learning for and with engineering applications

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1 Recursive Neural Network

2 Generative AI

## ORDER MATTERS

- Language Models
- Time series

### Language model

- Prediction of the next word
- Prediction of next sentence

### Time Series

- Weather data
- Stock market
- Monitoring
- Trajectories
- Etc

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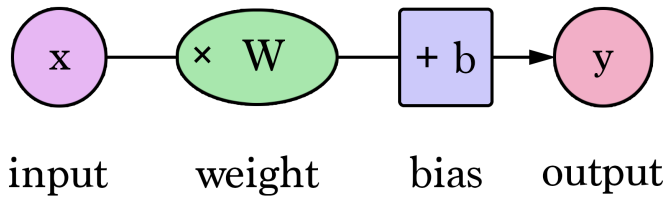
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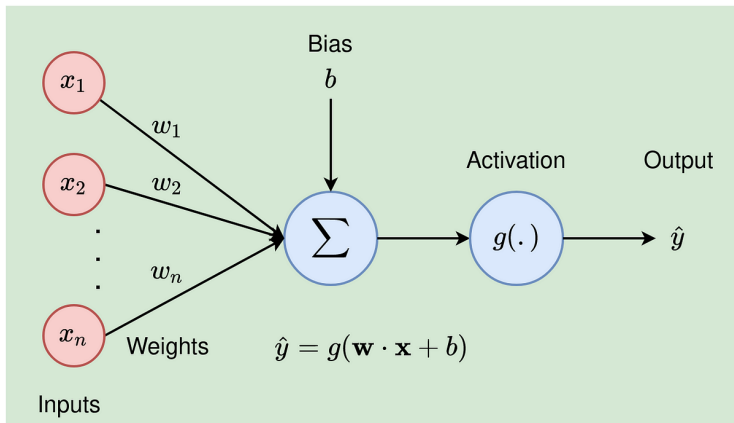
# Feedforward (FF) vs Recurrent NN (RNN)

## FF network

- One set of input
- One set of output
- Different parameters at each layer

- Multiple input set
- Multiple output
- Same parameter set



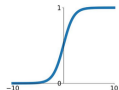




# Activation Functions

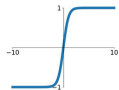
## Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



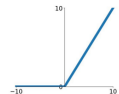
## tanh

$$\tanh(x)$$



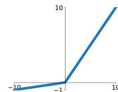
## ReLU

$$\max(0, x)$$



## Leaky ReLU

$$\max(0.1x, x)$$

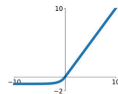


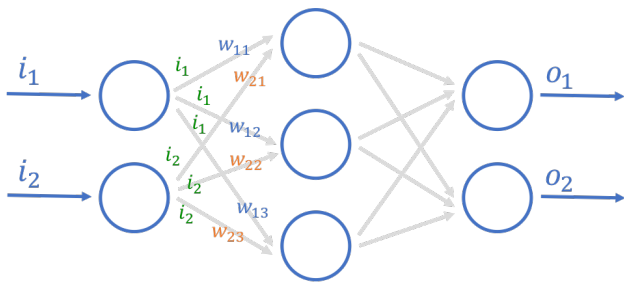
## Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

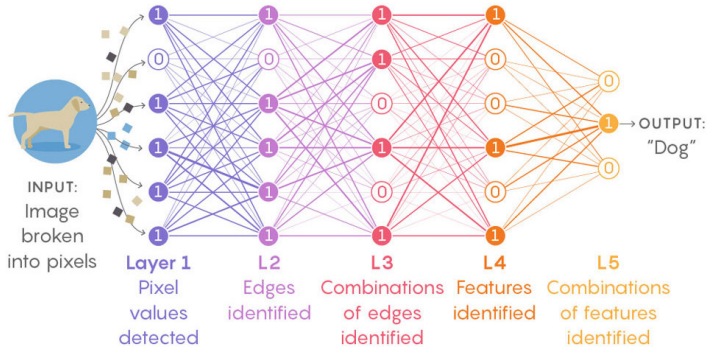
## ELU

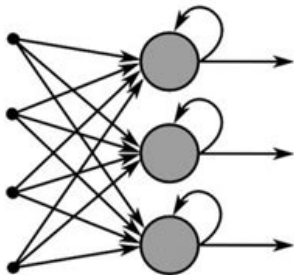
$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



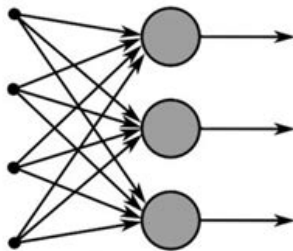


$$\begin{bmatrix} w_{11} & w_{21} \\ w_{12} & w_{22} \\ w_{13} & w_{23} \end{bmatrix} \cdot \begin{bmatrix} i_1 \\ i_2 \end{bmatrix} = \begin{bmatrix} (w_{11} \times i_1) + (w_{21} \times i_2) \\ (w_{12} \times i_1) + (w_{22} \times i_2) \\ (w_{13} \times i_1) + (w_{23} \times i_2) \end{bmatrix}$$





Recurrent Neural Network



Feed-Forward Neural Network

## Advantages

- Model size is fixed
- Each info is stored/learned
- The weights can be forwarded

## Problems

- Computationally demanding: long training times
- Problematic with Long series
- It can diverge (explode) or gradient vanish
- It cannot be very deep
- Unable to handle long time dependencies

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# RNN problems



## Exploding gradients

- Large weights update
- Gradient descent diverge (solution method)

## Vanishing gradients

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Filters forget data...

