Google DeepMind

(A not very gentle)

Introduction to Diffusion Models

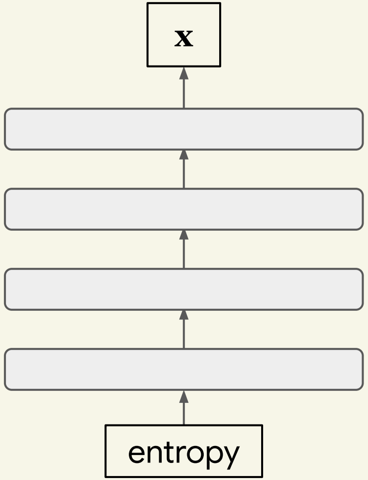
Yuge (Jimmy) Shi

Google DeepMind

1 Generative Models

Generative modelling: the probabilistic perspective

$$x \sim p(x)$$

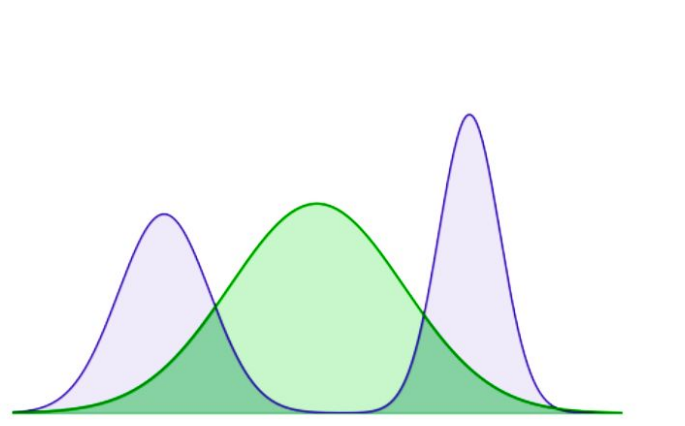


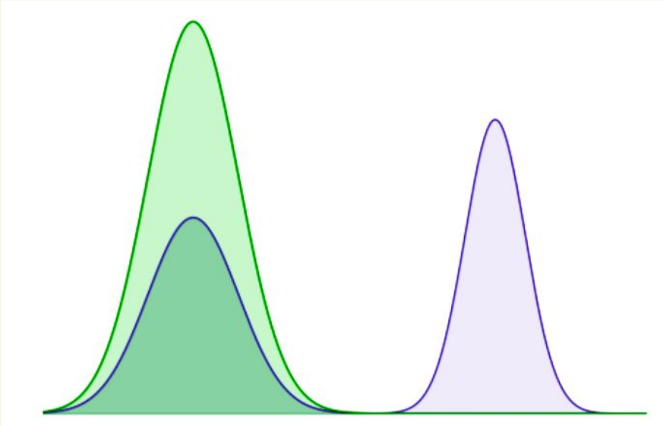
Explicit: autoregression, flows, VAEs, ...

Implicit: GANs, ...

Slide credit: Sander Dieleman

Mode-covering vs. mode-seeking behaviour





mode-covering
focus on **diversity**

e.g. likelihood-based models

mode-seeking
focus on **realism**

e.g. adversarial models

Slide credit: Sander Dieleman

2 Diffusion Models, a vibe-based overview

An Overview

Diffusion model **is**

- An **implicit** generative model
- Generates data ~ [images / videos / audio / text (?!) / …] from pure noise
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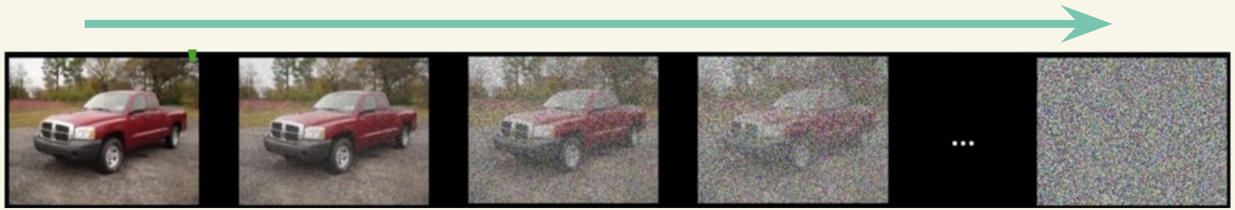

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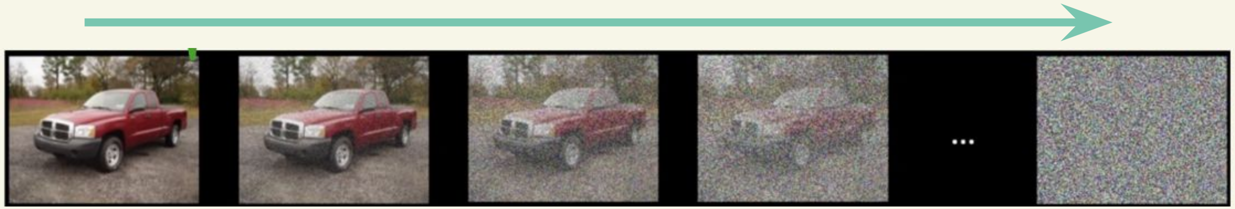

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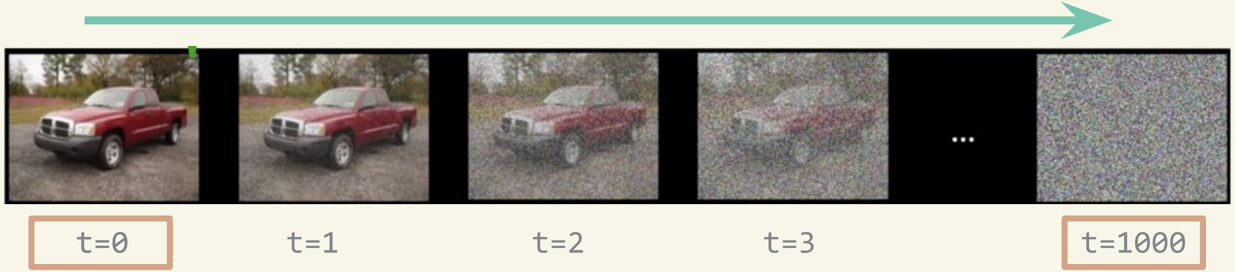

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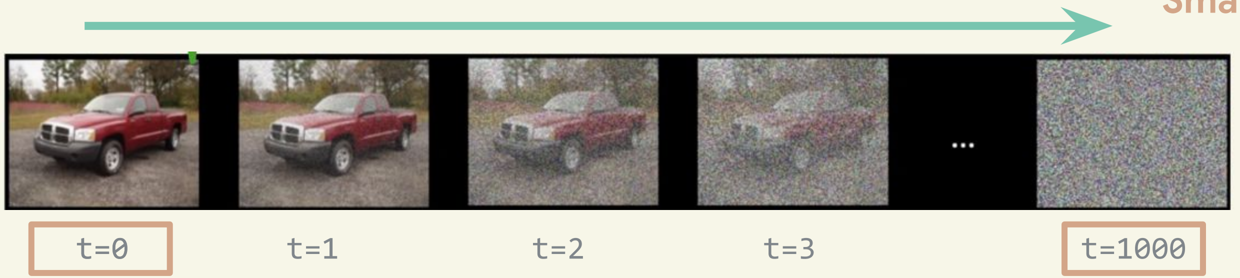
Big `t`: MORE noisy
Small `t`: LESS noisy



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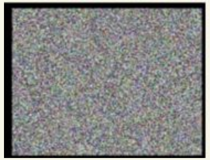
Start from pure noise



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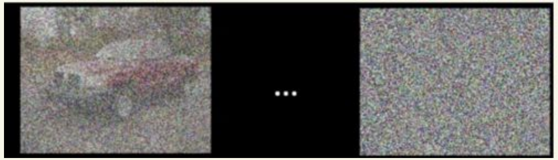
Start from pure noise, iteratively denoise until we get back to an un-noised image.



