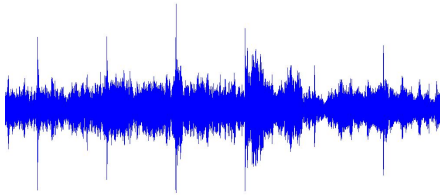
Introductory Seminar on Artificial Intelligence and Machine Learning

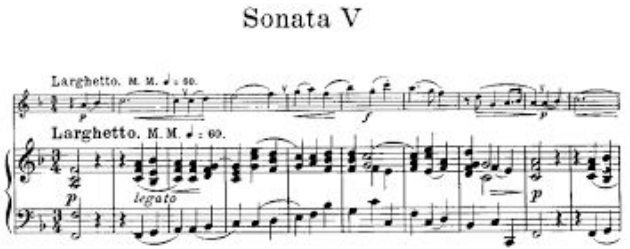
Emanuele Ledda, Cagliari Digital Lab 2024 - Day 4

Recurrent Neural Networks (RNN)

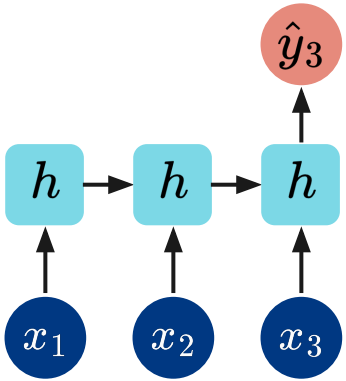
The Notion of Sequence

One Piece (stylized in all caps) is a Japanese manga series written and illustrated by Eiichiro Oda. It has been serialized in Shueisha's *shōnen* manga magazine *Weekly Shōnen Jump* since July 1997, with its individual chapters compiled in 108 *tankōbon* volumes as of March 2024.

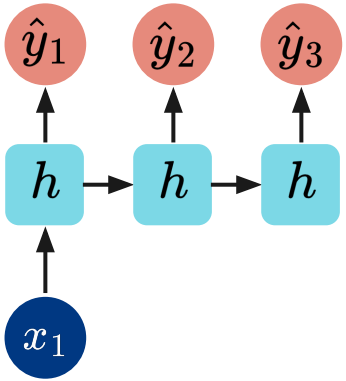




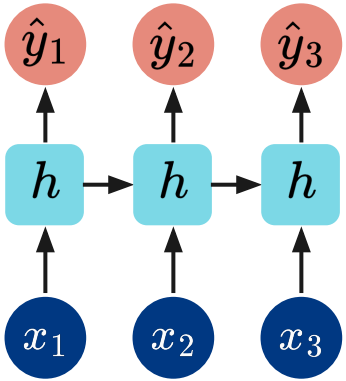
Sequence modelling



Many-to-One



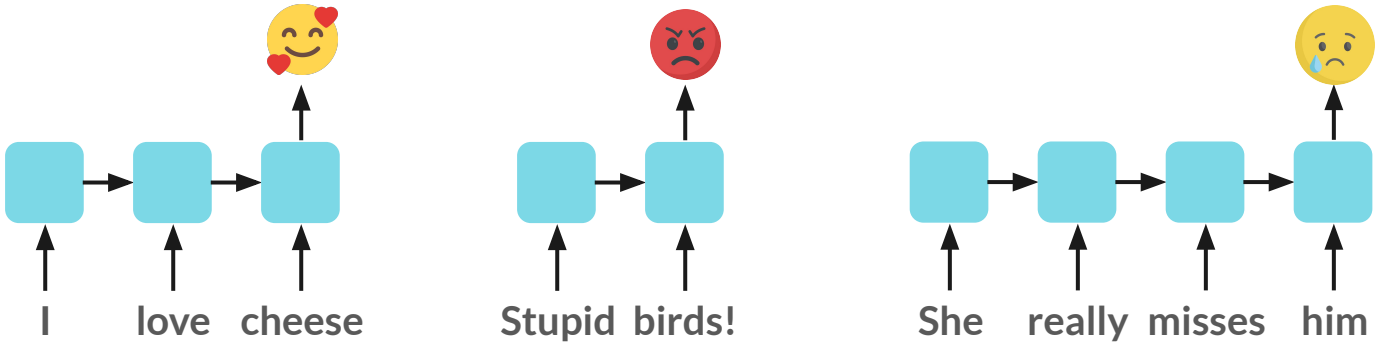
One-to-Many



Many-to-Many

Many-to-One

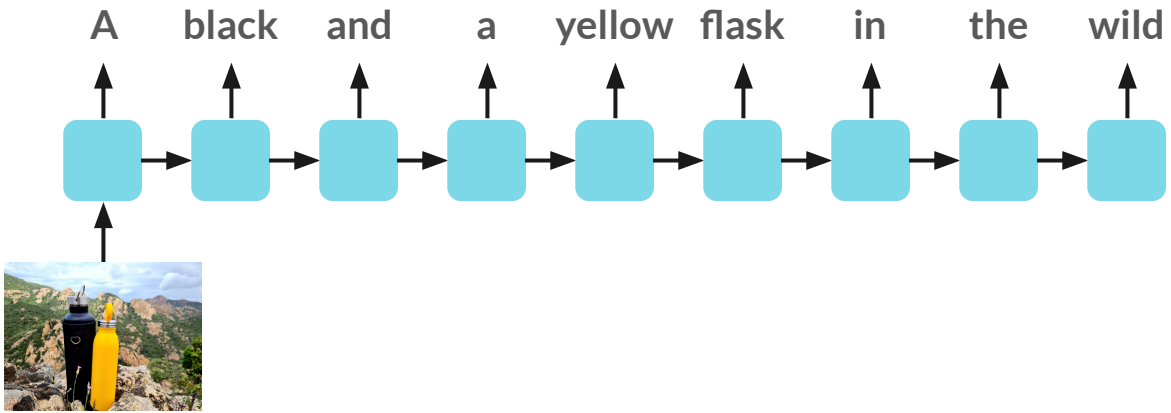
- In **many-to-one** sequence modelling the **input represents a Serie** and the **output represent a single value** (e.g., Sentiment Analysis)
- The **input** has an **arbitrary length** (not specified a priori)



One-to-Many

- In one-to-many sequence modelling the **input represents a single 'object'** and the **output represent a Serie** (e.g., Image Captioning)

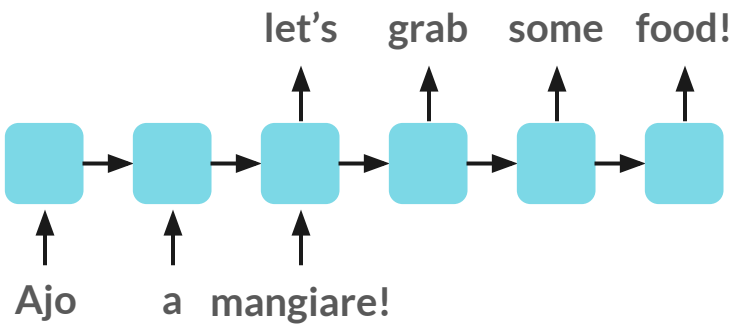
- The **output** has an **arbitrary length** (not specified a priori)



Many-to-Many

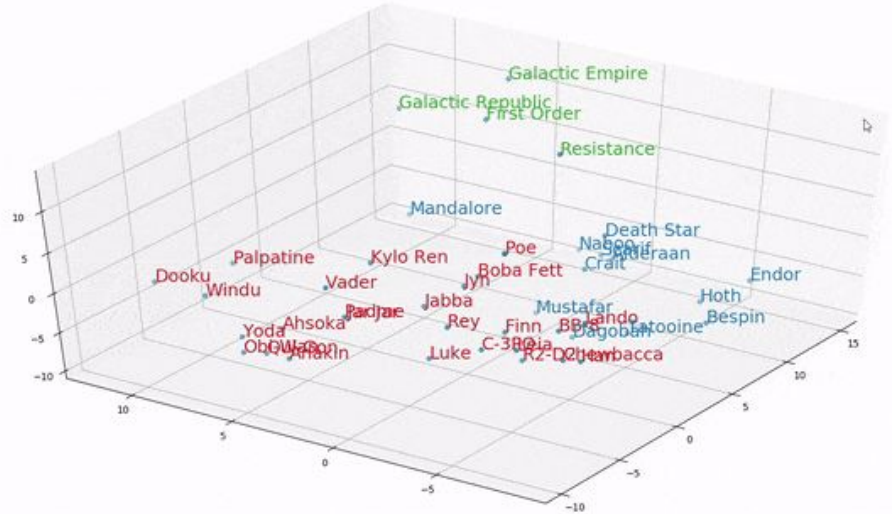
- In one-to-many sequence modelling the **both the input and the output represent Series** (e.g., Machine Translation)

- **Both the output and the input has arbitrary length**

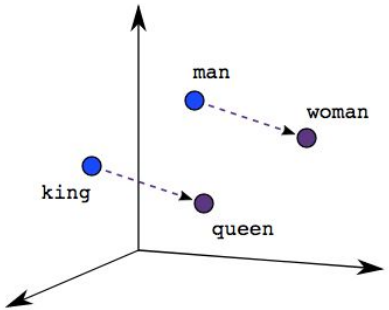


Natural Language Processing

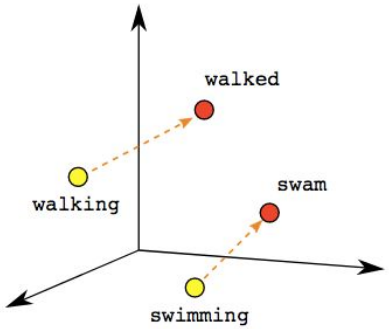
- If we want to encode natural language in deep learning models we need a strategy for encoding each word
- Generally, we use standard pre-computed embeddings which are dictionaries mapping words in multidimensional vectors



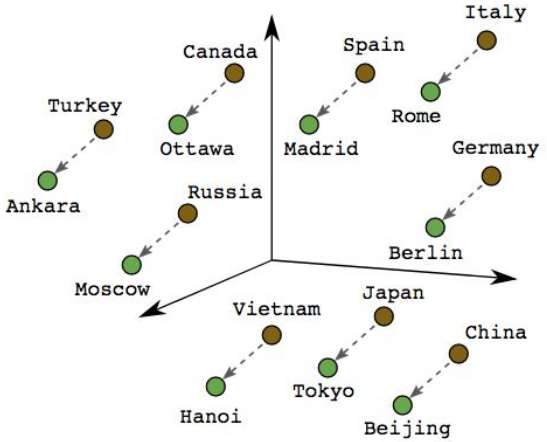
Word Embedding



Male-Female



Verb Tense

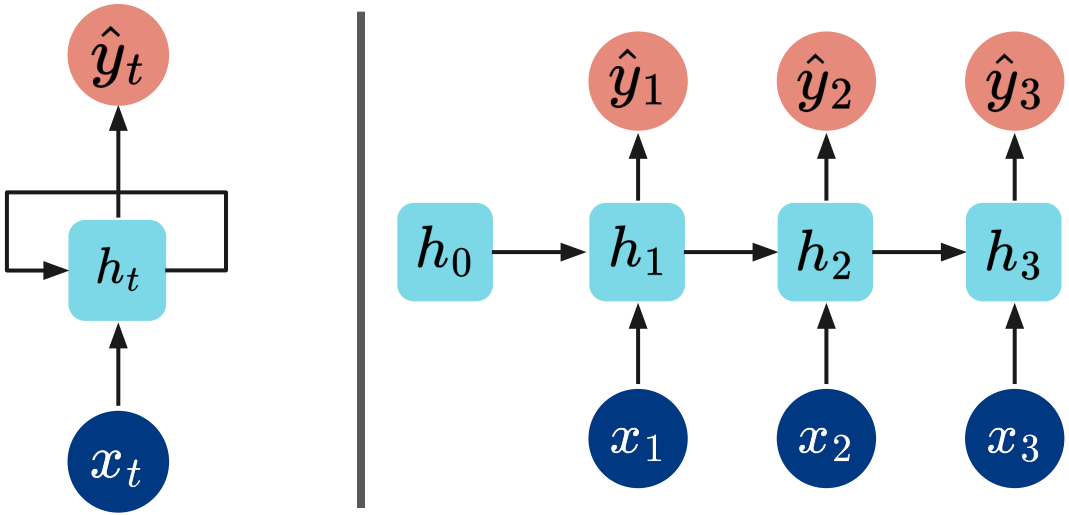


Country-Capital

Recursive Neural Network (RNN)

$$\hat{y}_t = f(x_t, h_{t-1})$$

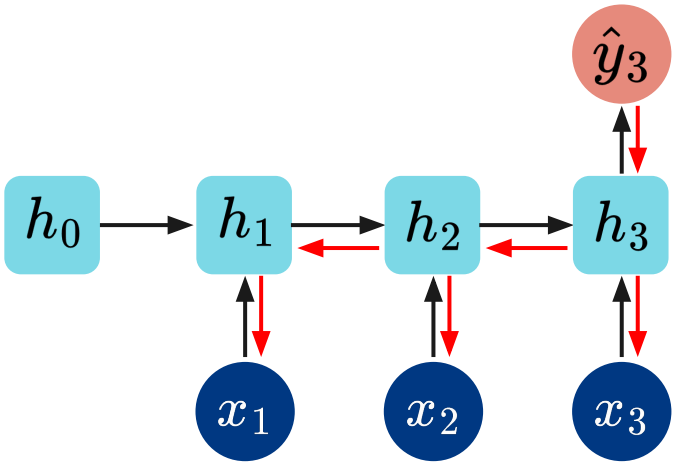
$$h_t = f^W(x_t, h_{t-1})$$



- The **hidden state encodes** in some sense the information about the **past tokens**
- At each timestep we update the hidden state

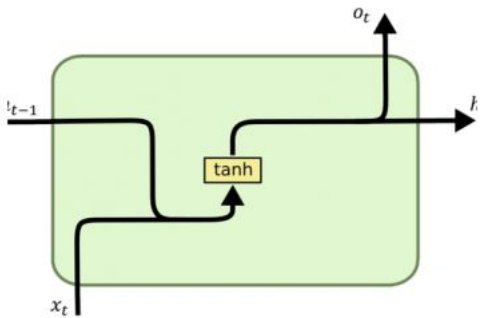
Backpropagation Through Time (BPTT)

$$\frac{\partial \mathcal{L}(\hat{y}_k, y)}{\partial h_k} \cdot \frac{\partial h_k}{\partial h_{k-1}} \cdot \frac{\partial h_{k-1}}{\partial h_{k-2}} \cdots \frac{\partial h_1}{\partial W_h}$$

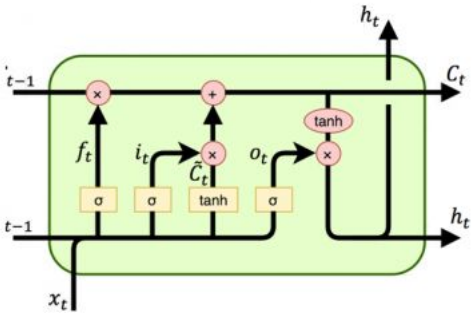


- The gradients propagate throughout all the time-steps
- High risk of vanishing or exploding gradients due to the serie of multiplication from the derivative chain rule
- Many solutions try to develop recurrent units which combine wisely the activation functions for avoiding exploding/vanishing gradients

