DDPM 演讲大纲

开场白

Hello, everyone, today our team would like share a paper called "Denoising Diffusion Probabilistic Models", and this work has done by the UC Berkeley, here is the authors.

大家好，今天我们小组分享的是 DDPM 这篇文章，这个工作是由UC Berkeley完成。这是作者

This is our team members, You can understand why we use these avatar at the end of this speech.

这是我们的小组成员，在这次演讲过后，你就会理解为什么我们使用这组头像

we will show it from 6 section.

我们将从六个方面介绍DDPM

1.背景介绍 Background

First is the Background. Maybe some of you don't know what is the generative model

首席是背景，也许你们中的一些人并不知道什么是生成模型

什么是生成模型?

in Wikipedia, there is a complex definition, but ...

在维基百科，有非常复杂的定义，不过......

【读ppt】

【图片例子】

This picture is generated by Novel AI, which is a popular repository in Github.

深度生成模型

【读ppt中的文字】

Those models we list here are very popular in recent years, like GANs, or VAEs.

all of those model is very popular.

2. DDPM模型介绍 Introduction

什么是DDPM

【读ppt】

forget about it, let us see some picture to understand it intuitively.

忘记这些定义，让我们看一些图片，以便于直观地理解它

直观理解 Intuitive understanding

【会放一张图片】

Each molecular movement follows a Gaussian distribution

每个分子运动都遵循高斯分布

3 扩散模型的特点 Features

对比图

【表格，看懂表格，组织语言】

compare to other models, each model has its own feature, for example, VAEs speed is fast and generates a picture one time.

some paper shows that DDPM is better than GANs in some aspect.

与其他模型相比，每个模型都有自己的特点，例如，VAEs的速度很快，一次生成一张图片。

但一些论文表明，DDPM在某些方面优于GAN。

DDPM比GANs更好的理由

【对照表格】

Look here. The Data here shows the performance in DDPM is better than GANs.

可以看到数据显示DDPM 比 GANs 更加好

4 扩散模型的原理 Theory

扩散过程

The left figure is the initial state, and in every step, we add some noise into the picture, then those points will diffuse in the whole space, and after thousands of steps, finally the results will close to the Gaussian Distribution

左图是初始状态，每一步，我们在画面中加入一些噪点，然后这些点会在整个空间中扩散，几千步后，最后结果会接近高斯分布

【图片】

前向扩散公式

This equation shows after we add noise, how those points changed in mathematical form.

这个方程显示了，在我们添加噪声之后，这些点是如何以数学形式变化的。

Here is the Derivation of the formula, if you are interested in it. we can discuss it after the speech.

这是公式的推导，如果你对它感兴趣。我们可以在演讲后讨论。

反向扩散公式

This is the backward equation, which shows how the Gaussian Distribution reverses to a real picture in mathematical form.

这是逆向方程，它显示了高斯分布如何以数学形式反演为真实图片。

Ignore that derivation, we put our attention on Except and Variance. This is the key to generating a picture.

忽略这个推导，我们把注意力放在 except 和 Variance 上。这是生成图片的关键。

Using those formulas, we could build a model with code to simulate this process.