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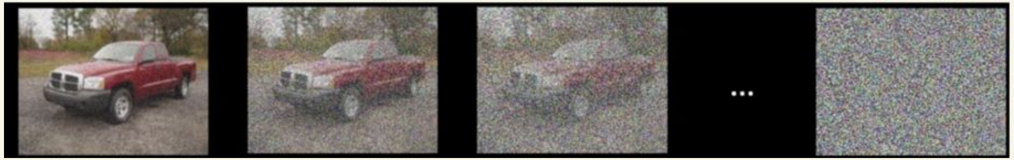

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3 Diffusion Models, Forward Process

Forward process, q

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original image

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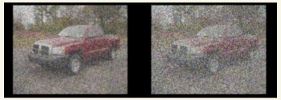

t=2 t=3

⋮

product of

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the entire forward pass =

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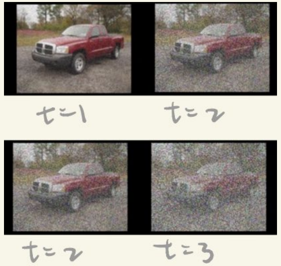

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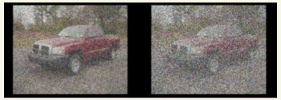

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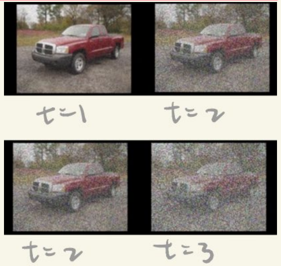

How do we parameterise this?

product of

Parametrisation of $q(x_t | x_{t-1})$

$q(x_t | x_{t-1})$ = Gaussian distribution with mean noisily at the previous time step & fixed variance, i.e.

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Side quest: all about noise level

β_t controls the noise level through either **1)** shifting or **2)** widening the gaussian distribution parametrising $q(x_t \mid x_{t-1})$

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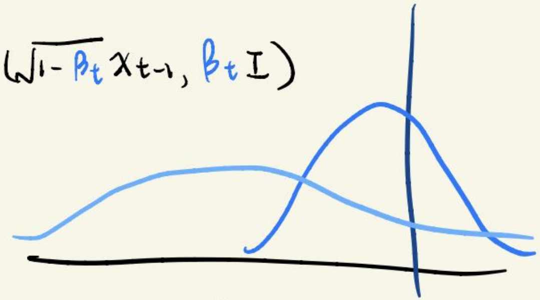

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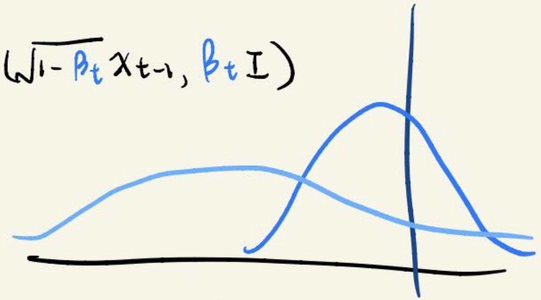

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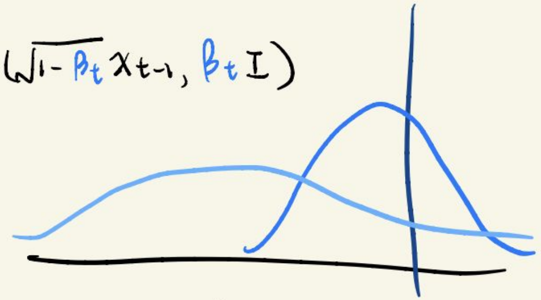

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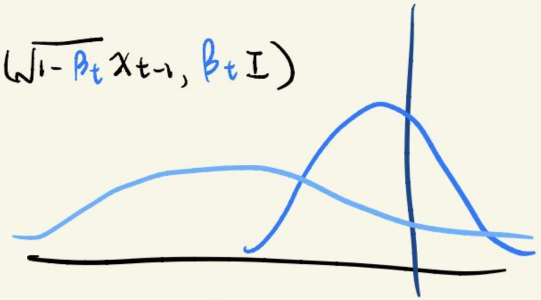

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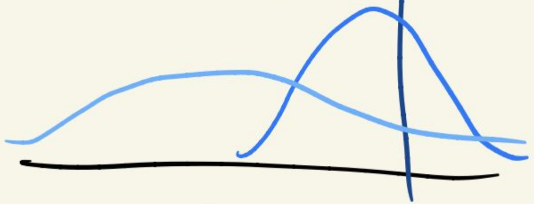

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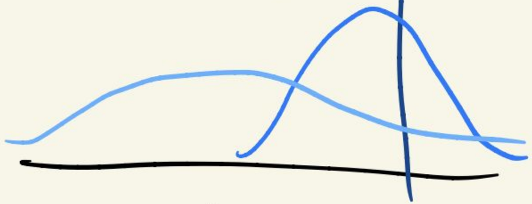

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A sensible noise scheduler is important!

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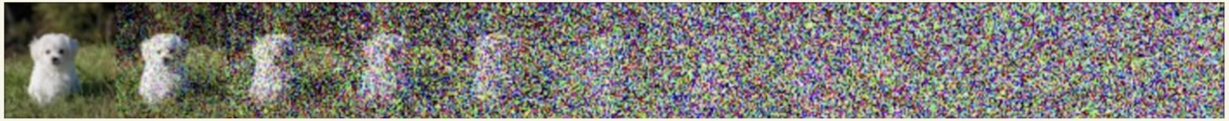
DDPM (2020): linear schedule



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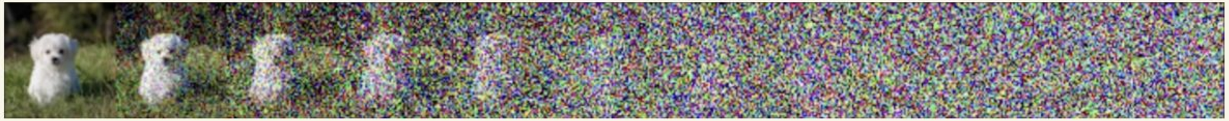

Problem: information gets destroyed too quickly

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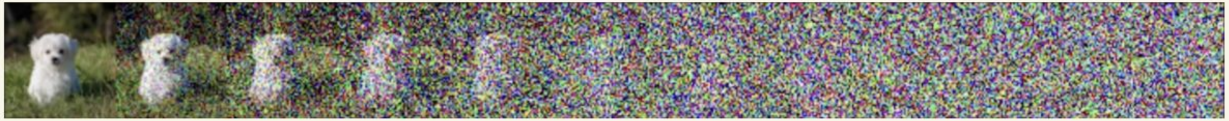