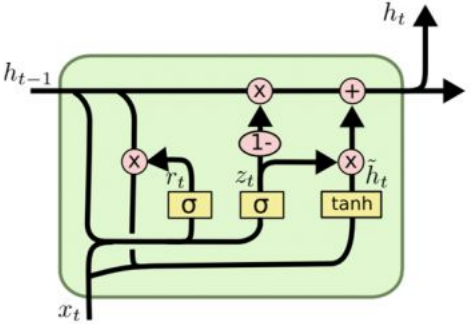
Different types of RNNs



Regular RNN



LSTM

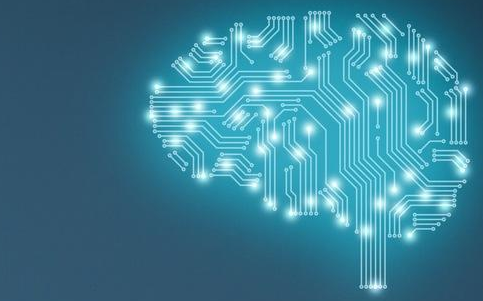


GRU

https://colah.github.io/posts/2015-08-Understanding-LSTMs/

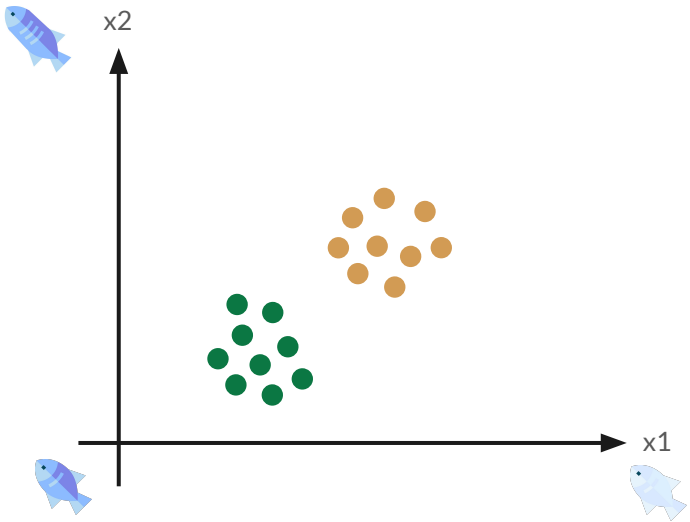
Modern AI Ides

- Generative Models
- Attention and Transformers
- Self-Supervision
- Multi Modality
- Foundation Models

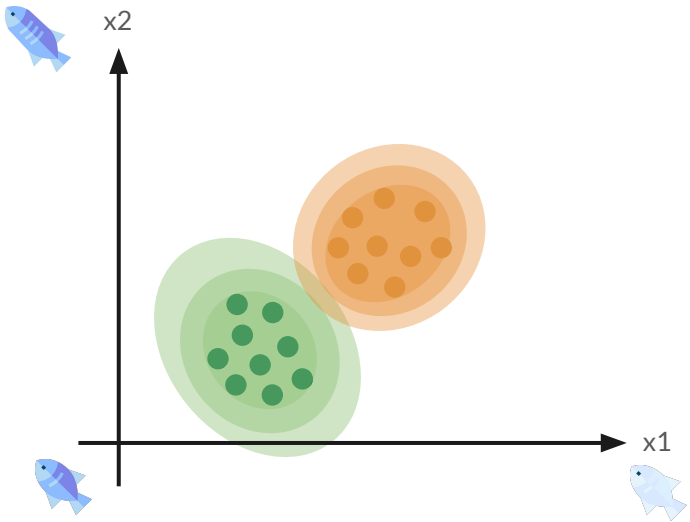


Generative Models

Generative Modelling

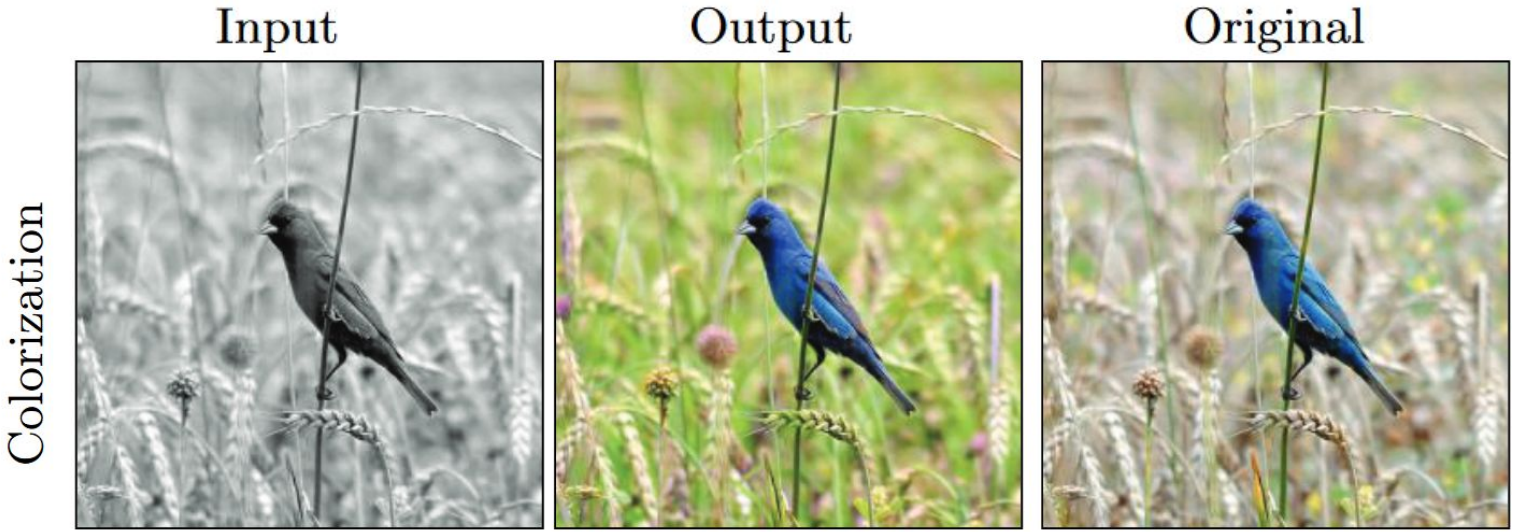


Generative Modelling

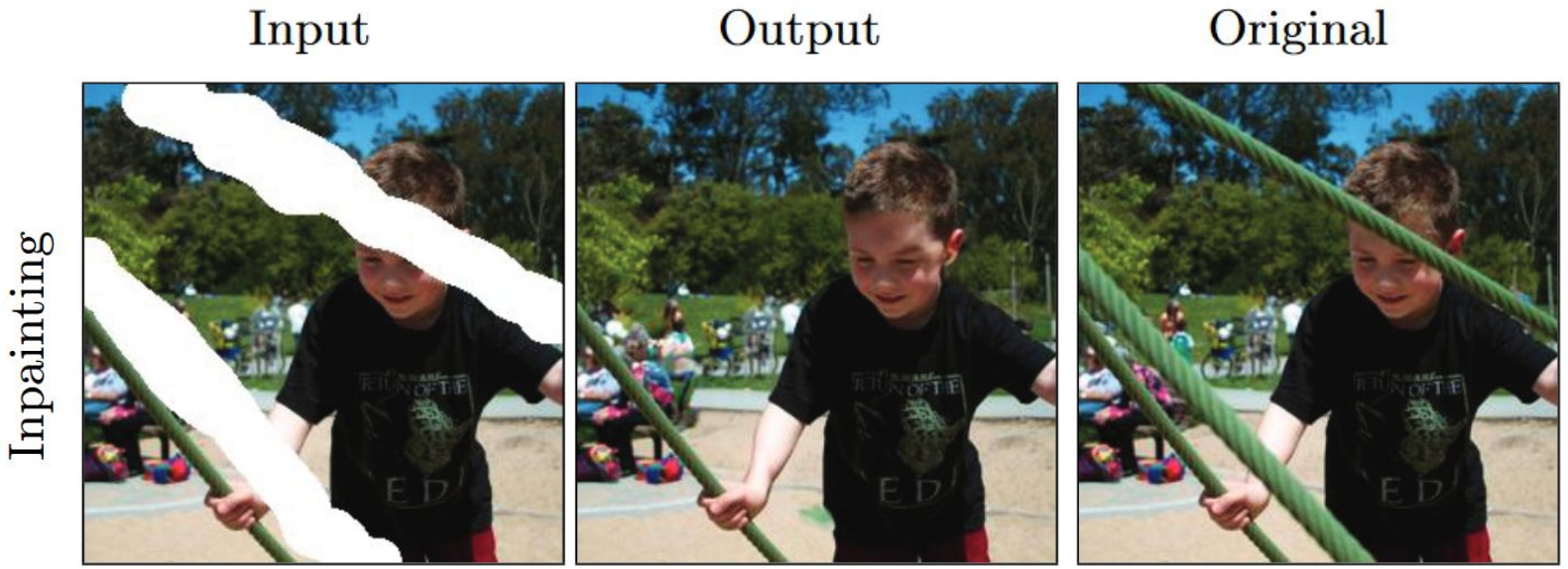


- The idea is to imagine the data as if they were sampled from a **generative distribution**
- Generative models just try to **fit this probability distribution**
- One fitted, one can **sample from this distribution** for **creating new samples**