使用这些公式，我们可以构建一个带有代码的模型来模拟此过程。

5. 扩散模型的应用 Application

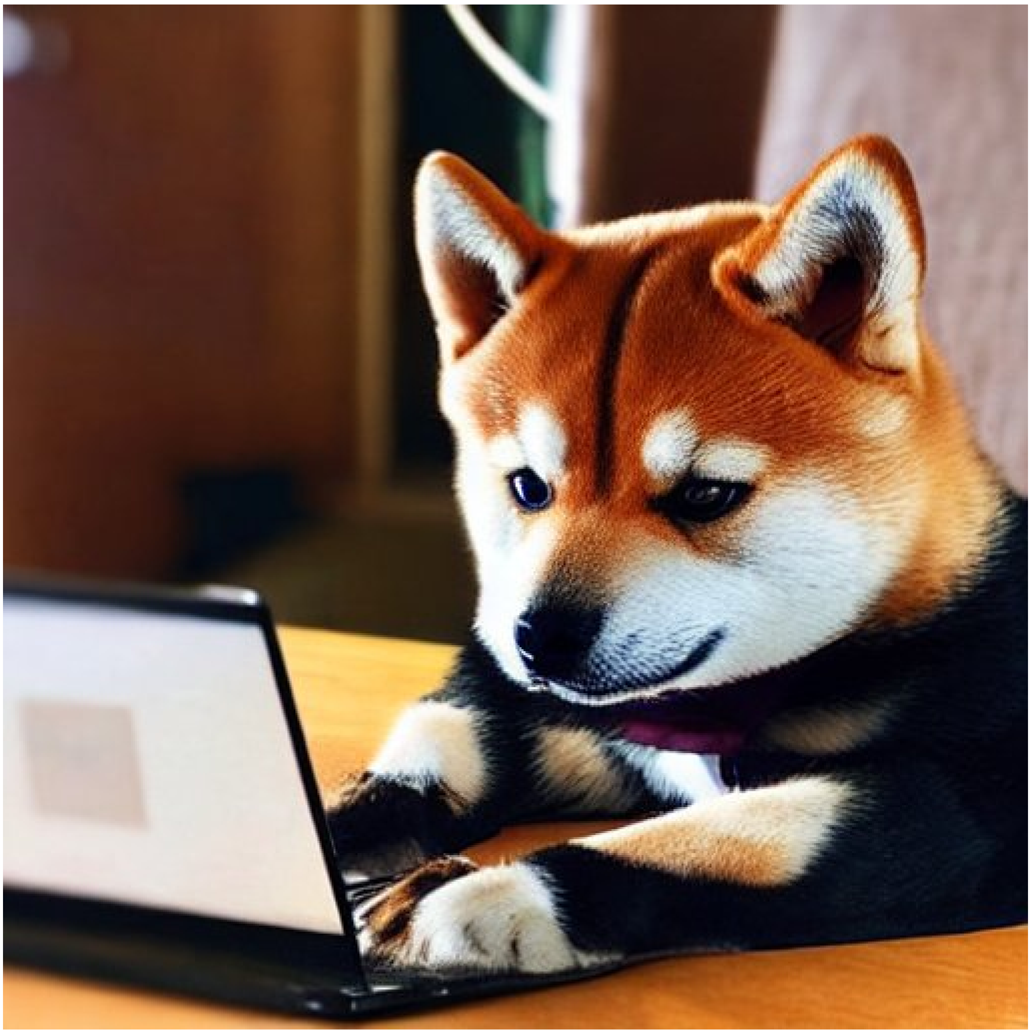
文本图像 Text2Image

【读ppt】

根据文本生成符合描述的图像，给出一些描述，可生成符合描述的图片。

Here we show an example of a description dog is reading, which can generate a picture of a puppy being read