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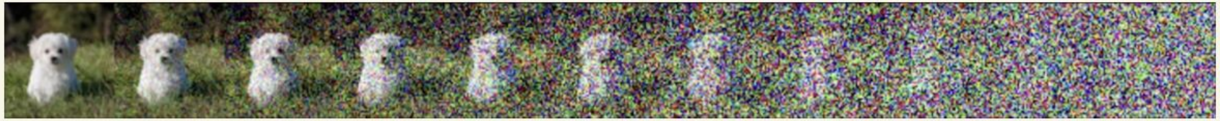
OAI (2021): cosine schedule



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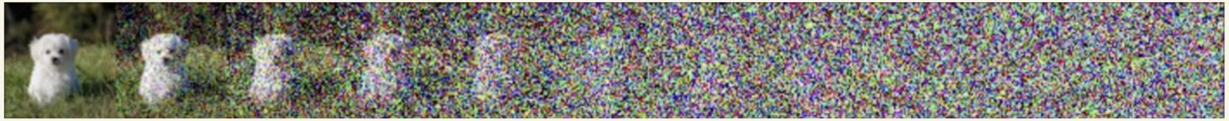

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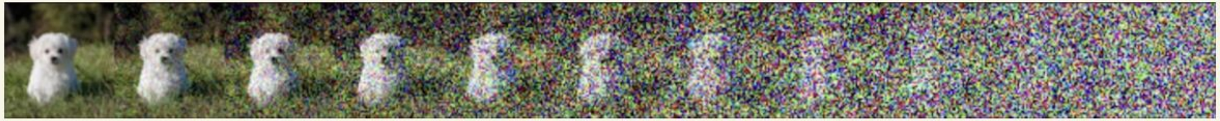

More sensible as information gets destroyed more evenly as time grows.

Forward process, q

$$q(x_{1:T} \mid x_0) = \prod_{t=1}^{T} q(x_t \mid x_{t-1})$$

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At training time, you want to be able to randomly sample `t~(1, T)`, and have the model predict the noise at that level `t`

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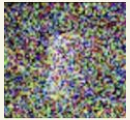
x_t =  , t=3

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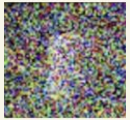
x_t =  , t=3

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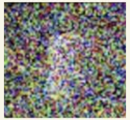
$x_t =$  , t=3

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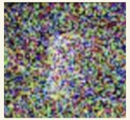
$x_t =$  , t=3

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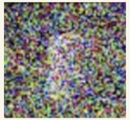
x_t =  , t=3

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Seems like a lot of work :/

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Fun fact: Product of Gaussian is still Gaussian

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maths ✨

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🚨 **Derivation incoming**

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Derivation:

Let us first define

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$\alpha_t = 1 - \beta_t$ — Information kept at t since (t-1)

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Let us first define

β_t Noise added at t

$\alpha_t = 1 - \beta_t$ Information kept at t since (t-1)

$\bar{\alpha}_t = \prod_{s=1}^{t} \alpha_s$ Information kept at t since 0

Derivation:

Given the original forward process

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

β_t	Noise added at t
$\alpha_t = 1 - \beta_t$	Information kept at t since `(t-1)`
$\bar{\alpha}_t = \prod_{s=1}^{t} \alpha_s$	Information kept at t since `0`

Derivation:

β_t Noise added at t

$\alpha_t = 1 - \beta_t$ Information kept at t since `(t-1)`

$\bar{\alpha}_t = \prod_{s=1}^{t} \alpha_s$ Information kept at t since `0`

Given the original forward process, we can use **reparametrisation trick** to get

$$q(x_t | x_{t-1}) = \mathcal{N}(x_t; \sqrt{1-\beta_t}\, x_{t-1}, \beta_t I)$$
$$= \sqrt{1-\beta_t}\, x_{t-1} + \sqrt{\beta_t}\, \varepsilon$$

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$$= \sqrt{1-\beta_t}\, x_{t-1} + \sqrt{\beta_t}\, \epsilon$$

Gaussian noise

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

β_t	Noise added at t
$\alpha_t = 1 - \beta_t$	Information kept at t since `(t-1)`
$\bar{\alpha}_t = \prod_{s=1}^{t} \alpha_s$	Information kept at t since `0`

Google

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This allows for batch training with different values of t:

t=0.76

t=0.92

t=0.12

$\Rightarrow$ Model

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⇨ Model

Also means that we need to tell the model the value of t so it doesn't get confused!

3 Diffusion Models, Objective

Objective

We mentioned before that the diffusion model is trained to predict the noise added to the input, given the timestamp `t` and the noised input x_t :

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We mentioned before that the diffusion model is trained to predict the noise added to the input, given the timestamp t and the noised input x_t :

added noise

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predicted noise

Objective

We mentioned before that the diffusion model is trained to predict the noise added to the input, given the timestamp t and the noised input x_t :

$$\mathcal{L} = \mathbb{E}_{t, x_0, \epsilon} \|\underbrace{\epsilon}_{\text{added noise}} - \underbrace{\epsilon_\theta(x_t, t)}_{\text{predicted noise}}\|^2$$

Note: *the actual objective is maximising the log likelihood of $p(x)$ through* ***variational lower bound****, but we skip these dark magic for now and show this simple objective instead :)*

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- ϵ epsilon-prediction, most common

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- ϵ
- x_0 **x0-prediction, more direct/intuitive**

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- x_0
- $\alpha_t \epsilon - \sigma_t x_0$ v-prediction, "direction" to move in to reach x0

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- $\epsilon - x_0$ **flow matching**

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- $\epsilon - x_0$

All equivalent except for relative weighting of noise levels!

4 Diffusion Models, Backward Process

Backward process, p

Sampling iteratively from x_T (pure noise) to x_0 (original data).

$$p_\theta(x_{0:T}) = p_\theta(x_T)\prod_{t=1}^{T} p_\theta(x_{t-1} \mid x_t)$$

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*** ish, let's look at this a little closer**

A closer look at $p_\theta(x_{t-1} | x_t)$

Google

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Let's say our model is predicting noise. Given the original forward process formulation it is easy to get the mean prediction of x_{t-1} :

$$\mu_\theta(x_t, t) = \sqrt{\alpha_t}\, x_{t-1} + \sqrt{1-\alpha_t}\, \varepsilon$$

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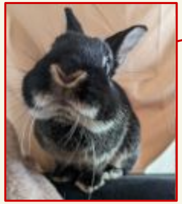
We do this iteratively until we get to the original image at t=0!