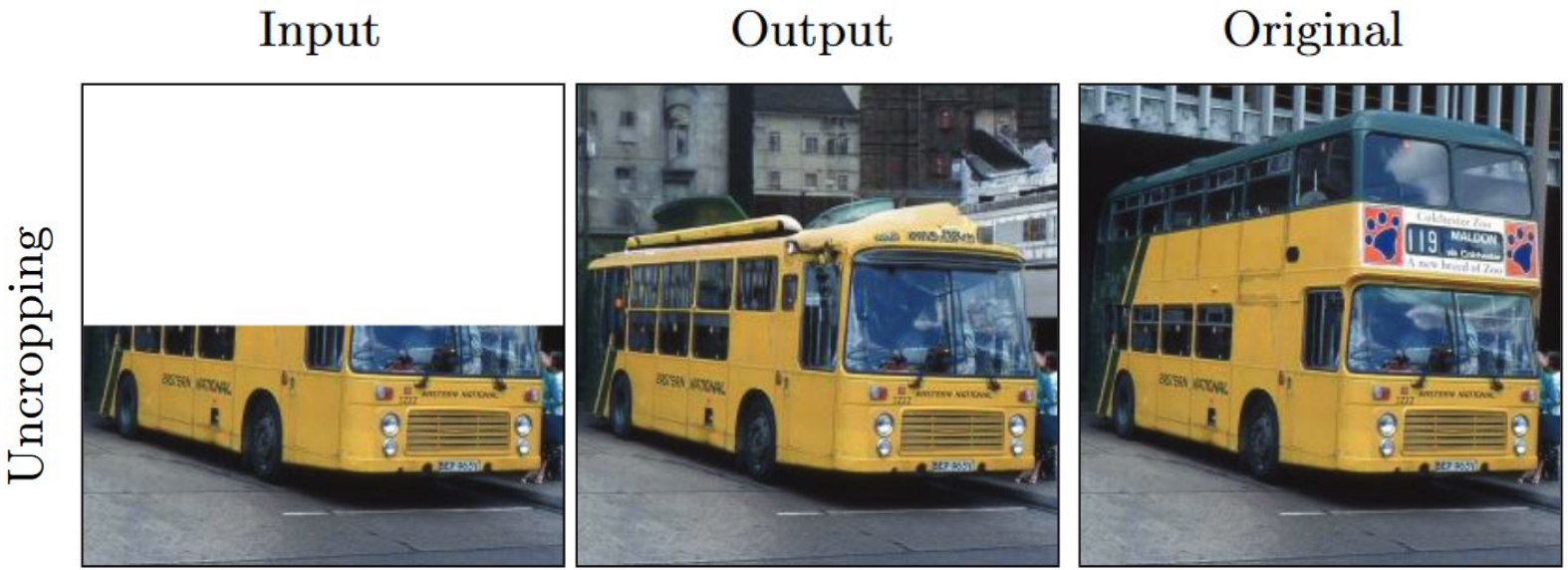
Applications of Generative Models



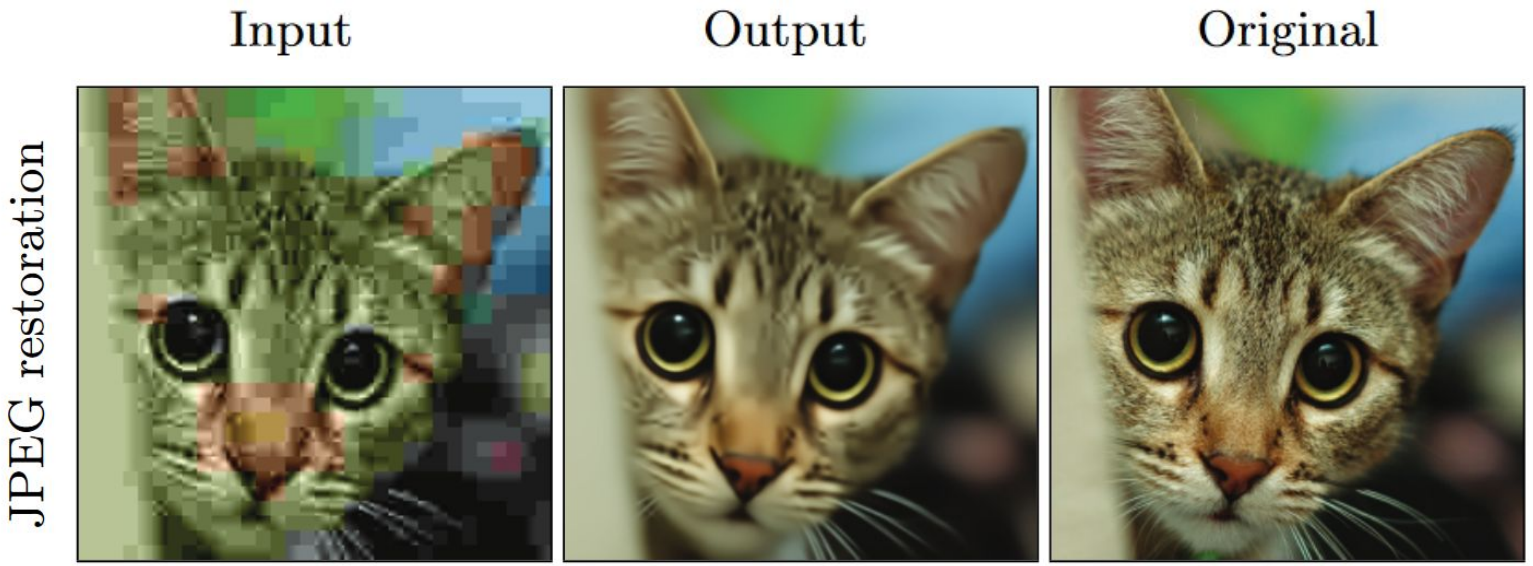
Applications of Generative Models



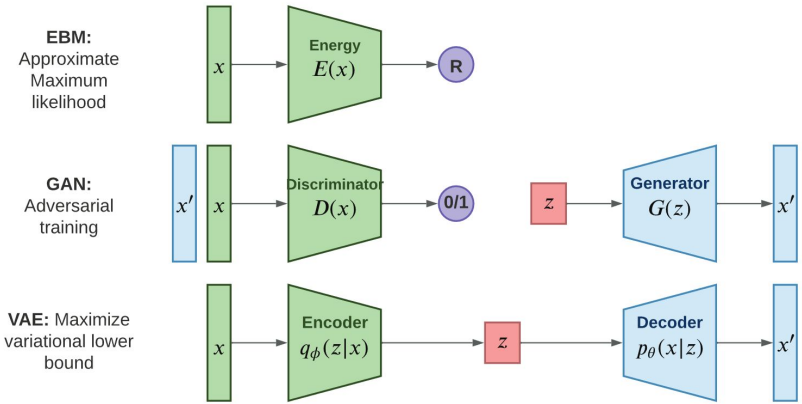
Applications of Generative Models

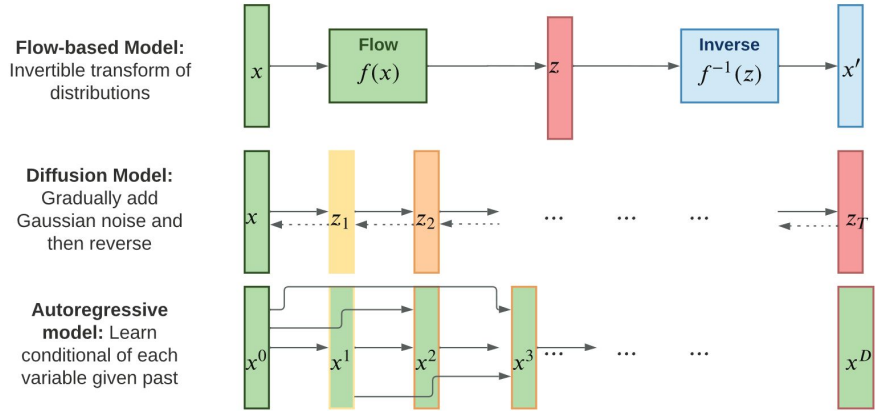


Applications of Generative Models

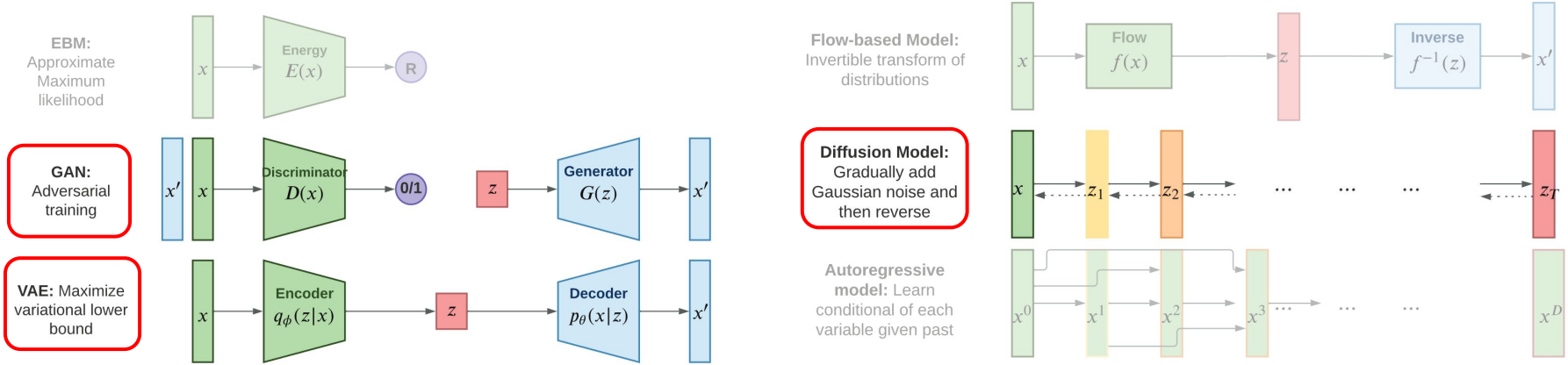


Types of Generative Models



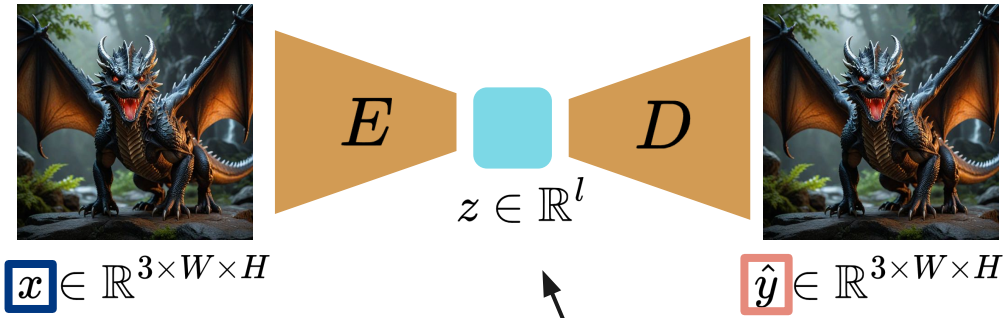


Types of Generative Models



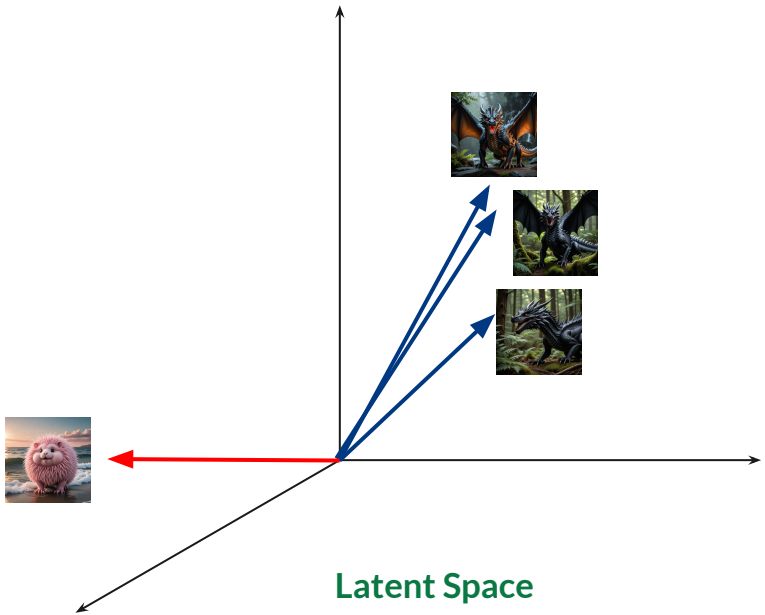
Auto-Encoders (AEs) - idea

- I want to “compress” all the information describing data points in a space with smaller dimensionality



- I can fit a model which at first **“compress”** and then tries to **“reconstruct” the input** by using an **Encoder-Decoder network**
- The only way the model can minimize the loss is to **find a compact form for describing the input**!

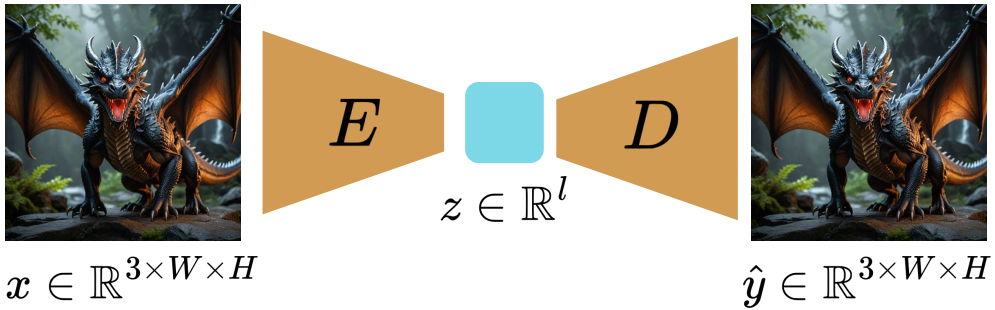
Auto-Encoders (AEs)



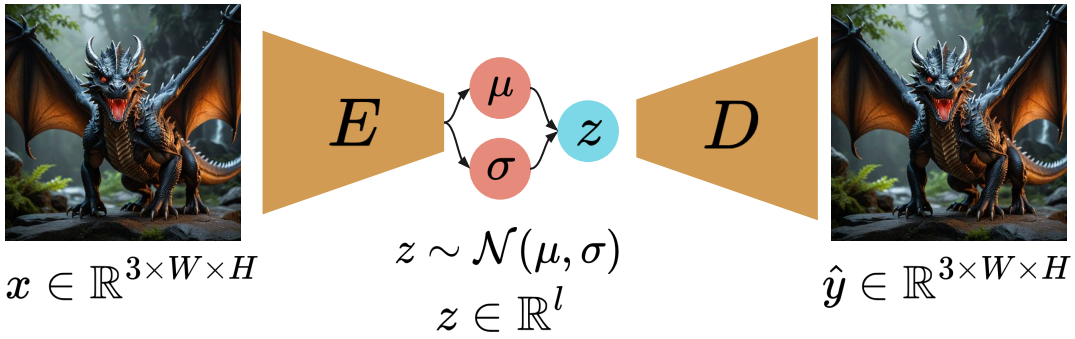
- In the latent space, similar vectors encode similar data…
- So, by exploring the latent space one can eventually find similar data, which when reconstructed will create new data
- But can we do better?

Variational Auto-Encoders (VAEs)

- Instead of just encoding…

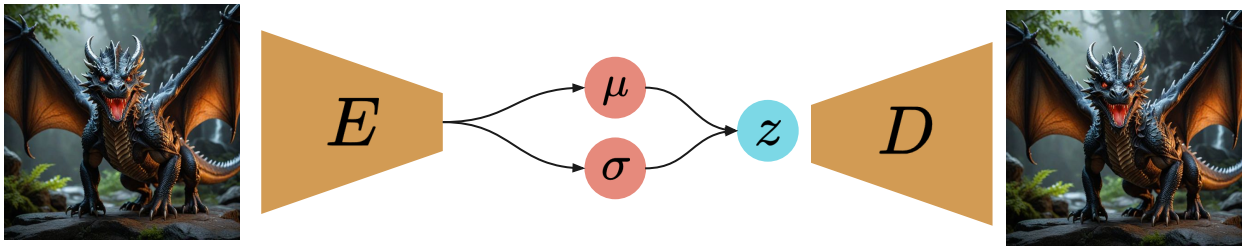


Variational Auto-Encoders (VAEs)



- Instead of just encoding…
- We can try to directly encode the **probability distribution of the latent space**!
- But we need sophisticated strategies for backpropagating

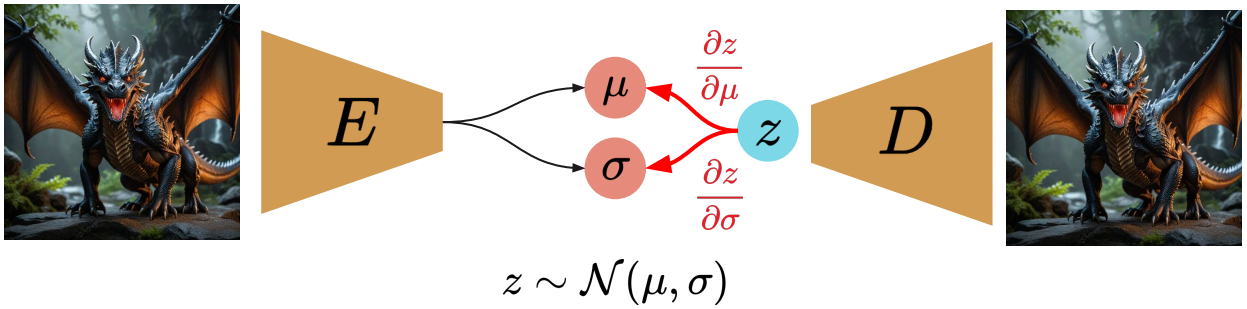
Reparametrization Trick



$$z \sim \mathcal{N}(\mu, \sigma)$$

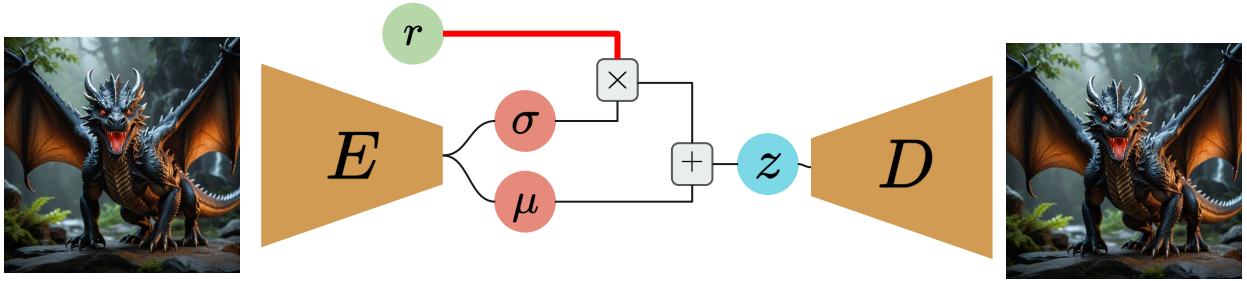
- I need to compute the derivative with respect to the distribution parameters….

Reparametrization Trick



- I need to compute the **derivative with respect to the distribution parameters….**
- **But we cannot compute the derivative**!