这里我们展示了一个例子，给出描述dog is reading，可以生成一张正在阅读的小狗的图片



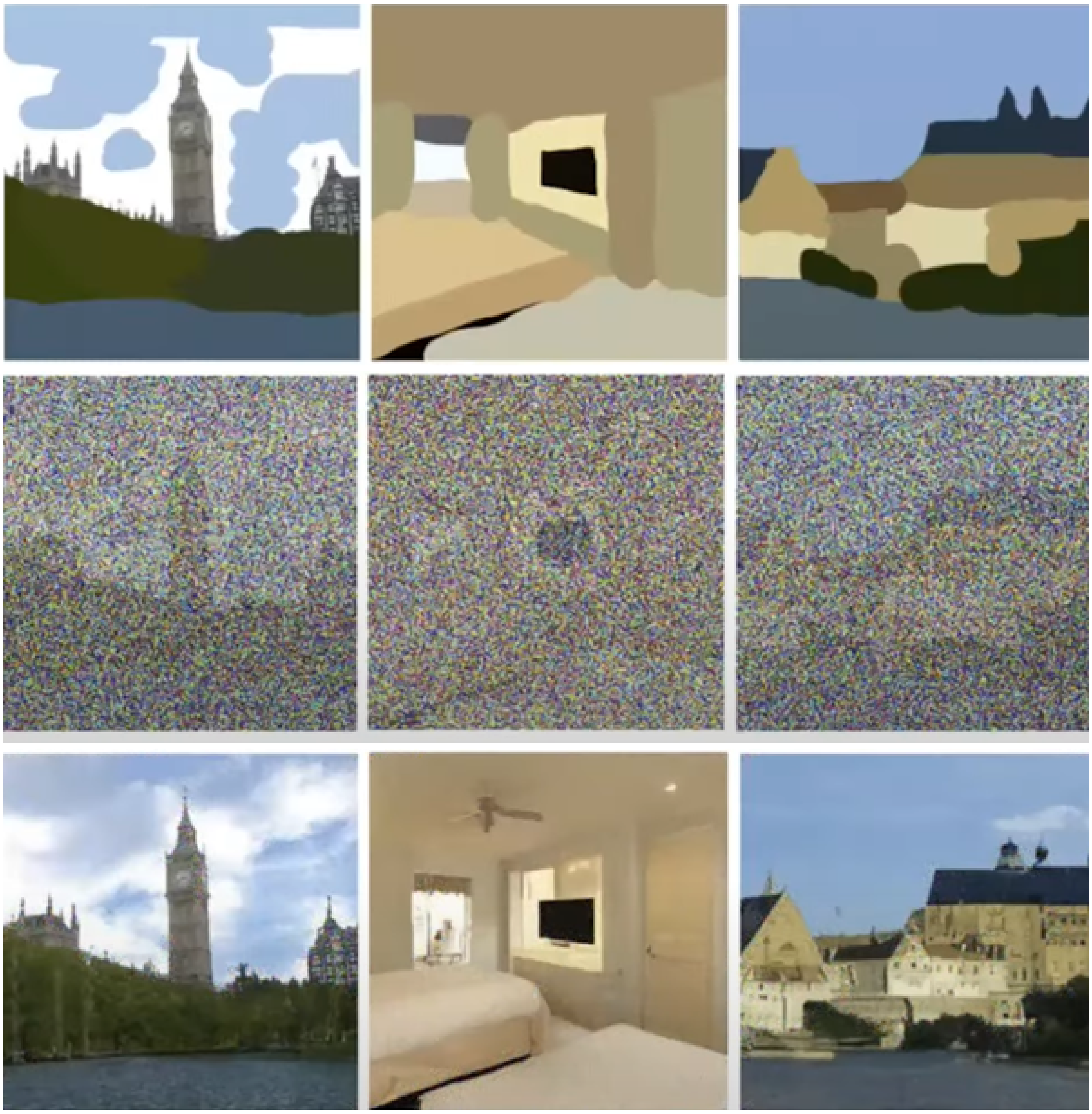
图像精细化 Image Refinement

Refine the blurry image to give the picture more detail.

对模糊的图像进行精细化，给图片更多的细节。

Here we give an example, give some blurry pictures, can produce a clearer, more detailed picture with more detailed features