Backward Process: a visualisation

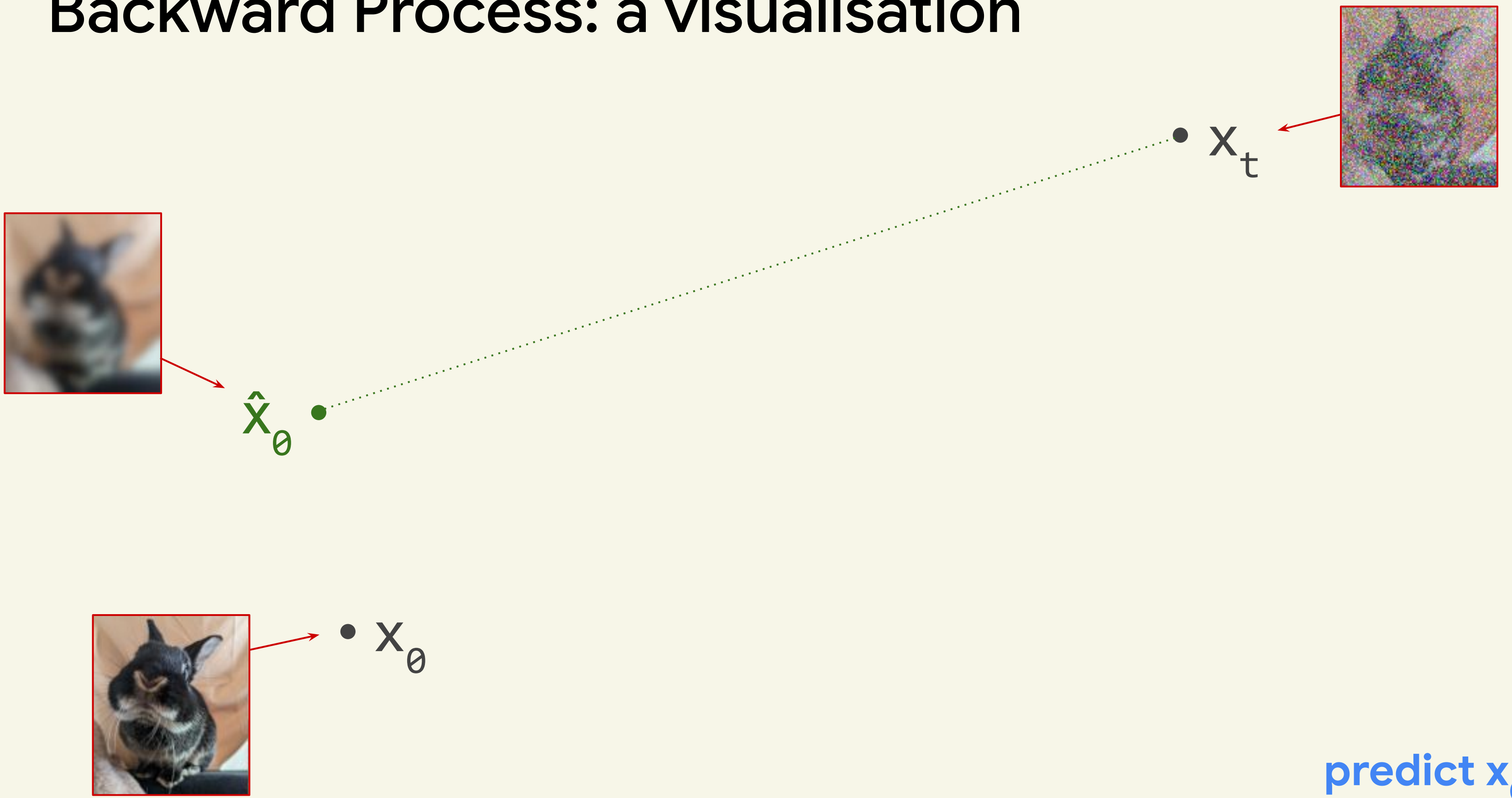
- x_t



- x_0

Slide credit: Sander Dieleman

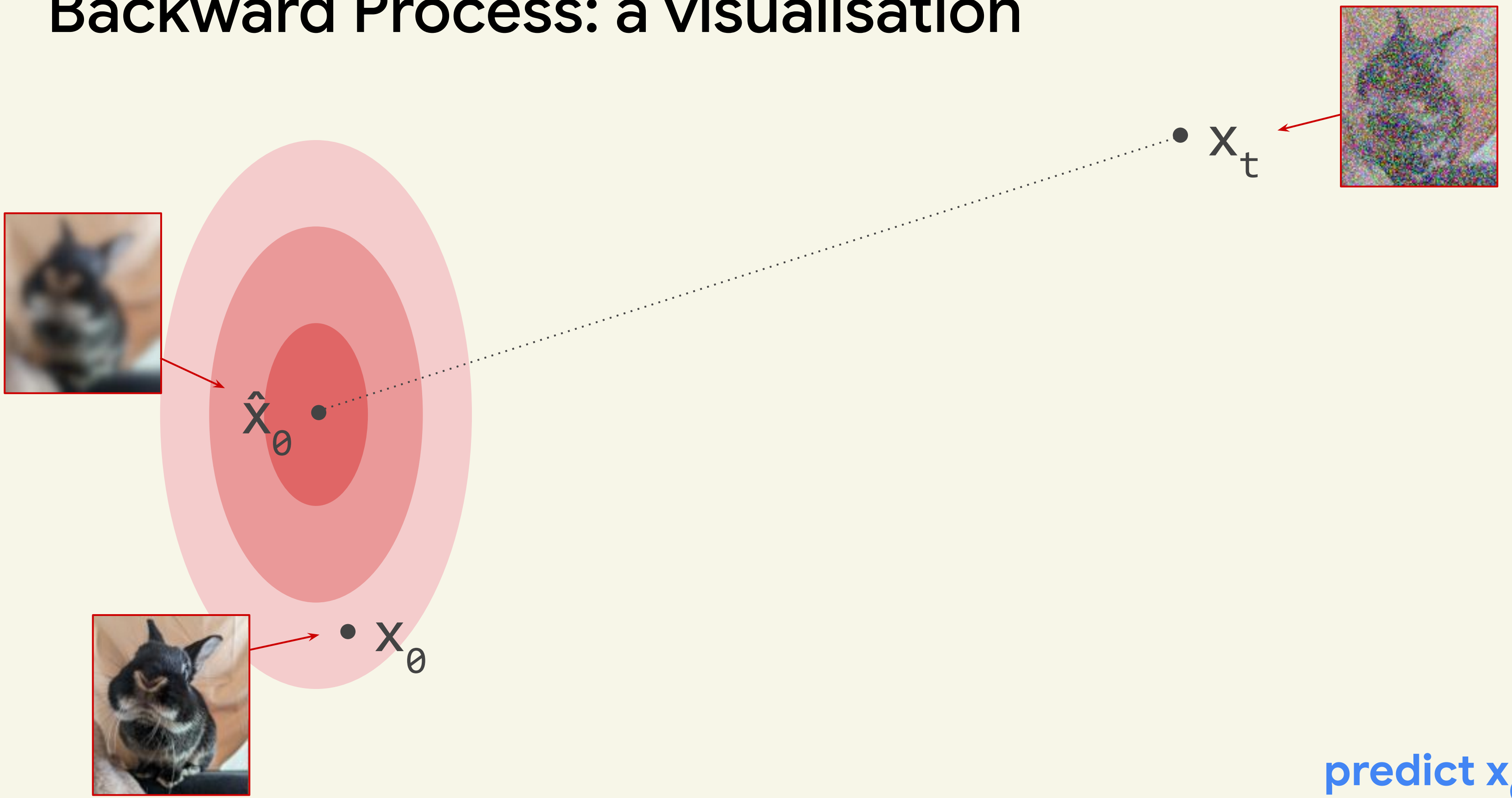
Backward Process: a visualisation



predict x_0

Slide credit: Sander Dieleman