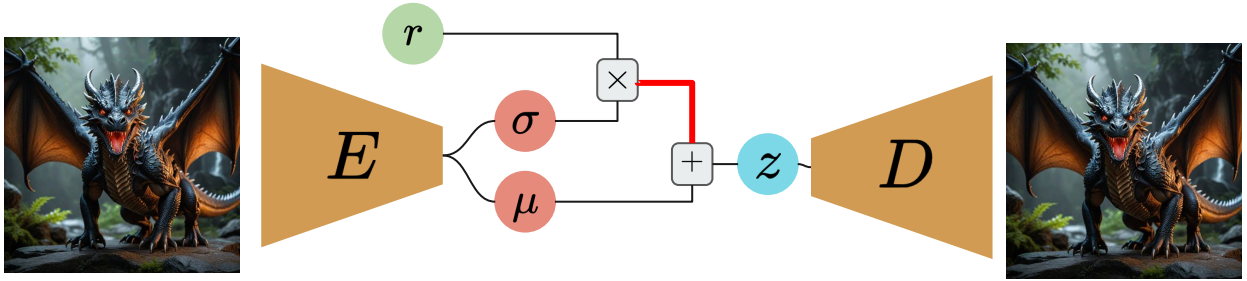
Reparametrization Trick



$$r \sim \mathcal{N}(0, 1)$$

- I need to compute the **derivative with respect to the distribution parameters**….
- But we **cannot compute the derivative**!
- However, we can indeed **separate the random part**

Reparametrization Trick



$$r \sim \mathcal{N}(0, 1)$$
$$r \cdot \sigma \sim \mathcal{N}(0, \sigma)$$

- I need to compute the **derivative with respect to the distribution parameters**….
- But we **cannot compute the derivative**!
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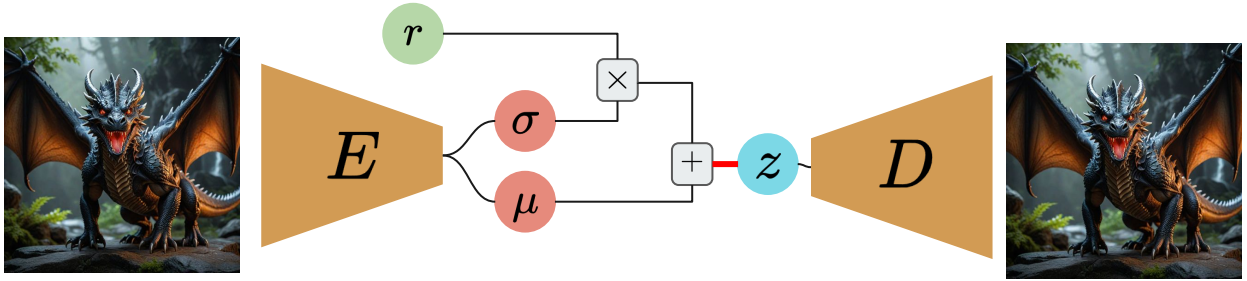
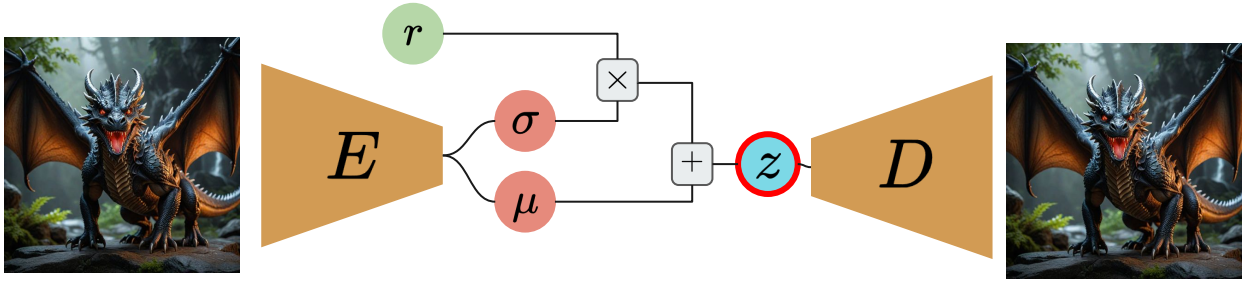
Reparametrization Trick



$$r \sim \mathcal{N}(0, 1)$$
$$r \cdot \sigma \sim \mathcal{N}(0, \sigma)$$
$$\mu + r \cdot \sigma \sim \mathcal{N}(\mu, \sigma)$$

- I need to compute the **derivative with respect to the distribution parameters**….
- But we **cannot compute the derivative**!
- However, we can indeed **separate the random part**

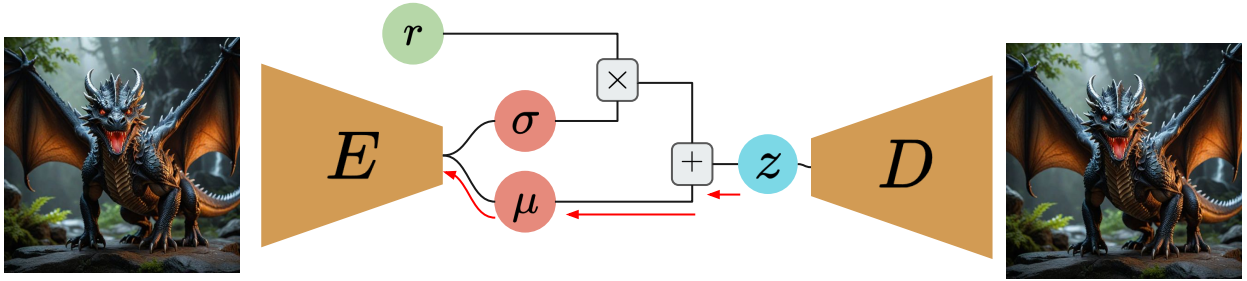
Reparametrization Trick



$$r \sim \mathcal{N}(0, 1)$$
$$r \cdot \sigma \sim \mathcal{N}(0, \sigma)$$
$$\mu + r \cdot \sigma \sim \mathcal{N}(\mu, \sigma)$$
$$z \sim \mathcal{N}(\mu, \sigma)$$

- I need to compute the **derivative with respect to the distribution parameters**….
- But we **cannot compute the derivative**!
- However, we can indeed **separate the random part**

Reparametrization Trick



$$r \sim \mathcal{N}(0,1)$$
$$r \cdot \sigma \sim \mathcal{N}(0,\sigma)$$
$$\mu + r \cdot \sigma \sim \mathcal{N}(\mu,\sigma)$$
$$z \sim \mathcal{N}(\mu,\sigma)$$

By doing so we can now compute the derivatives!

- I need to compute the **derivative with respect to the distribution parameters**….
- But we **cannot compute the derivative**!
- However, we can indeed **separate the random part**

VAEs Latent Space Exploration

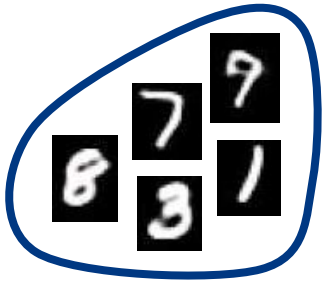
Generative Adversarial Networks (GANs) - idea

Legit Picasso

Fake Picasso

Generative Adversarial Networks (GANs) - idea

$(x, y) \sim \mathcal{G}(\mathcal{X}, \mathcal{Y}), \quad \forall (x, y) \in \mathcal{D}$



$\mathcal{D}_{train}$

Legit Data

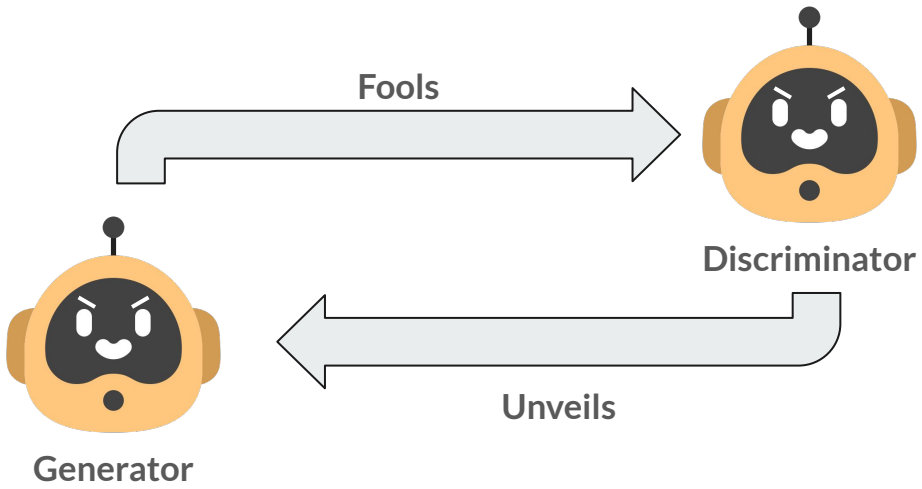
Generator

(x', y)

Fake Picasso

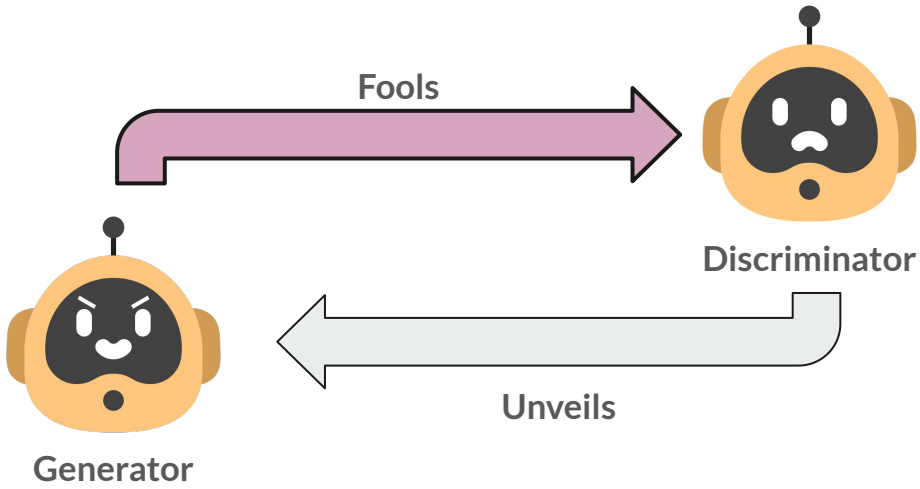
Discriminator

Generative Adversarial Networks (GANs) - idea



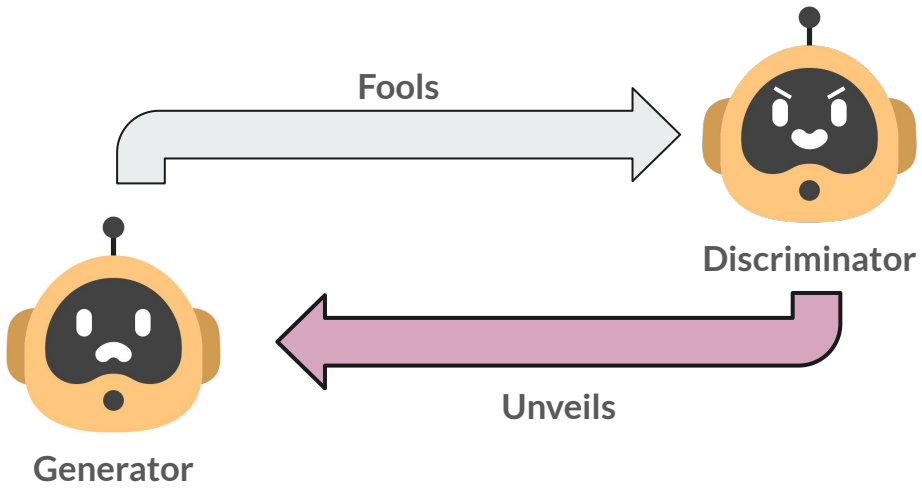
- The **Generator** and the **Discriminator** play a **game against each other**

Generative Adversarial Networks (GANs) - idea



- The **Generator** and the **Discriminator** play a **game against each other**
- Sometimes the **generator** is able to **fool the discriminator**...

Generative Adversarial Networks (GANs) - idea



- The **Generator** and the **Discriminator** play a **game against each other**
- Sometimes the **generator** is able to **fool the discriminator**...
- And sometimes the **discriminator** can **unveil the generator**

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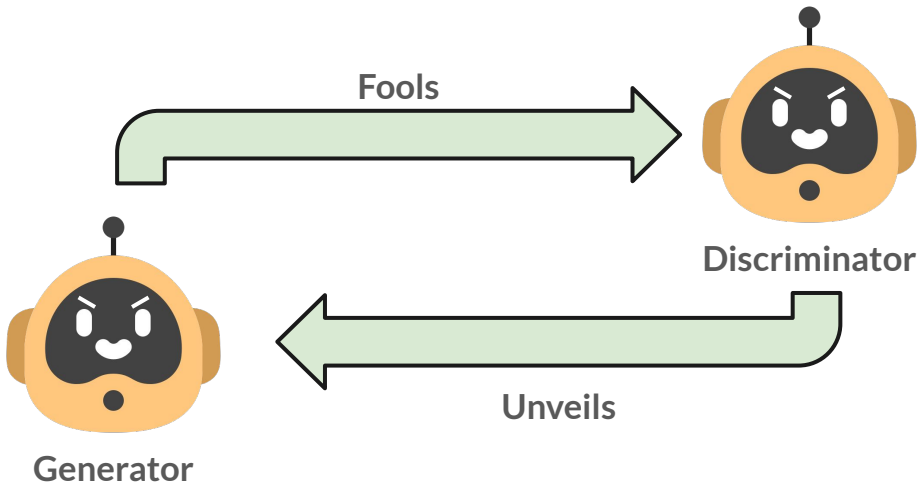
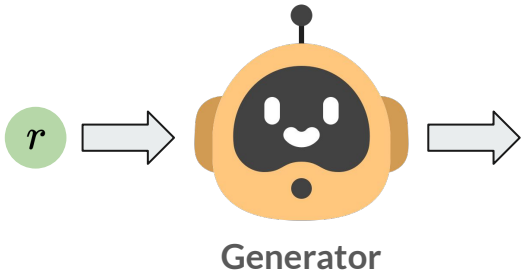
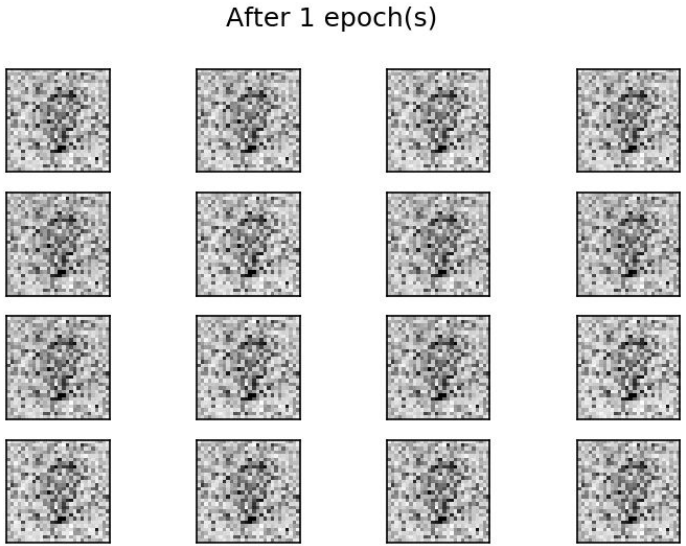