What about if we purposely forget data?

LSTM includes Forget Gates

Automatic filter!

The forget gates learn to forget what is not interesting

This is extremely useful but also rather worrisome: you have no control!

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What is GRU?

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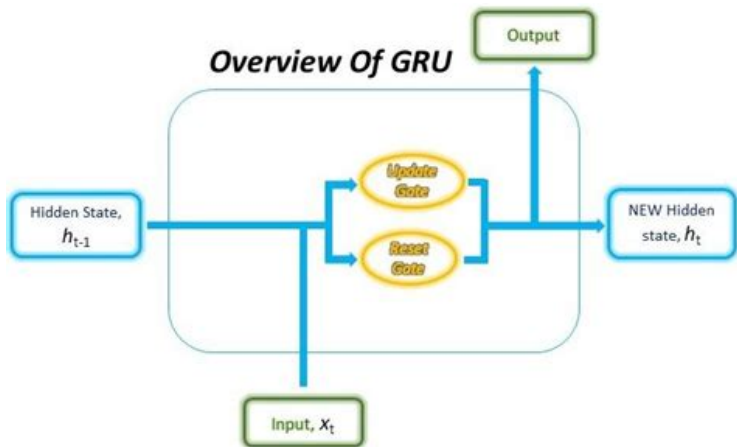
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Reset gates

To capture short-term dependencies

Update gates

To capture Long-term dependencies

Each gate has its own weight

## Reset gates

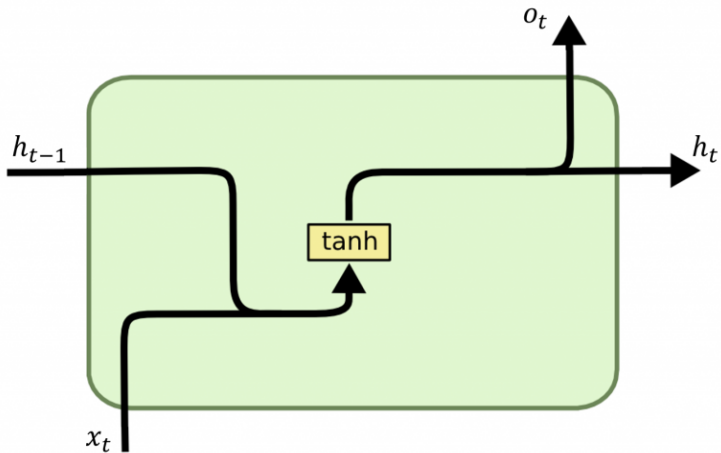
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## Update gates

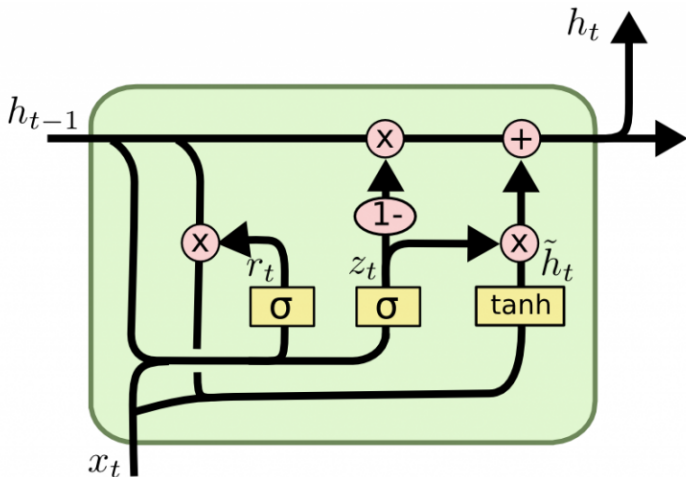
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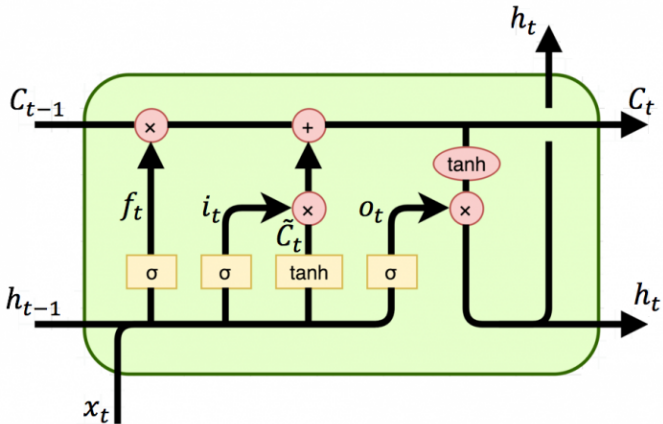


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# LSTM



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# Generative AI

A generative AI model is a type of artificial intelligence that is designed to generate new content, based on the data it has been trained on.