Backward Process: a visualisation



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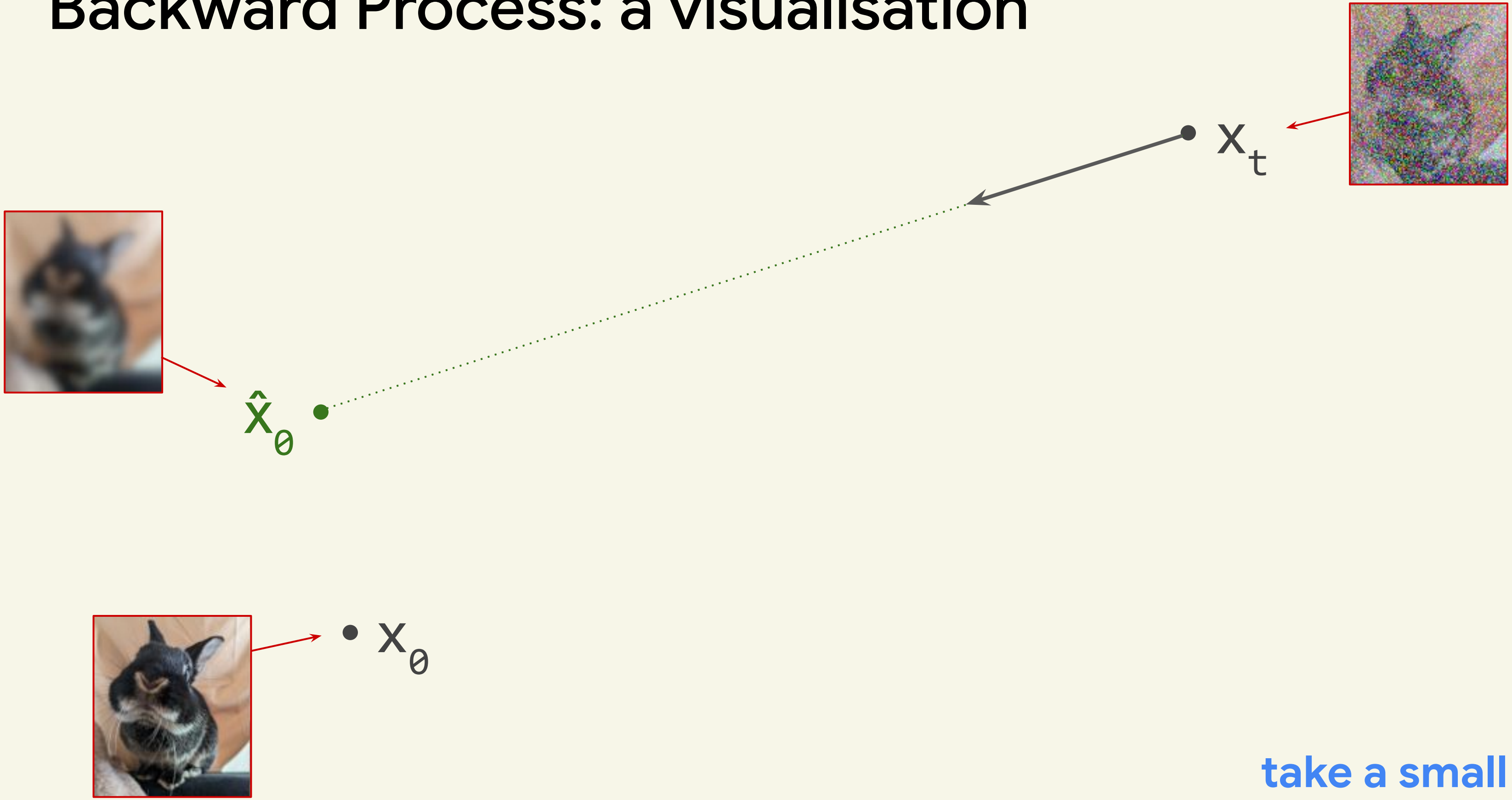

take a small step

Slide credit: Sander Dieleman

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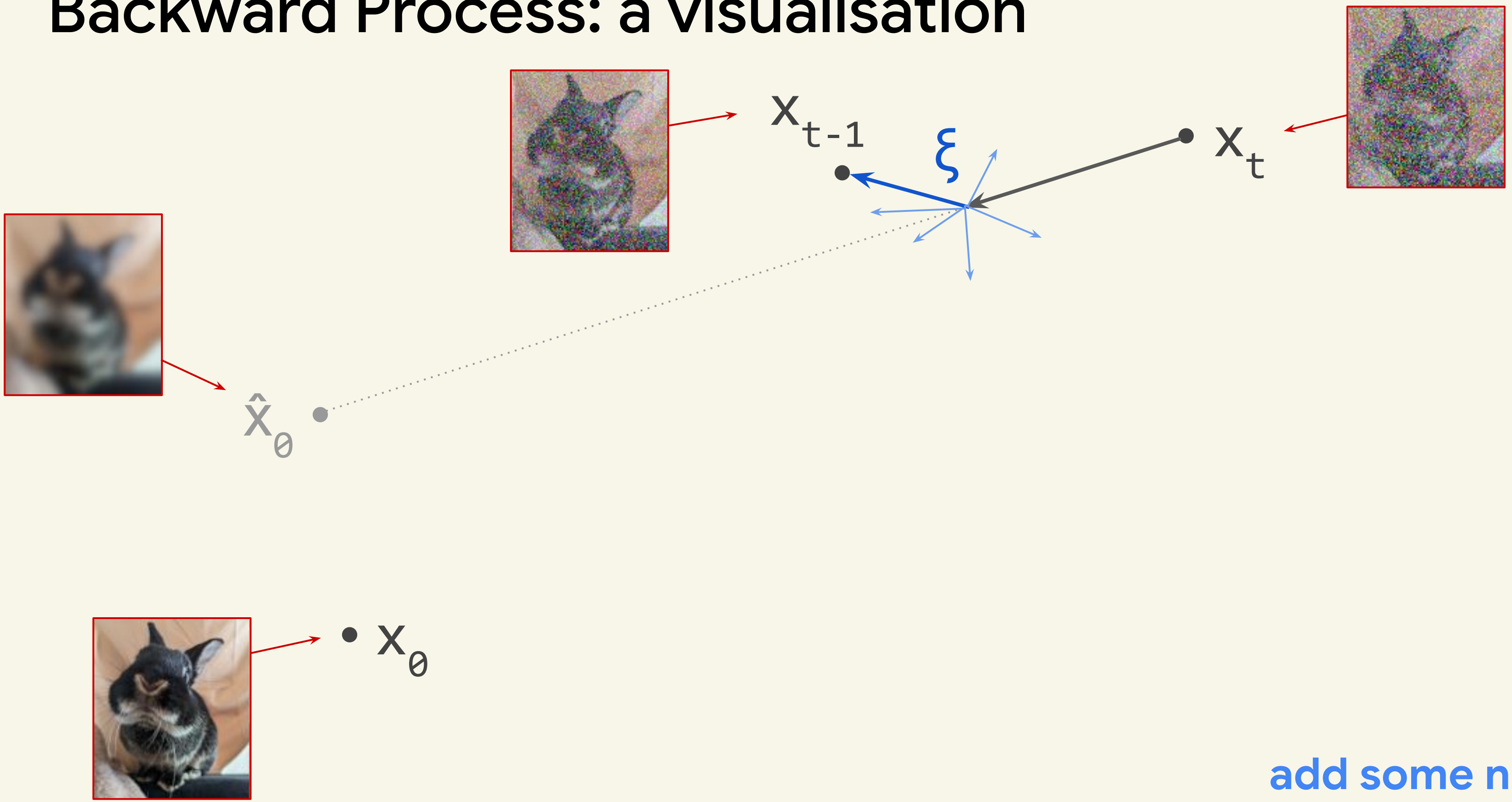