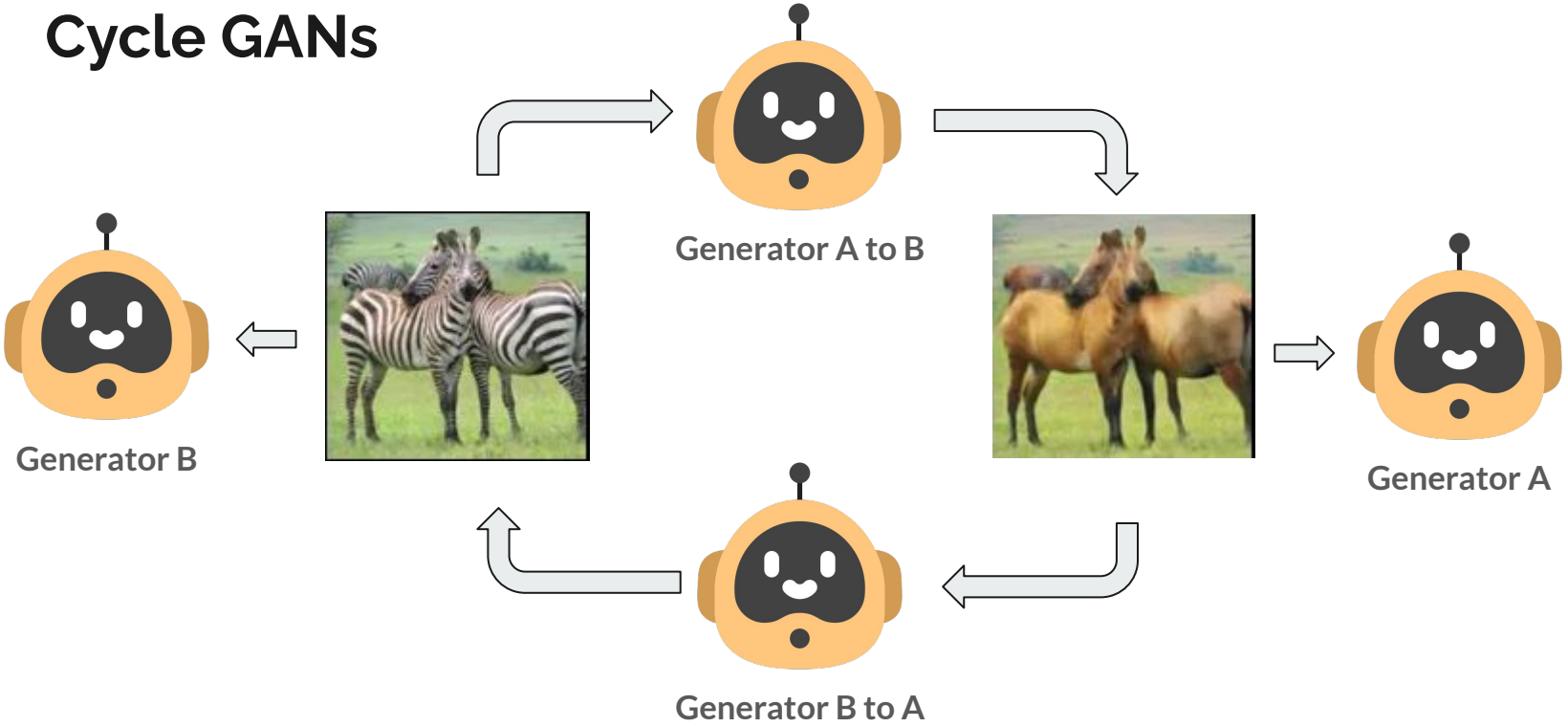
- The **Generator** and the **Discriminator** play a **game against each other**
- Sometimes the **generator** is able to **fool the discriminator**...
- And sometimes the **discriminator** can **unveil the generator**
- They both get better at their job, and **eventually they converge**

Generative Adversarial Networks (GANs)



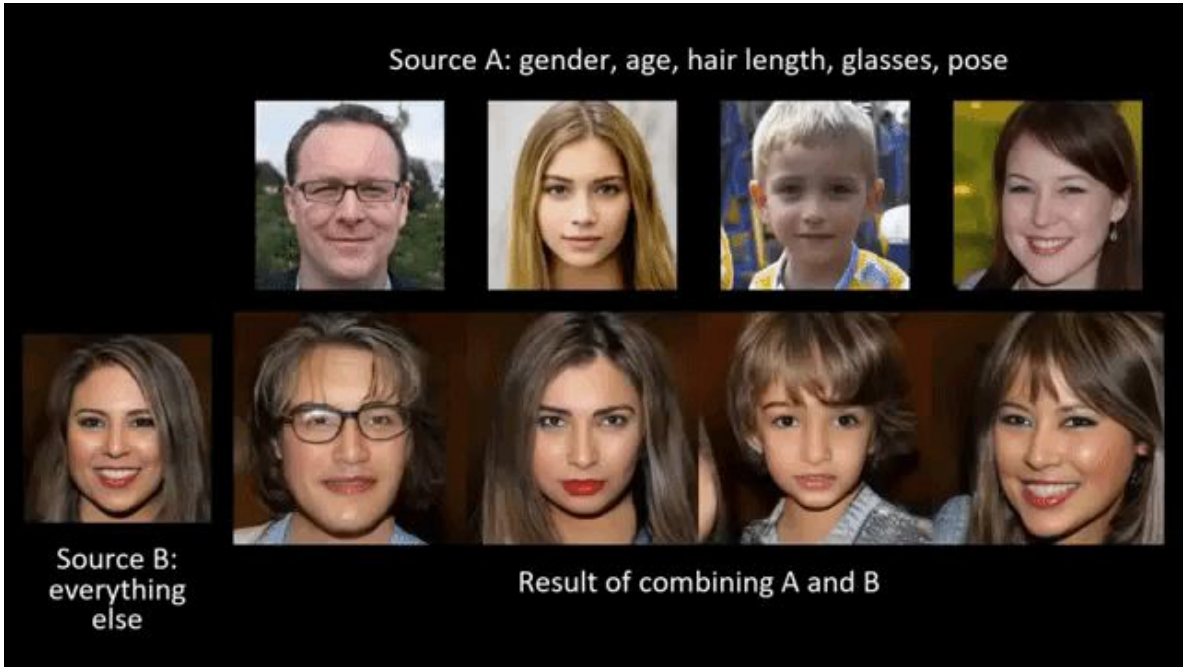


Cycle GANs

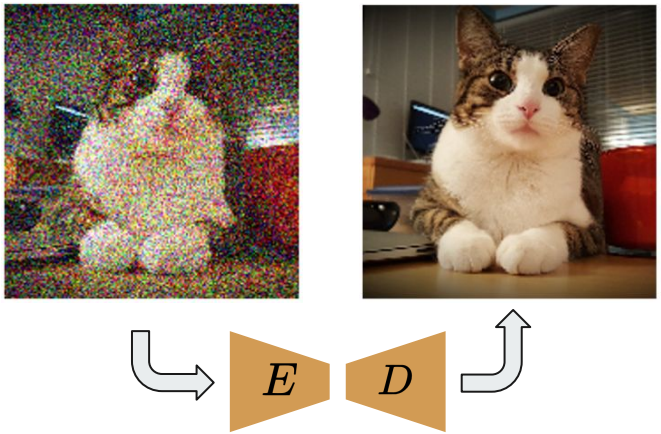


Cycle GANs - Style Transfer

StyleGAN

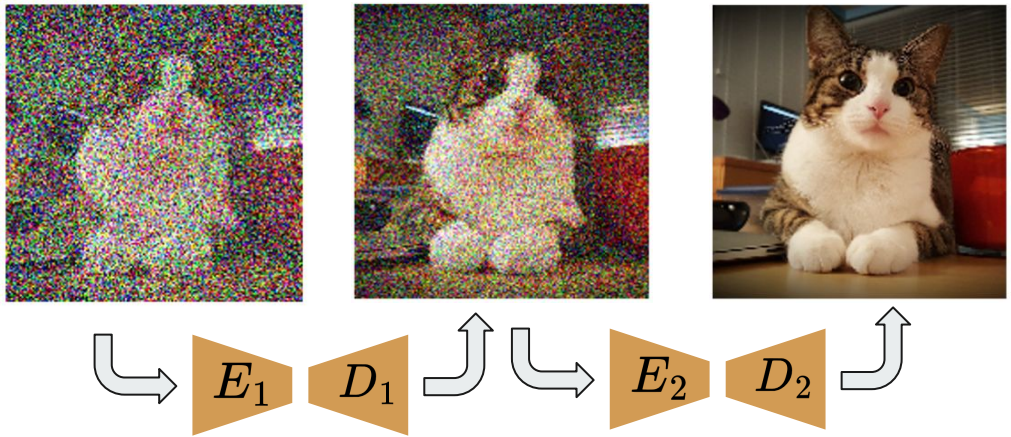

Source A: gender, age, hair length, glasses, pose
Source B: everything else
Result of combining A and B

Diffusion Models - idea



- The idea of reconstruction (from AEs) can be translated to noise reconstruction
- We can teach a network how to denoise the image

Diffusion Models - idea



- The idea of reconstruction (from AEs) can be translated to noise reconstruction
- We can teach a network how to denoise the image
- Even with multiple levels of noise

Diffusion Models - idea

$$q(\mathbf{x}_t|\mathbf{x}_{t-1}) = \mathcal{N}(\mathbf{x_t}; \sqrt{1-\beta_t}\mathbf{x_{t-1}}, \beta_t\mathbf{I})$$

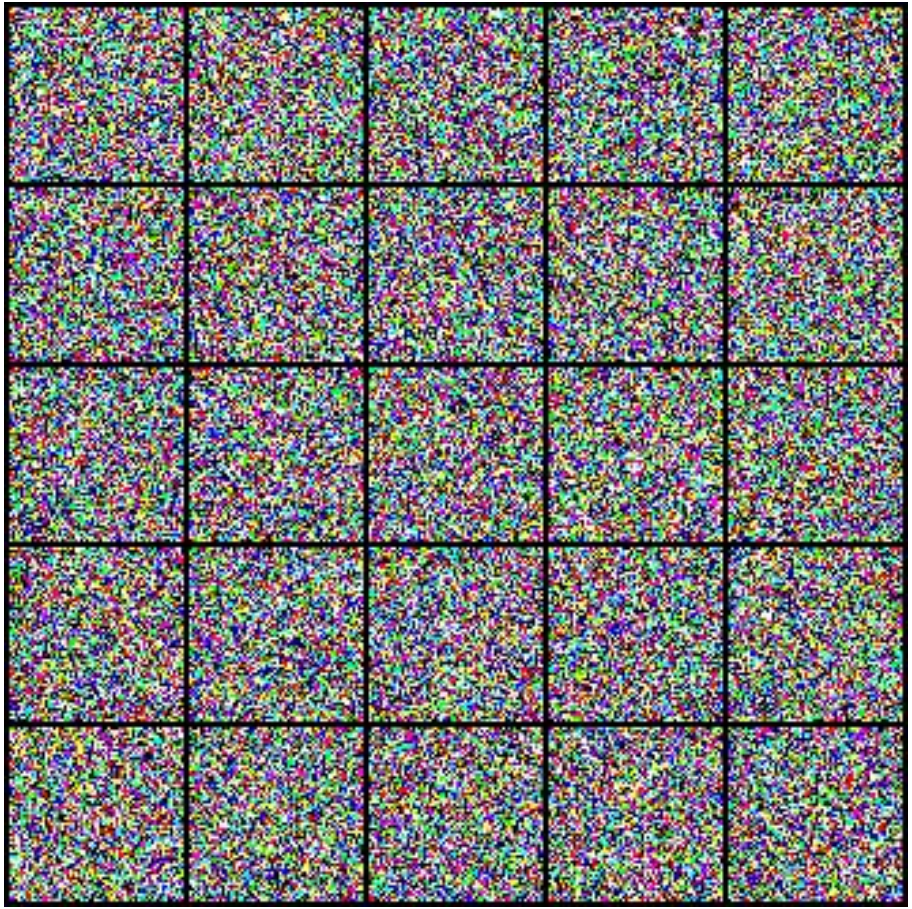
Data

Noise

$$p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) = \mathcal{N}(\mathbf{x}_{t-1}; \mu_\theta(\mathbf{x}_t, t), \sigma_t^2\mathbf{I})$$

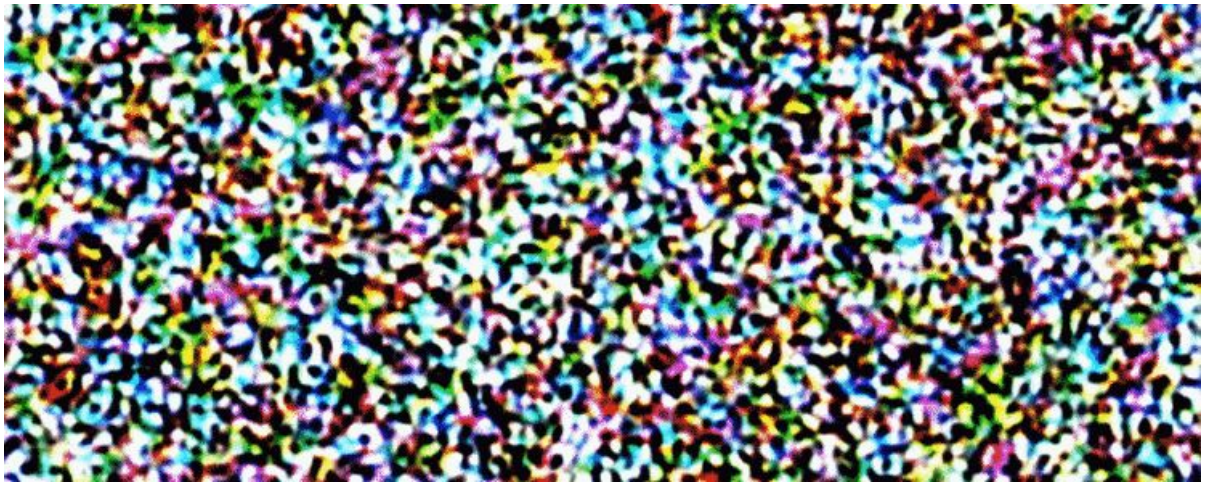
Eventually, the model will learn how to **generate images starting from random noise**!

Diffusion Models



Diffusion Models

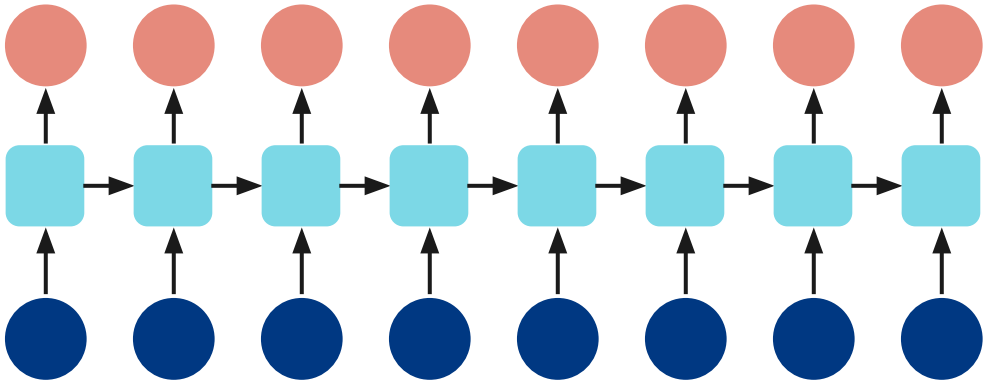
Diffusion Models



Attention Is All You Need!
The Transformer Architecture

To RNN or not to RNN?

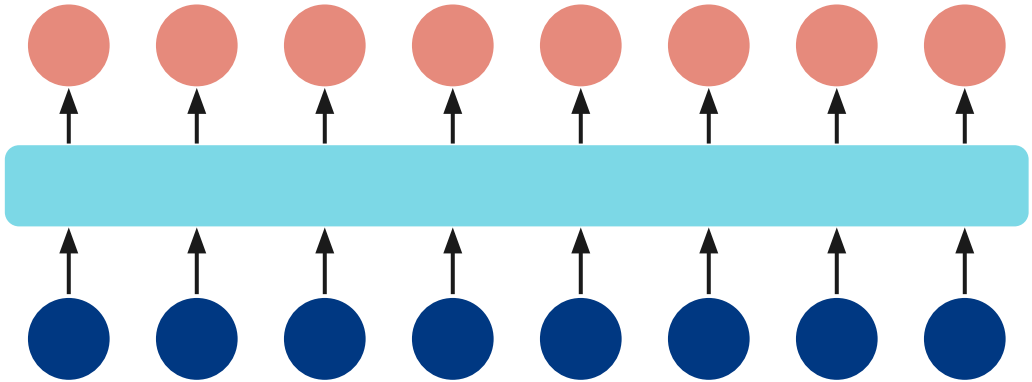
- Despite being specifically conceived for sequential data, RNNs have many issues



1. **Encoding bottleneck**
2. **Poor memory**
3. **No parallelization**

To RNN or not to RNN?