It started in 1932, with the **mechanical brain** by Georges Artsrouni that was supposed to translate automatically between languages,

Here [a nice recaps of Generative AI](#) and its [storyline](#)

## A valuable report

A foundation model, also known as large X model (LxM), is a machine learning or deep learning model that is trained on vast datasets so it can be applied across a wide range of use cases.

Key characteristics of generative AI models include:

- 1 Learning from Data: They are trained on large datasets, enabling them to learn patterns, styles, or features inherent in the data.
- 2 Generating New Content: Generative models can create new data instances. For example, a model trained on a dataset of paintings can generate new images in the style of those paintings.

Trained generative models are thus able to input information at a low resolution/dimension and give output with a much greater dimensionality.

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Here a list of possible applications:

- Images/video: Image generation, Super-resolution, Deep fakes.
- Music: noise filter, voice and music generation, voice deep fake.
- Text(LLM): chatGPT, bard, Gemini, etc.
- Chemistry: DeepMind (Alphafold).
- Coding (co-pilot)
- Speech
- Attacks and Hacking (Security testing)
- Generating training sets
- And many more

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- 2 Medical images to show diseases consequences
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New possibilities do not come with side effects.

- ❶ Lack of transparency: how the output is generated, and why?
- ❷ Accuracy: a lot of hallucinations
- ❸ Bias: human biases are kept, supported and eventually increased
- ❹ Intellectual properties (IP): who owns what is produced?
- ❺ Cybersecurity and frauds: mass cyber attacks can be created
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# Where generative AI is ?

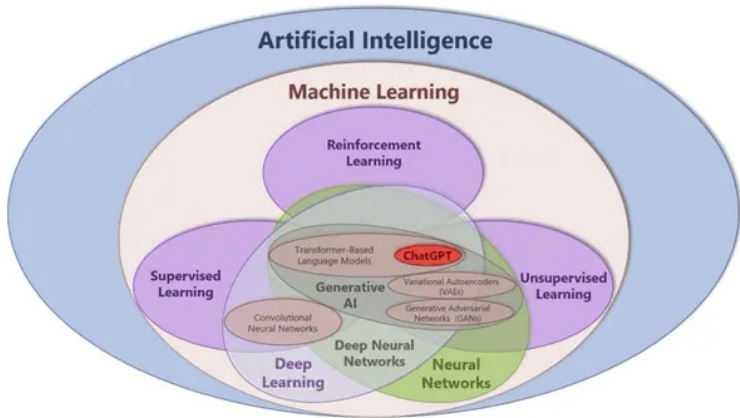


Image: <https://iot-analytics.com>

# Structure of generative AI

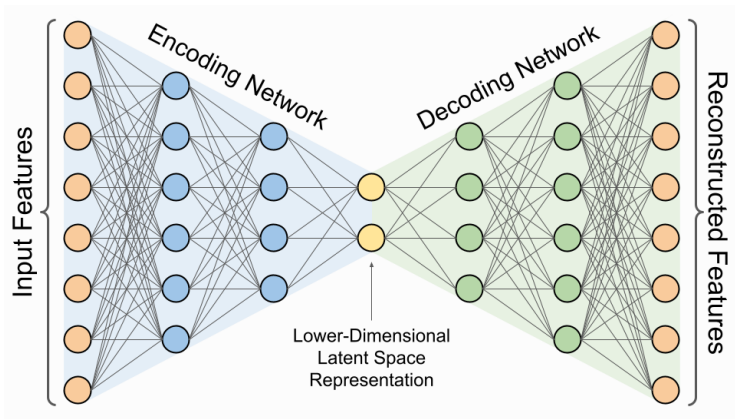


Image: <https://www.rapidops.com>

# A new field?

Generative AI is actually a new evolution.

It is based on Neural Network, and in comprises a set of advanced tools (numerical recepites):

- 1 Generative Adversarial Networks
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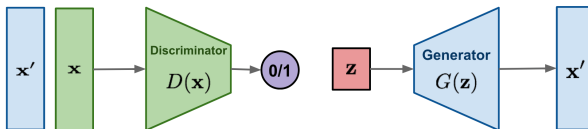
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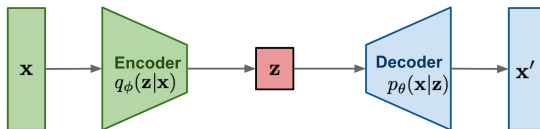
# Types of generative AI

It is quite an advanced technique

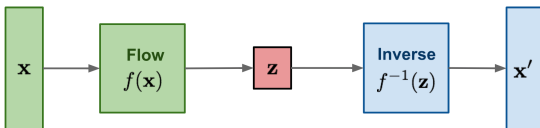
**GAN:** minimax the classification error loss.



**VAE:** maximize ELBO.



**Flow-based generative models:** minimize the negative log-likelihood



Source: [Lilian Weng](#)