add some noise

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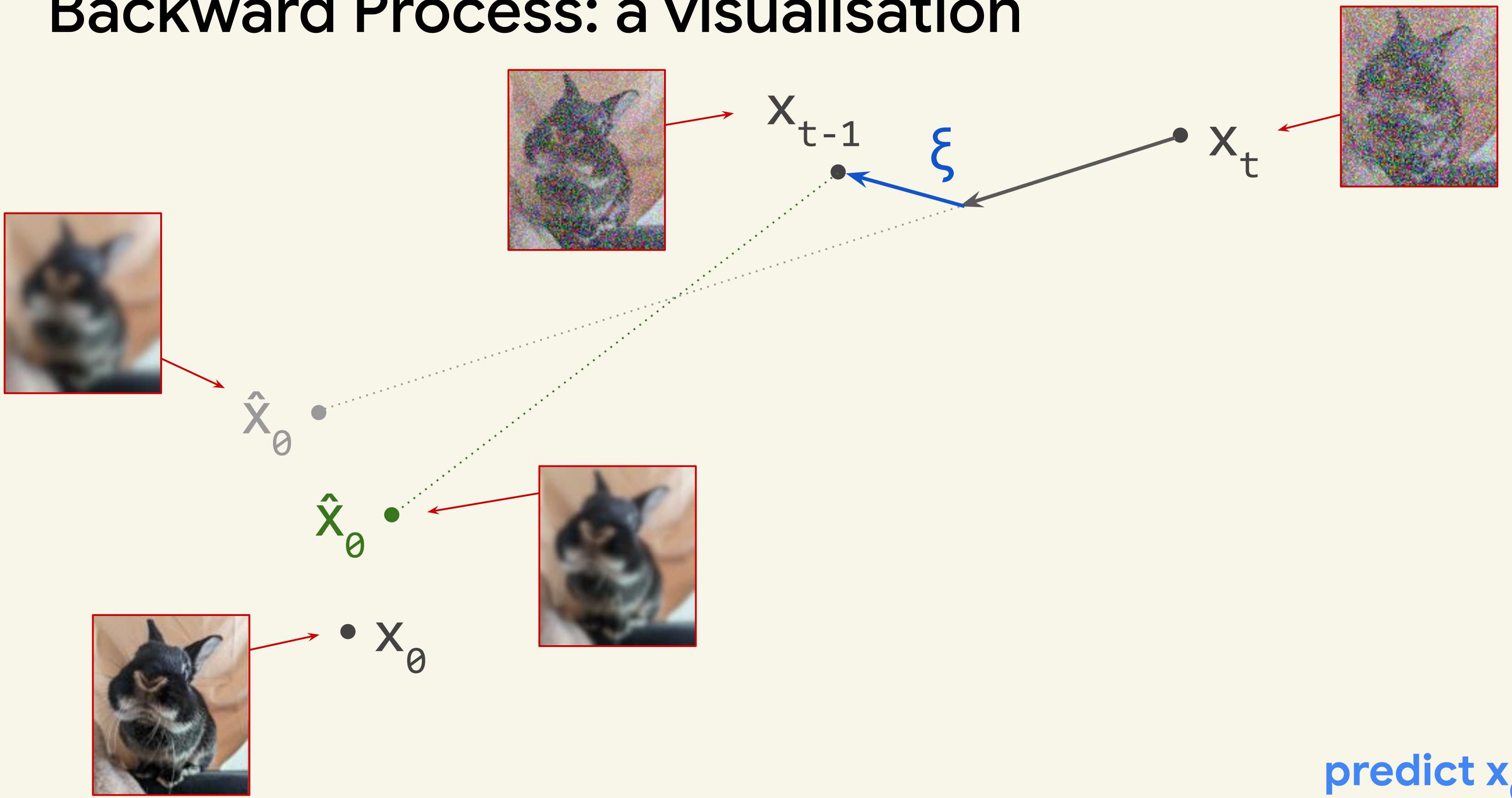
Backward Process: a visualisation



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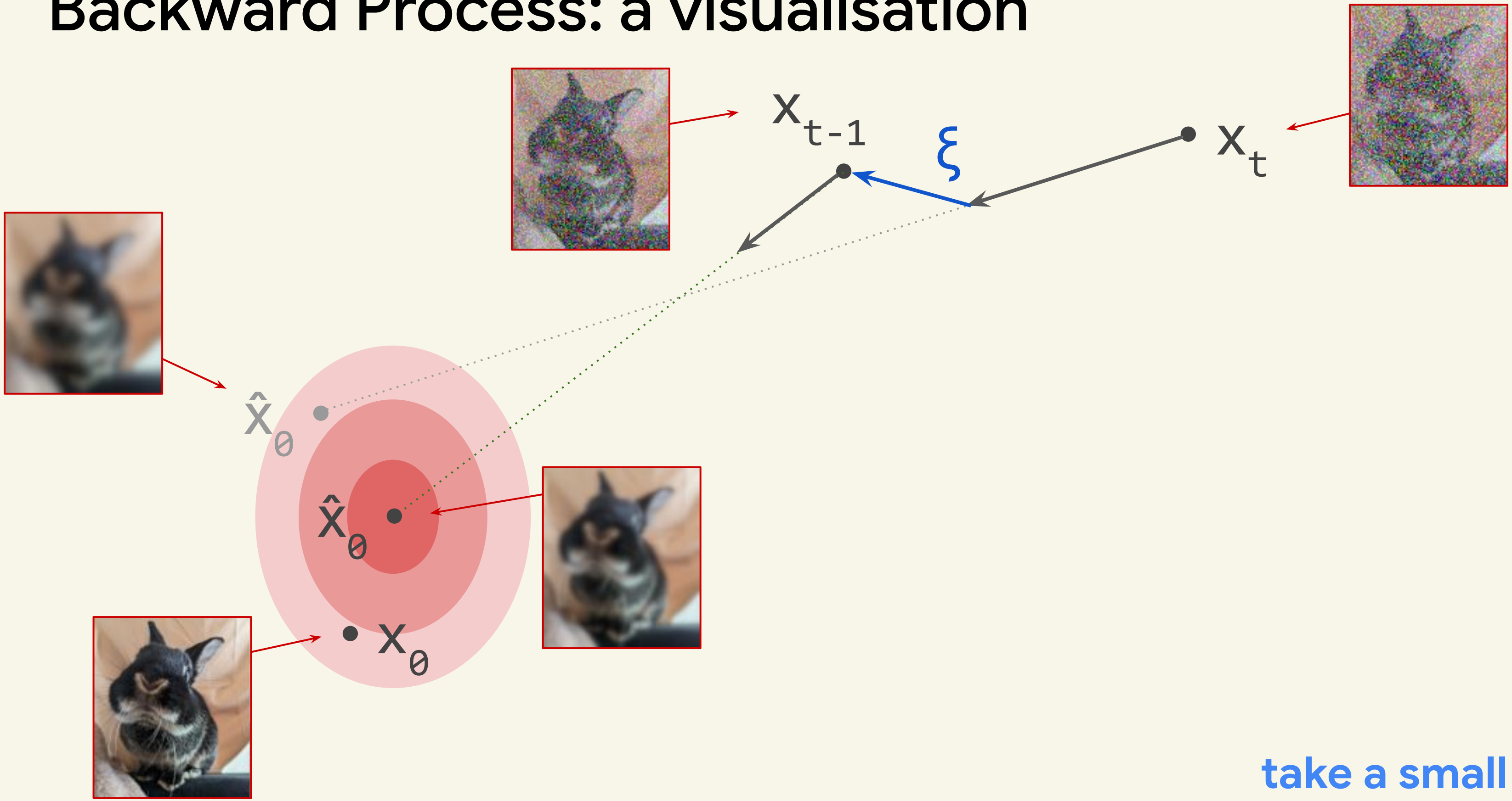