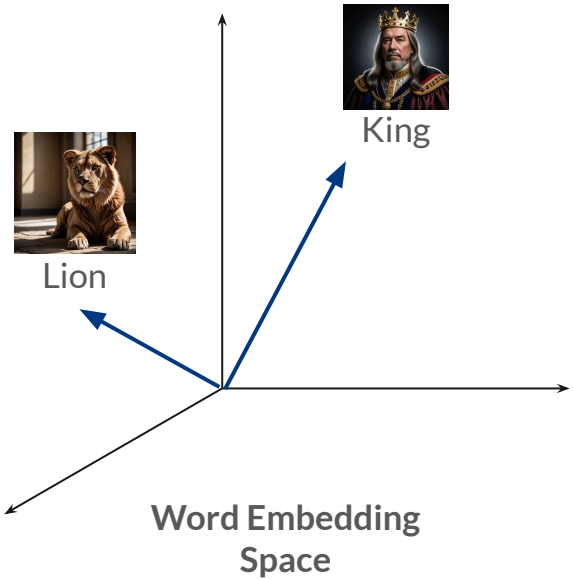
- Despite being specifically conceived for sequential data, RNNs have many issues



1. **Encoding bottleneck**
2. **Poor memory**
3. **No parallelization**

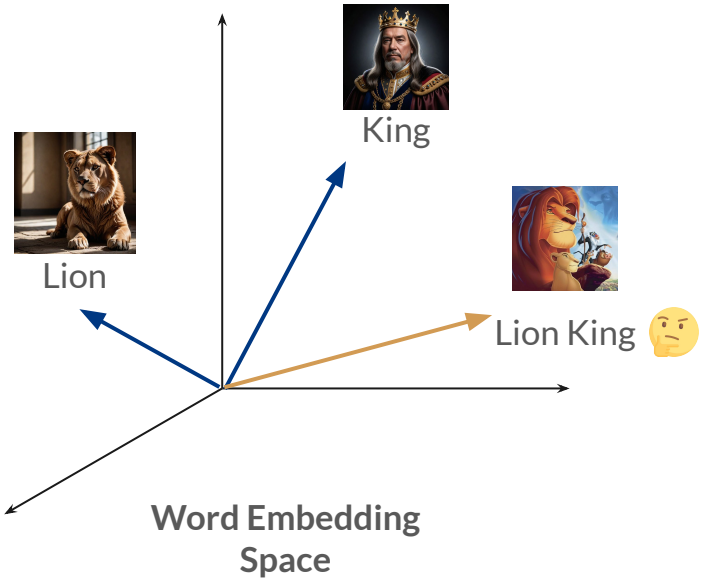
We can aggregate the entire input with a compact solution!

Rethinking the work embeddings



- Each token (word) is encoded using a specific vector
- Two vector may be more or less close to each other

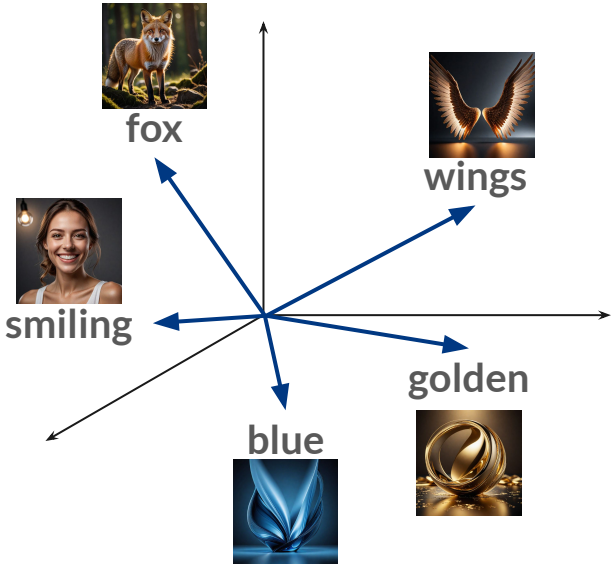
Rethinking the work embeddings



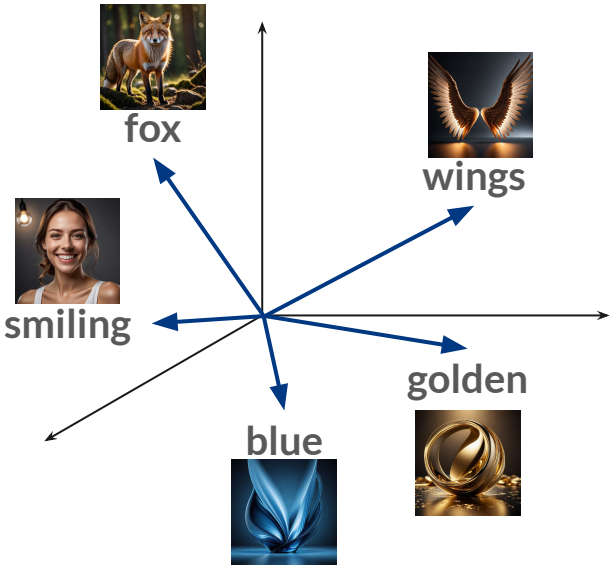
- Each token (word) is encoded using a specific vector
- Two vector may be more or less close to each other
- But context may add a lot of information to a single word, i.e., to an embedded vector!
- Encoding these relationships with would be a great solution… but how?

Too many combinations...

"A smiling blue fox with golden wings"



Too many combinations...



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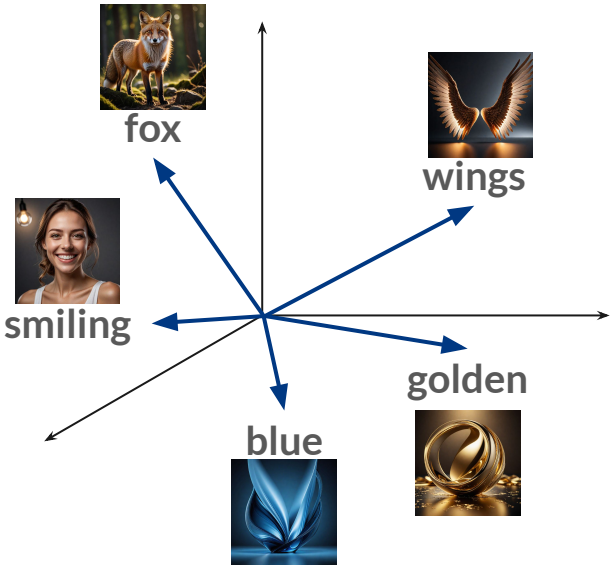
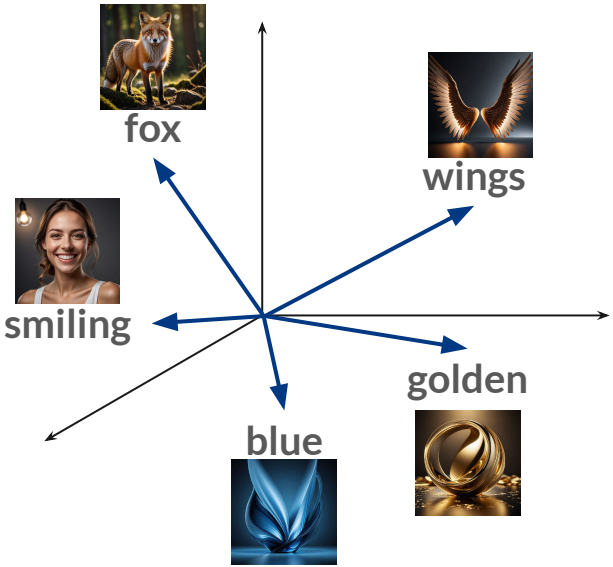


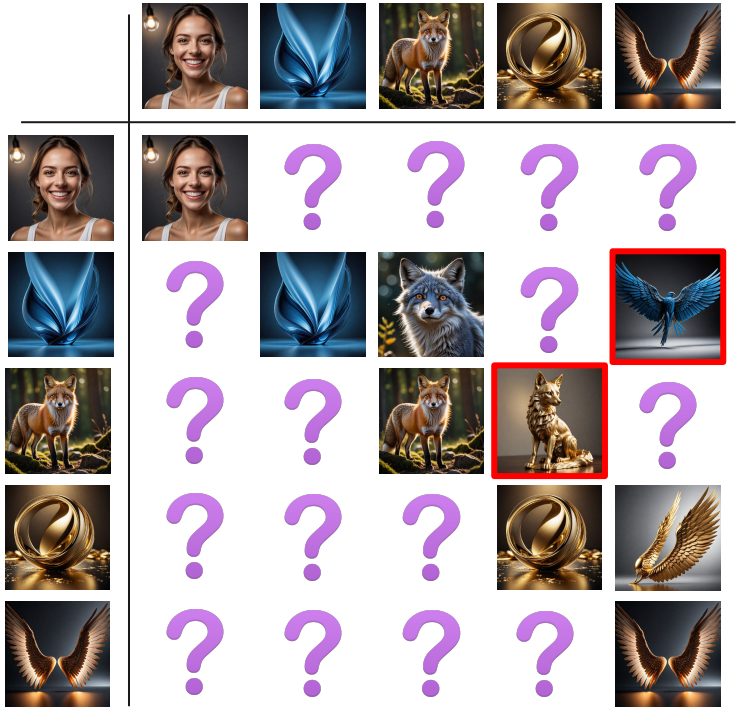
"A smiling blue fox with golden wings"

- Some relations are **useful**…

Too many combinations…



"A smiling blue fox with golden wings"



- Some relations are **useful**…
- But some are just **nonsense in this context**!

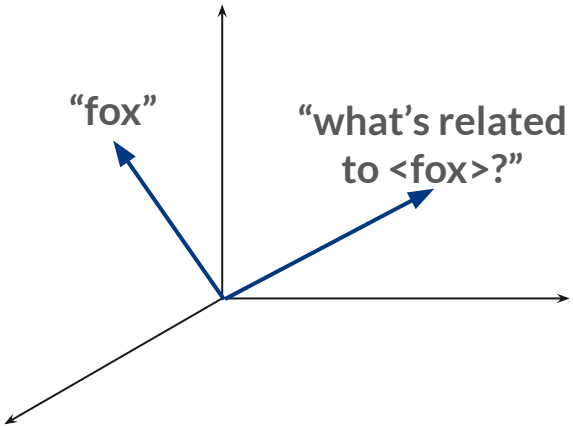
Relations

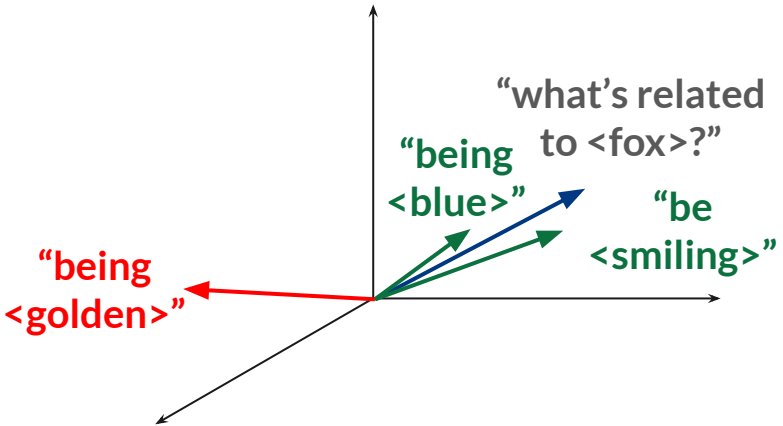
Useless association

Useful association

- Within the context of this sentence, there are some useful and some useless relationships
- The idea is that, for example, the “fox” is associated to the word “blue” but not to the word “gold”
- More in general we can ask the question: “what’s related to the fox?”

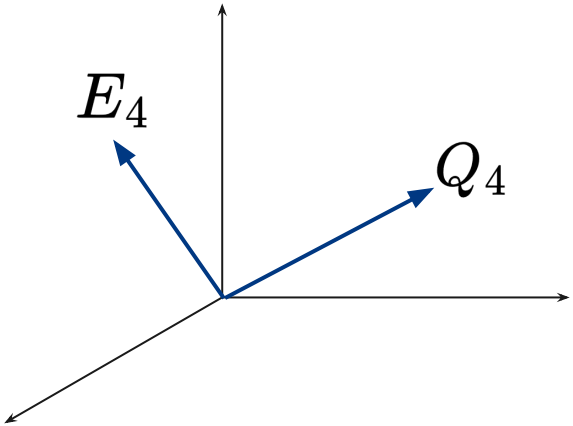
Relations

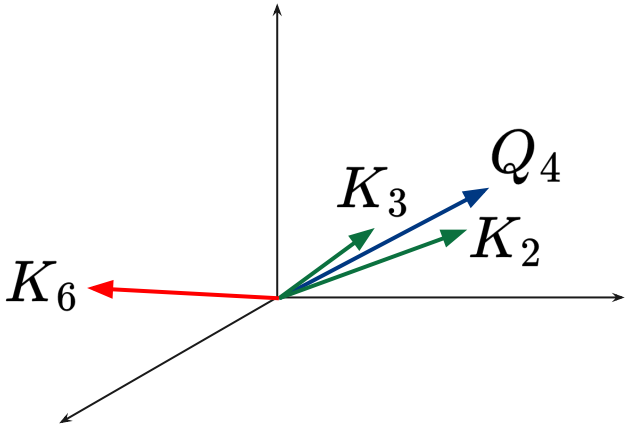




“A smiling blue fox with golden wings”