这里我们给出一个例子，给出一些模糊的图片，可以生成更加清晰的，有更多细节特征的图片



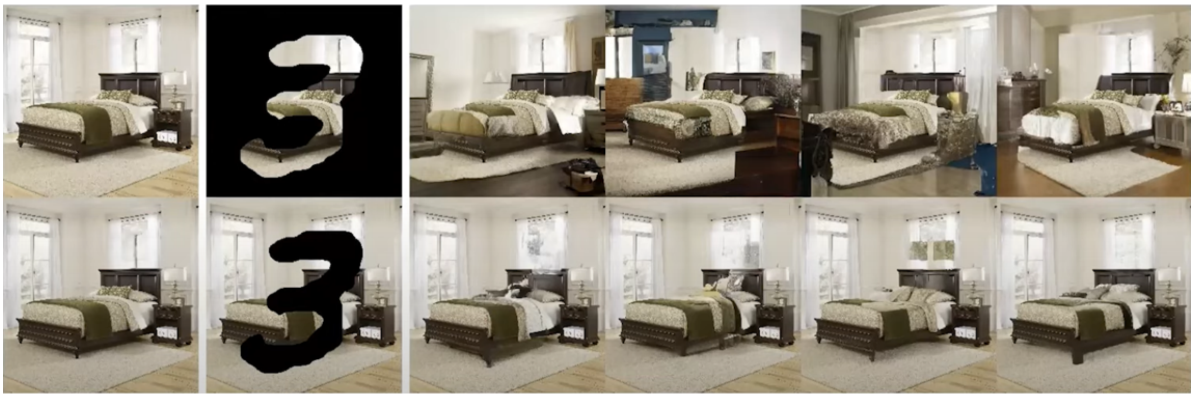
像素填充 Inpainting

Padding the missing image can complement the details and content of the image.

对缺失内容的图像进行填充，可以补充图像的细节和内容。

Here is a picture of the defect, restore it, restore it to a complete photo.

这里给出一张缺损的图片，对其进行还原，将其还原成一张完整的照片。



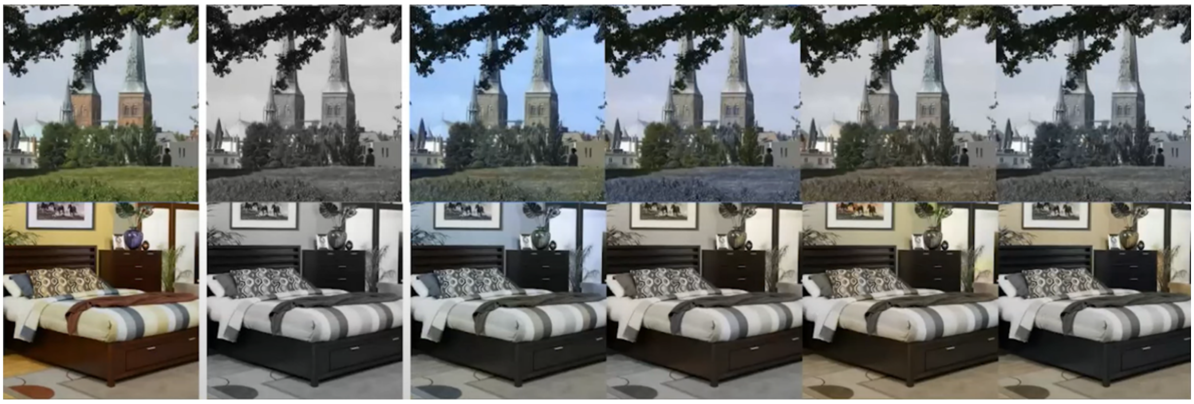
填色 Colorization

Color fill images with missing colors,

对缺少色彩的图像进行色彩的填充，

To give an example, we input a grayscale map to which the model can assign appropriate colors.

给出一个例子，我们输入一张灰度图，模型可以对其赋予合适的色彩。



6 担忧与未来 Worries and the future

Unfortunately, there are numerous well-known malicious uses of generative models. Sample generation techniques can be employed to produce fake images and videos of high profile figures for political purposes

不幸的是，生成模型有许多众所周知的恶意使用。样本生成技术可用于生成高调人物的假图像和视频政治目的

but diffusion models might also become viable for creative uses in art, photography, and music.

扩散模型也可能在艺术、摄影和音乐中的创造性用途中变得可行

7 引用 References