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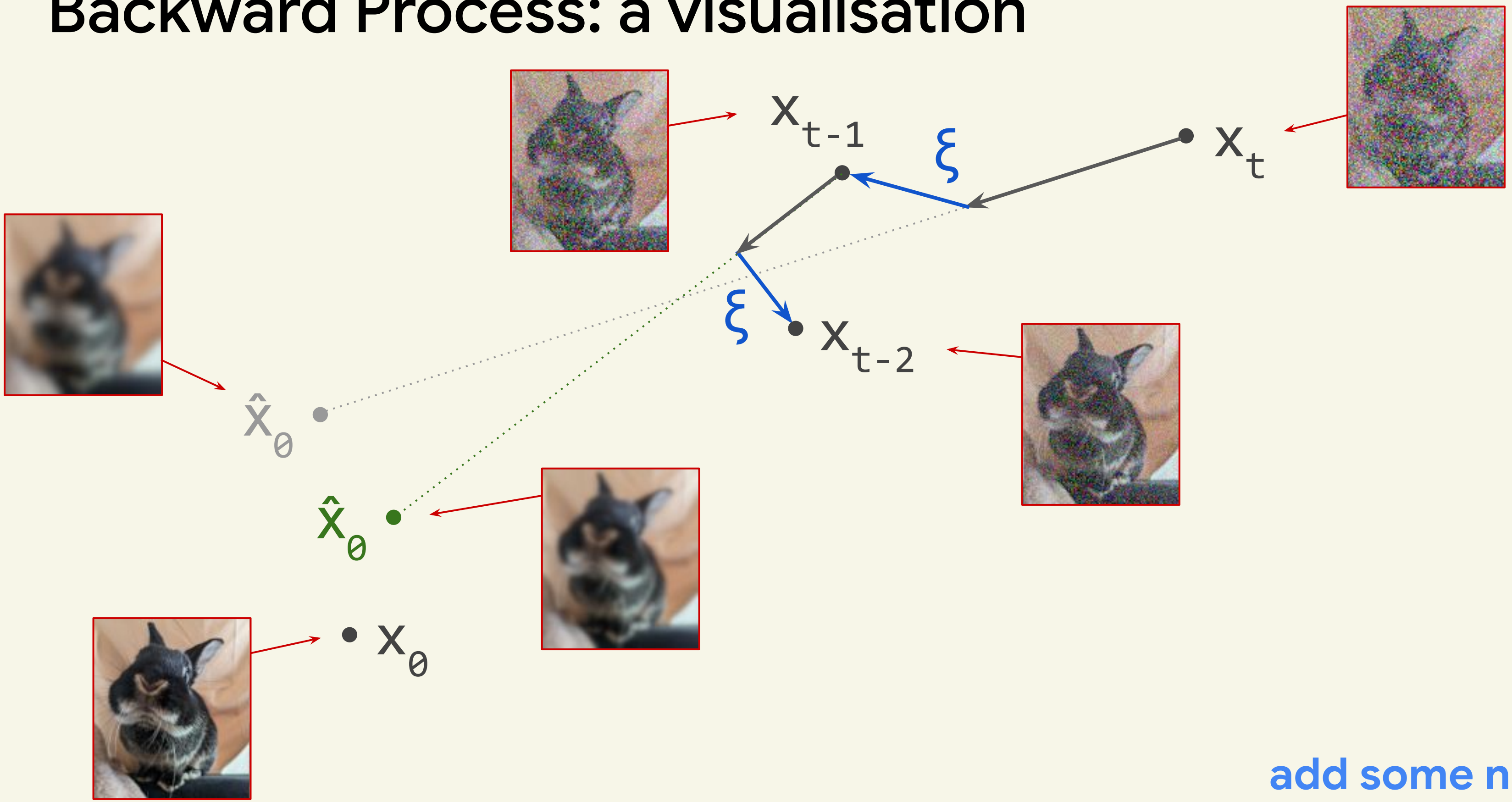

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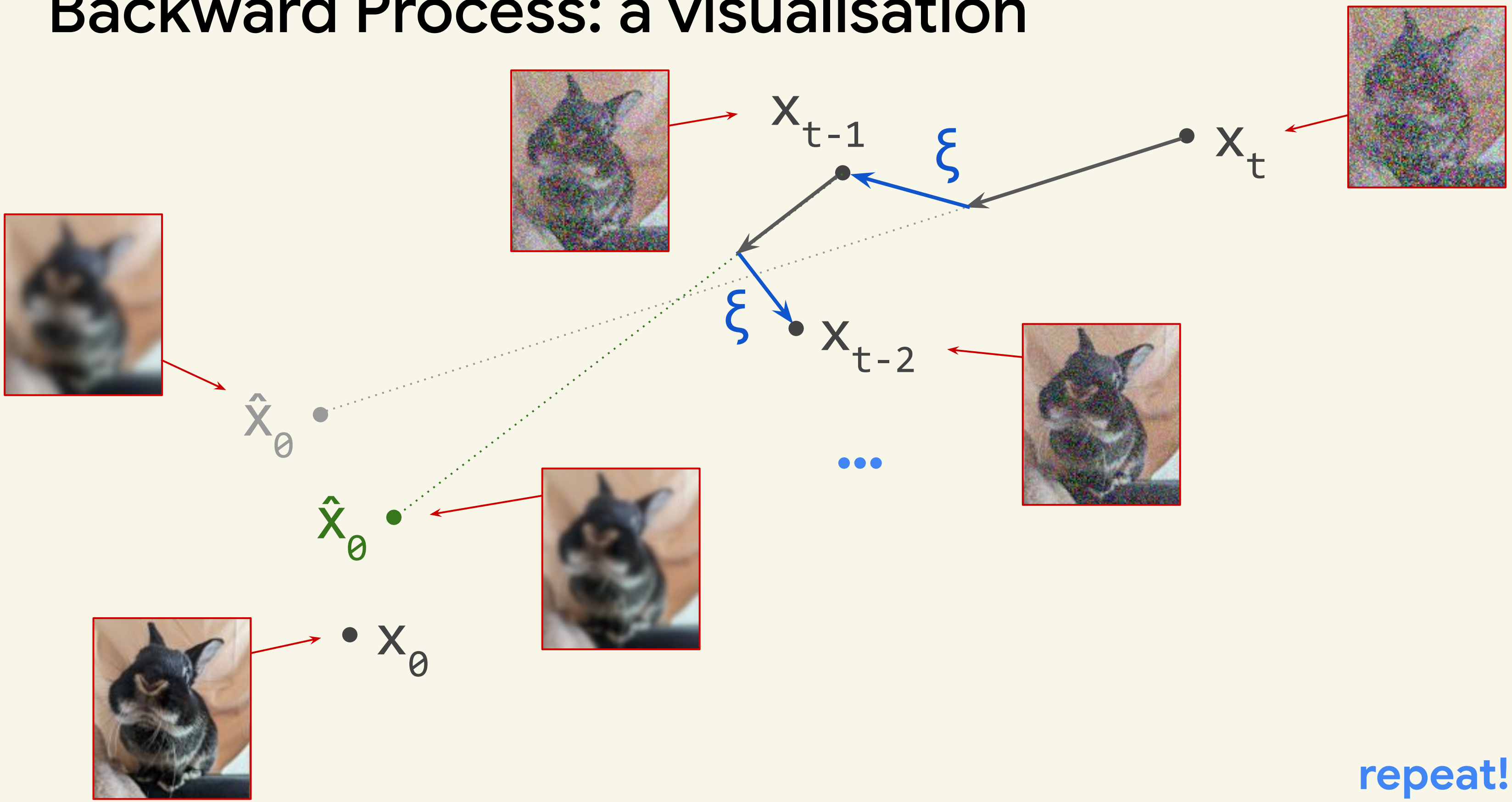