Keys and Queries

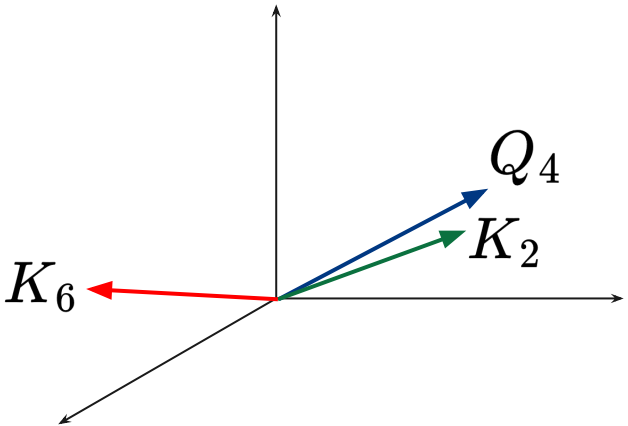




$$Q = E \cdot W_Q$$

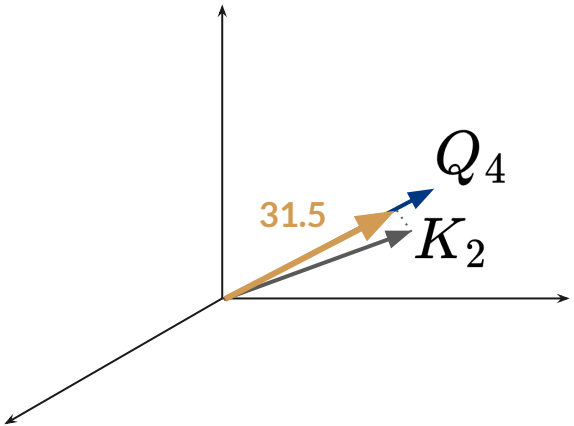
$$K = E \cdot W_K$$

Attention Mechanism



$$\frac{(Q \cdot K^T)}{\sqrt{d_k}}$$

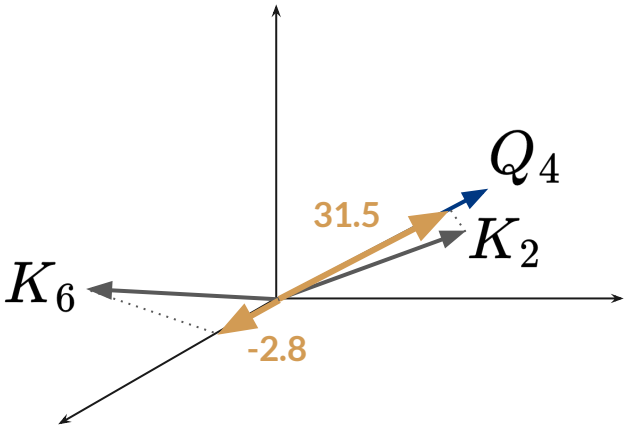
Attention Mechanism



$$\frac{(Q \cdot K^T)}{\sqrt{d_k}}$$

- Keys closer to the Query should be taken into consideration more than keys which are far from the query

Attention Mechanism



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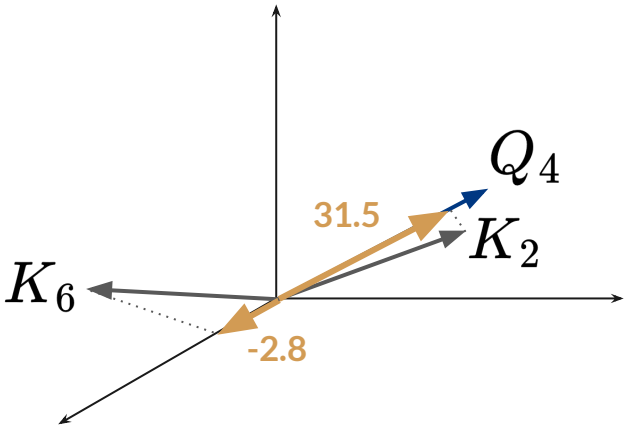
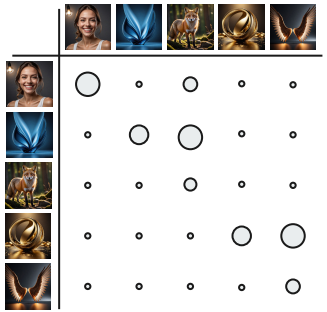
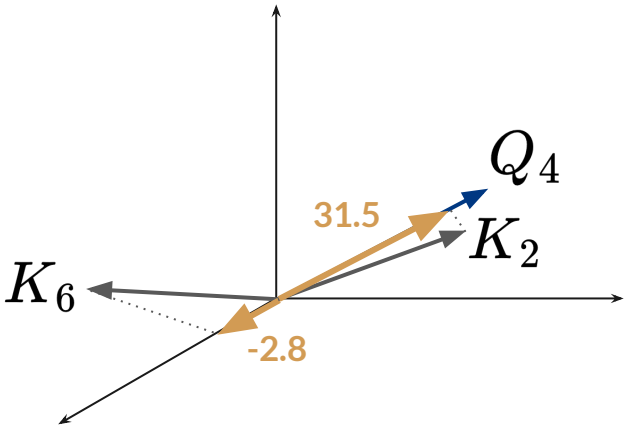


$$\text{softmax}\frac{(\mathrm{Q}\cdot\mathrm{K}^{\mathrm{T}})}{\sqrt{\mathrm{d_k}}}$$

- Keys closer to the Query should be taken into consideration more than keys which are far from the query
- We can normalize the values for obtaining a probability distribution for each query

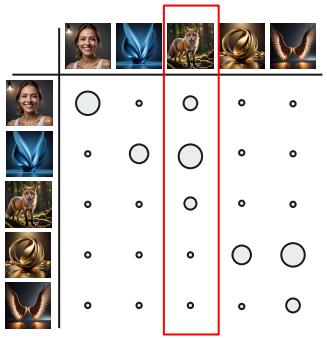


Attention Mechanism

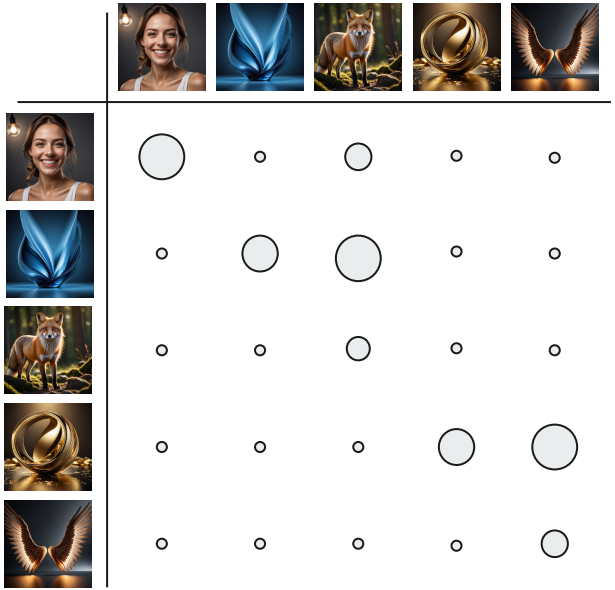


$$\text{softmax}\frac{(\mathrm{Q}\cdot\mathrm{K}^{\mathrm{T}})}{\sqrt{\mathrm{d_k}}}\cdot\mathrm{V}$$

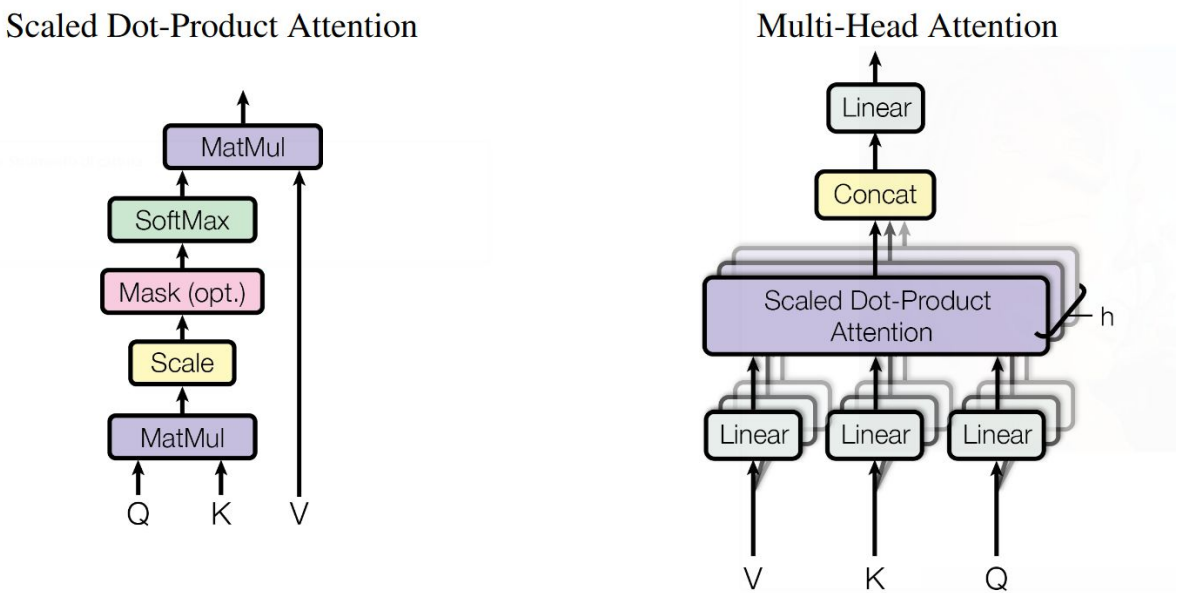
- Keys closer to the Query should be taken into consideration more than keys which are far from the query
- We can normalize the values for obtaining a probability distribution for each query
- Each weighted contribution is multiplied for the respective **value**



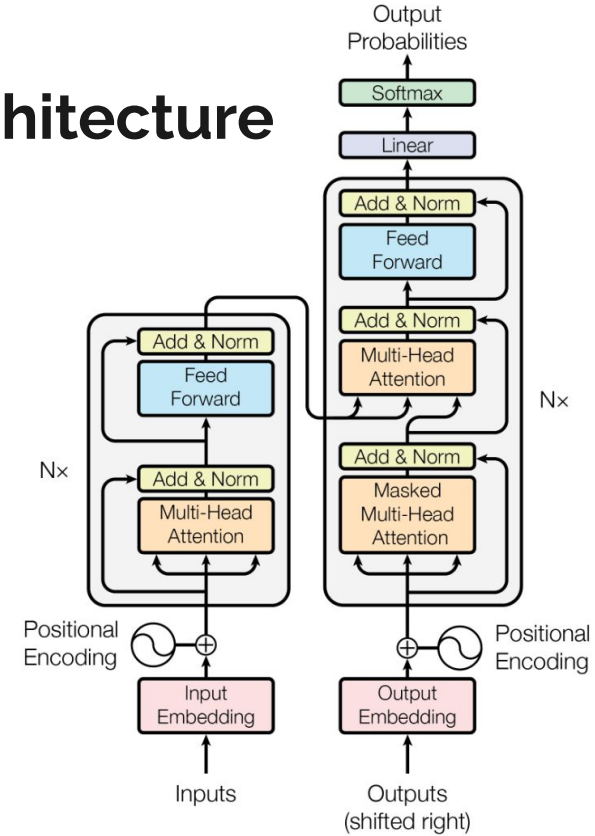
Attention Mechanism



Attention is all you need!

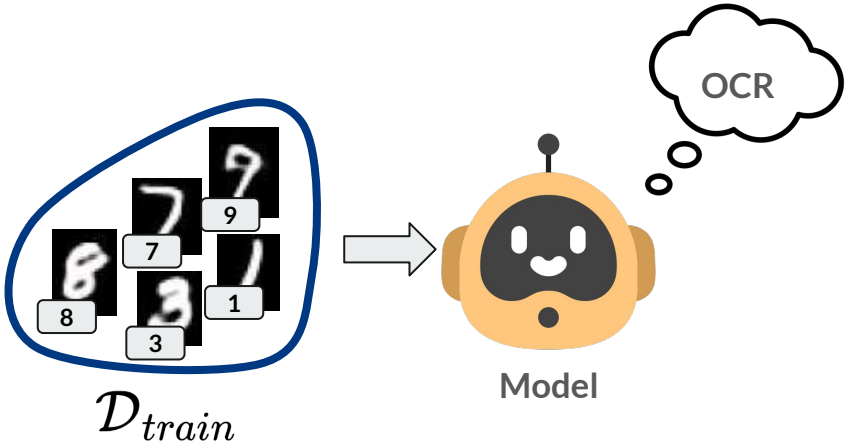


Transformer Architecture

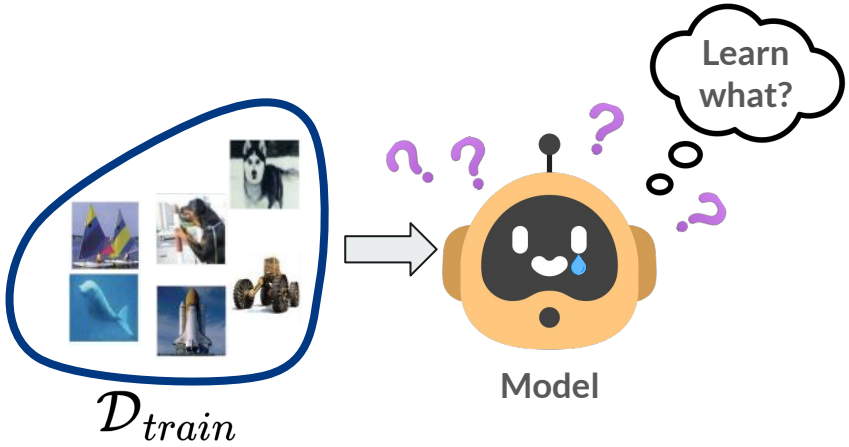


Foundation Models: From Self-Supervision to Multimodality

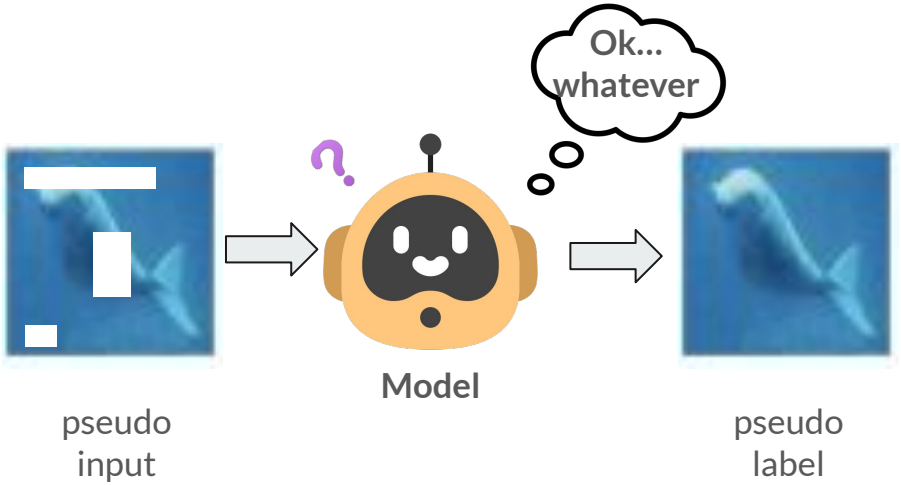
Supervised Learning



Supervised Learning



Supervised Learning - Reconstruct the input



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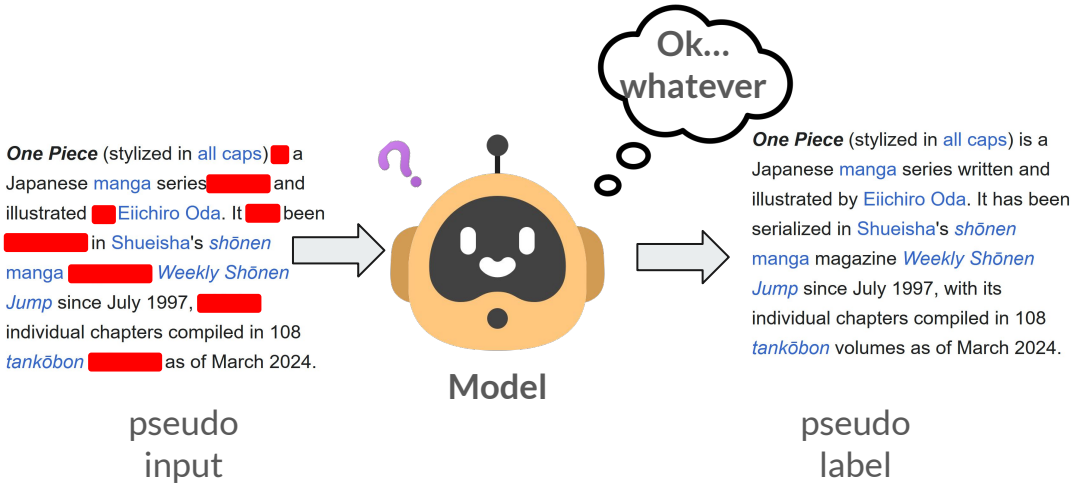

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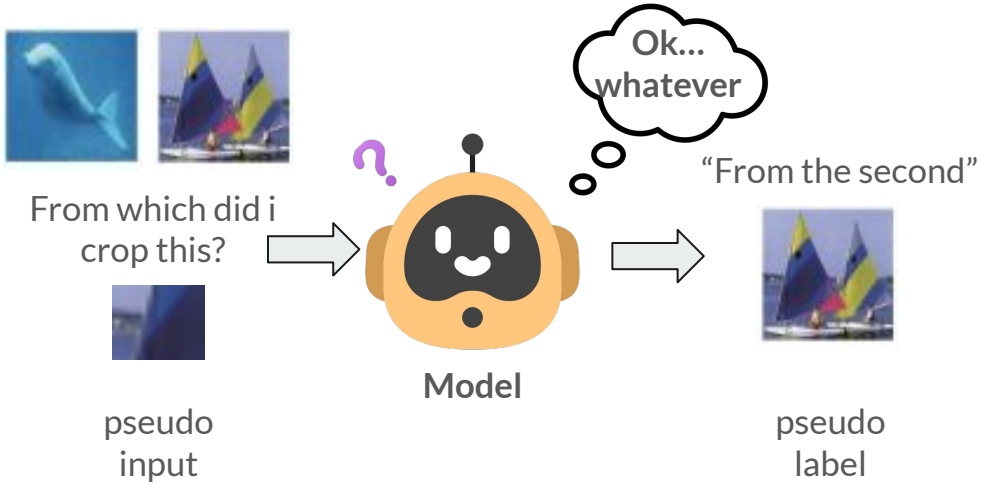
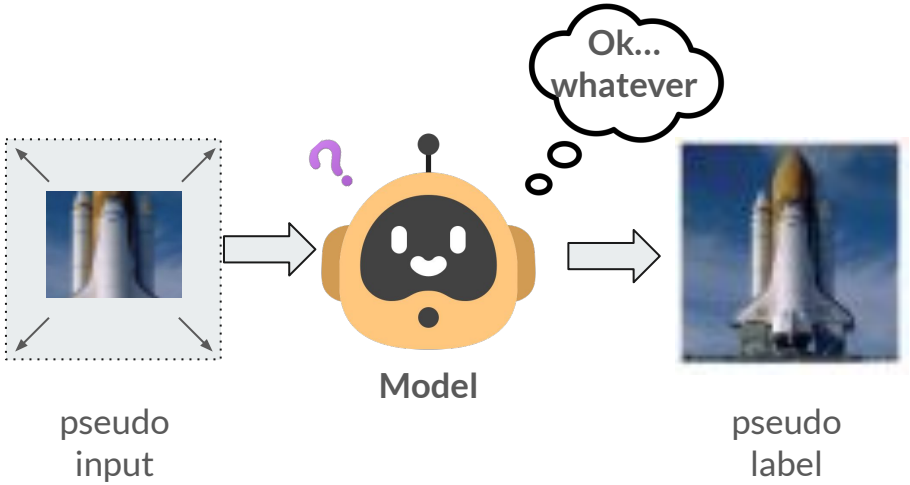


Supervised Learning - Reconstruct the input



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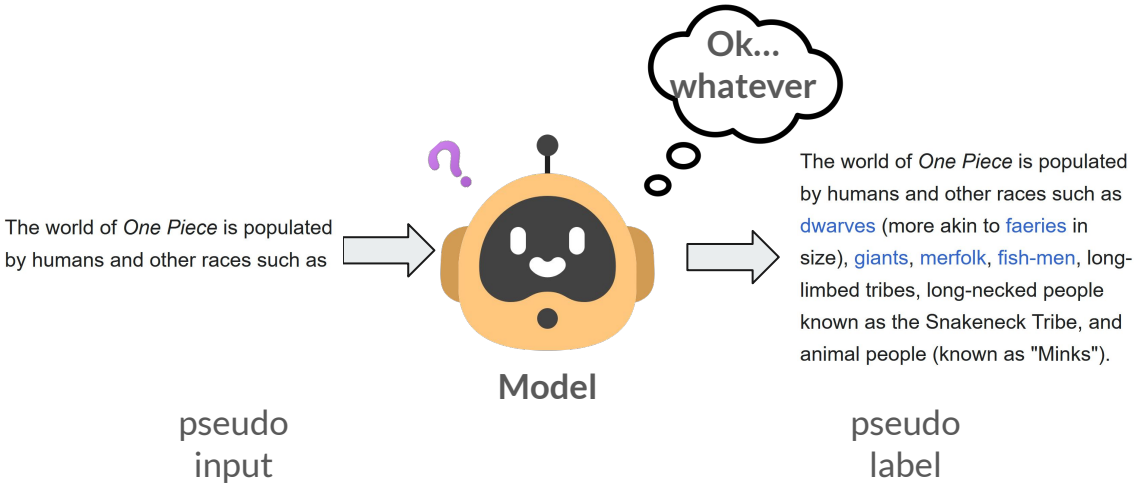
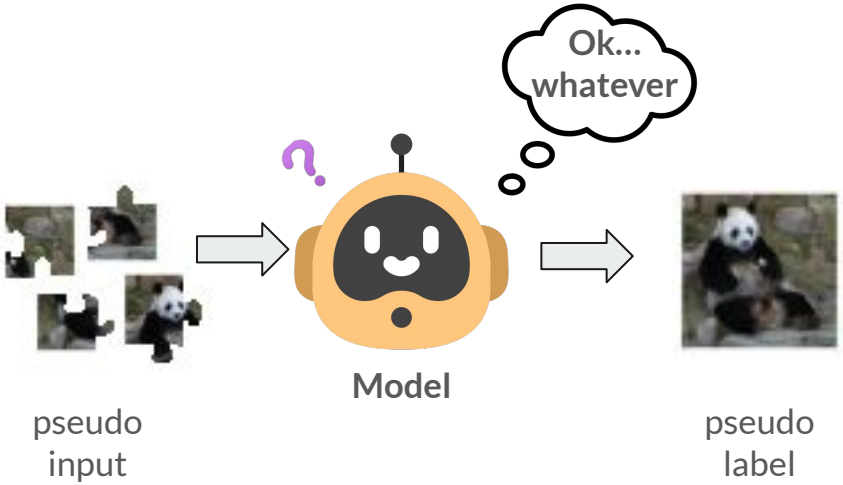


Supervised Learning - Reconstruct the input



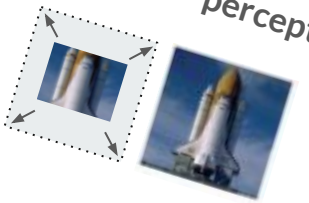
Self-Supervision

“The Dark Matter of Intelligence”

Understanding consistency

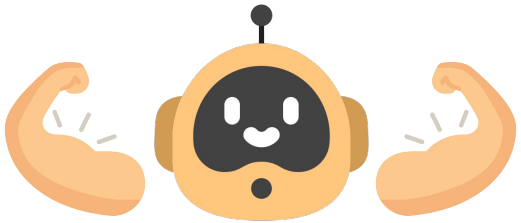
Discrimination capabilities

Low and High-level perception skills



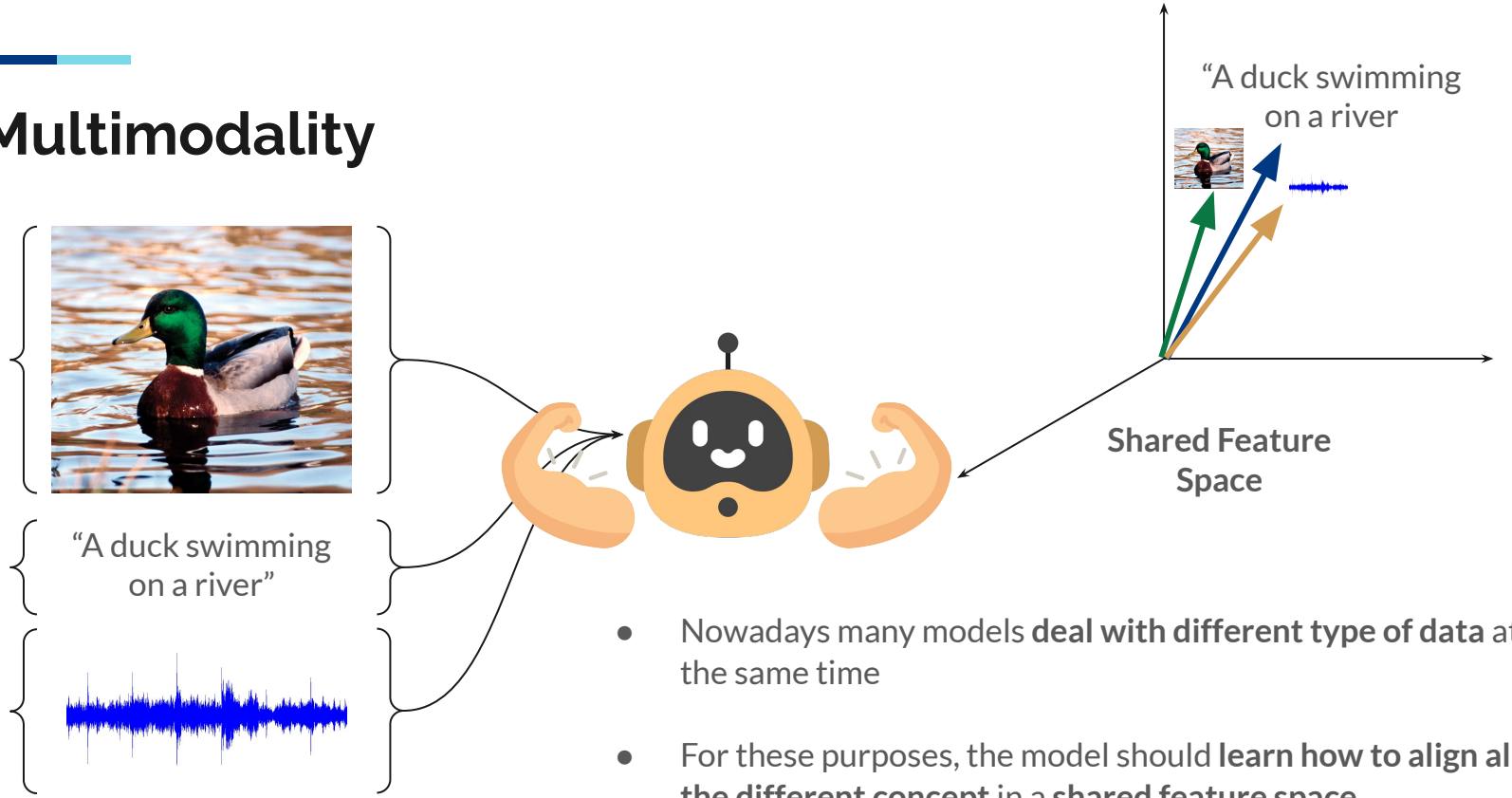

Foundation Models

Foundation Models



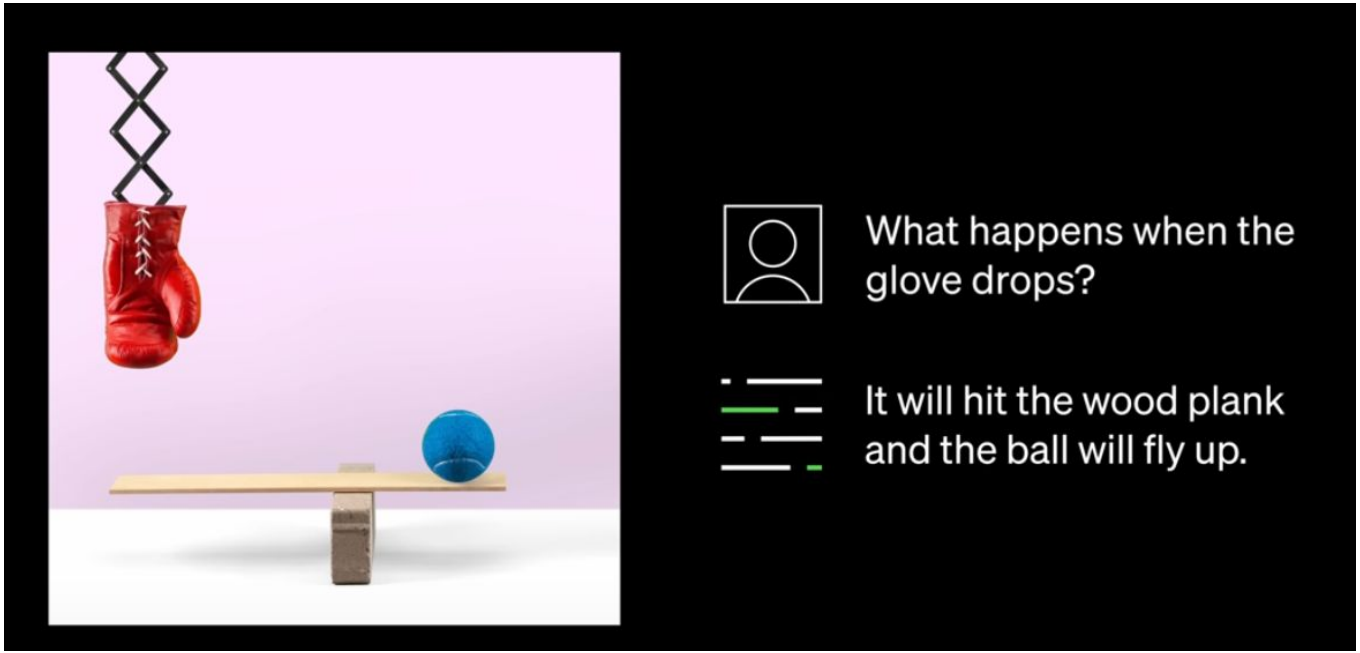
- **Very Large Models** (usually based on Transformer technologies)
- Trained with **huge set of data** (e.g., on the entire Wikipedia!)
- **General Purpose**: have not been trained explicitly for solving any specific “task”
- Massive use of **self-supervision**

Multimodality



- Nowadays many models **deal with different type of data** at the same time
- For these purposes, the model should **learn how to align all the different concept** in a **shared feature space**

Multimodality: GPT 4



Multimodality: Gemini

https://www.youtube.com/watch?v=UIZAiXYceBI