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5 Diffusion Models at Scale!

Genie: action => video!

Genie is an interactive generative model that is real-time playable.

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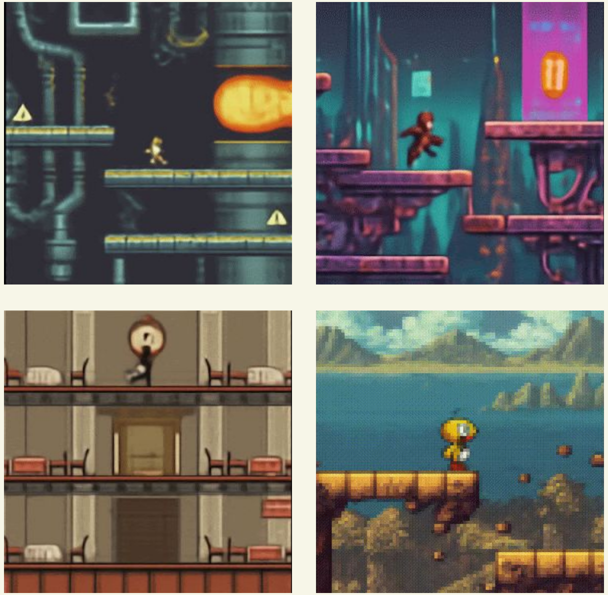
Genie1, Pre-diffusion (2024)



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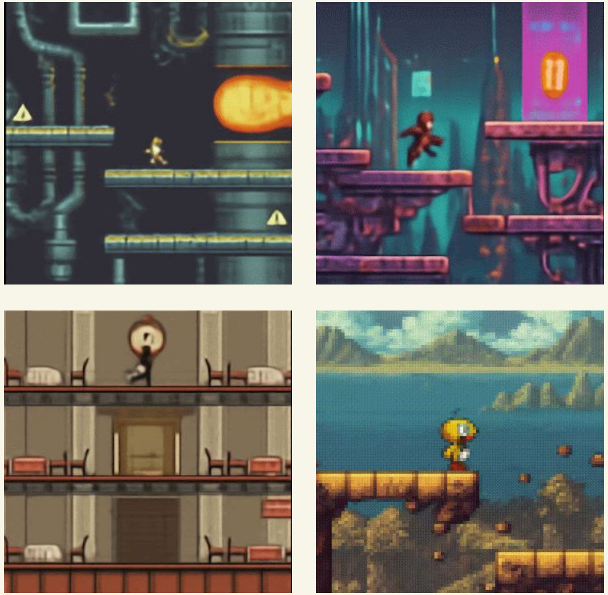

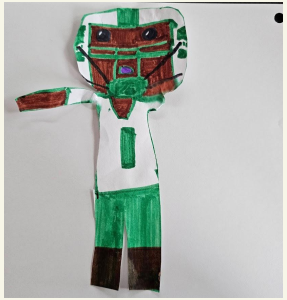

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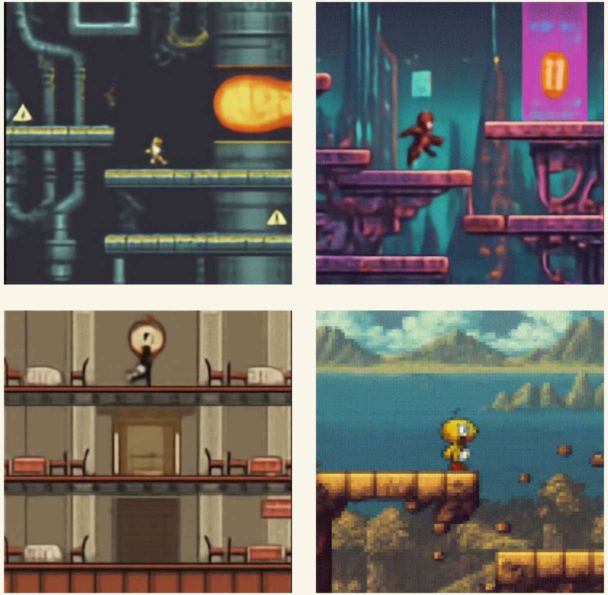

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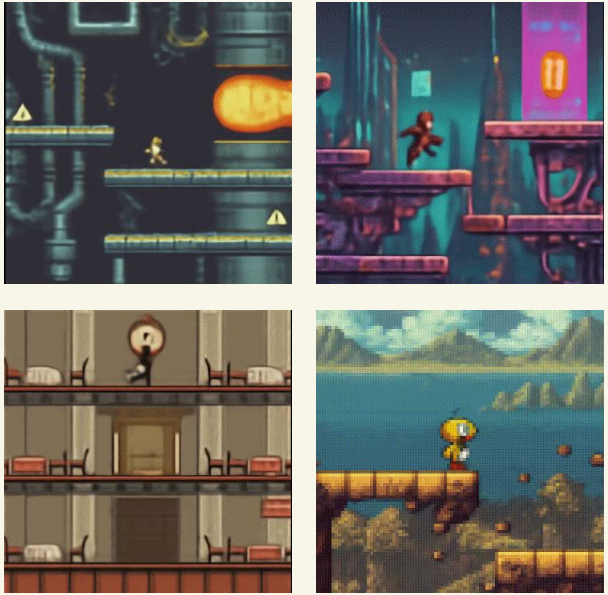

Genie2, Post-diffusion (2025)

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The Veo team is hiring,
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