复试准备

1. 自我介绍

Thank you for the opportunity.

My name is Gao Zhe, from Nanjing. I majored in computer science in Nanjing tech university.

One of my greatest strengths is my ability to learn quickly. It doesn't matter if I have to switch to a different field or prepare for a hard test like the postgraduate entrance exam, I have always relied on my own resources to master the material. I always have a strong sense of planning and organization, I like to stick to a well-scheduled plan for both my personal and academic life. This way, I can really develop a deep understanding of the subjects I study and feel confident to take on new challenges with exitement.

However, when faced with unexpected events, and when my schedule got disrupted, my efficiency goes down a lot. Fortunately, I have learned to adapt and modify my plans to stay on track, which has helped me develop great flexibility and resilience in the face of uncertainty.

As for my hobby, music has always been an important part of my life, I love to sing and play the piano in my spare time. I find music a great source of inspiration and relaxation, and it helps me stay focused and motivated.

I believe that having diverse interests and experiences can help us enhance our creativity and problem-solving skills. I'm looking forward to using this perspective in my studies and research and to help create new technologies.

研究方向

I'm really interested in diving deep into the field of AI, or deep learning. During my undergraduate studies, I realized that my true interests lay not in Java web development but rather in the exciting and rapidly evolving field of AI. As I explored this area more deeply, I became fascinated by the many ways in which AI is transforming our world and enhancing our ability to solve complex problems.

Currently, I'm still relatively new to deep learning, but I'm extremely passionate about it and constantly looking for ways to improve my knowledge and skills. I've taken a few online courses and read numerous research papers to expand my understanding of deep learning concepts and their practical applications.

择校（中英）

First of all, I have always had a great affection for the city of Hangzhou, and I'm hoping to make it my permanent home while pursuing my career.

Furthermore, I am attracted to the high level of expertise in computer science at Zhejiang University.'m confident that I'll gain the knowledge and skills I need to succeed in the highly competitive world of AI and other cutting-edge technologies. Plus, I really appreciate how fair and transparent the admissions process is.

Overall, I truly believe Zhejiang University is the perfect choice for me and I'm confident that I can make valuable contributions here.

对机器学习的看法，机器学习应用

Before diving into machine learning, I thought it was a very magical and obscure field, and I was unsure whether I could understand it. After studying for a while, I realized that there's such thing as "learning", what computer'd really doing is to compute, using massive data. However, as I learned more deeply, I found that the ability of machine learning is incredibly powerful, even beyond my understanding. That's why I became very interested in it and hope to dive deeper in the future.

项目（毕设）

One of my recent research projects involved developing a deep learning model for facial expression recognition using PyTorch. The application scenario is to detect students' emotions during online classes, which makes it convenient for teachers to check each student's learning status and dynamically adjust teaching methods to improve teaching quality.

One challenge I faced during this project was in the area of face detection. Although I was able to use OpenCV's built-in face detection algorithm, I realized that I had limited knowledge in this area. In the future, I hope to gain a deeper understanding of face detection techniques and their applications in computer vision.

家庭

I'm an only child. My parents are freelancers, and our family is relatively happy. I'm very grateful to them, and I hope to give them a better life in the future.

家乡

I'm from Nanjing. It is an ancient city with many scenic spots and specialties. But actually, I don't know much about Nanjing myself, all I can remember is the crowded traffic and tall buildings. So I would say it's not very suitable for long-term living.

为什么读研

The primary goal is to find an ideal job and earn enough money. However, I feel like my current abilities are inadequate, and besides, I'm not really interested in Java web development. So I was considering pursuing a master's degree and to find what I'm truly interested in. Maybe I'll be interested in scientific research, but I wouldn't know until I have actual experience.

失败怎么办

I'll look for a job first, maybe I'll take another year to prepare for the exam. But anyway, I'm confident in my future and there's no difficulty that I can't overcome.

南工大

The campus is huge, located on a hill with great scenery. My favorite spot there is the library - it has a fantastic environment and is perfect for studying. I am extremely grateful to my college.

读博意向

Not really. Firstly, I have very little exposure to scientific research, so I am not sure whether I would enjoy it or not. However, I am really interested in my current major and confident in my ability to achieve promising results. So, if I have the support of my mentor and my family, Ph.D is not bad choice for me.

兴趣

music has always been an important part of my life, I love to sing and play the piano in my spare time. I find music a great source of inspiration and relaxation, and it helps me stay focused and motivated.

Another hobby of mine is exploring nature and taking in the beauty of the world around us. I have a particular interest in remote and unspoiled landscapes, such as Iceland and Norway. My dream is to one day travel the world and experience all the wonders that our planet has to offer.

选专业

Actually, when I first got into college, my major was mechanical engineering. At that time, I didn't know much about any majors. However, after taking the course of engineering drawing, I realized that I wasn't interested in my major. On the contrary, when I started learning programming, I showed a strong interest in it,and since then I decided to study computer science. I'm really confident about my current major.

研究生应有什么特质

Graduate students should have strong self-learning ability, not be afraid of challenges, maintain a positive attitude, and be confident about themselves.

道歉语录

L6 抱歉我没听清

Sorry, I didn't catch that.

L6 这方面我不太了解

I'm not very knowledgeable about this topic.

NeRF翻译

1 Introduction

在这项工作中，我们通过直接优化连续的5D场景表示的参数来解决视角合成的长期问题，以最小化渲染一组捕获图像的误差。我们将静态场景表示为一个连续的5D函数，该函数在空间中的每个点（x，y，z）的每个方向（θ，φ）输出发射辐射度，以及在每个点处的密度，它起到类似微分的不透明度的作用，控制通过（x，y，z）的射线累积多少辐射度。我们的方法通过回归从单个5D坐标（x，y，z，θ，φ）到单个体积密度和视角相关的RGB颜色来优化一个深度全连接神经网络（通常称为多层感知器或MLP）来表示这个函数。为了从特定视点渲染这个神经辐射场（NeRF），我们：1）沿着相机射线穿过场景生成一组采样的3D点，2）使用这些点及其相应的2D观察方向作为输入到神经网络中，以产生一组颜色和密度的输出，3）使用经典的体积渲染技术将这些颜色和密度累积成一个2D图像。由于这个过程是自然可微分的，我们可以使用梯度下降来优化这个模型，通过最小化每个观察图像与我们的表示所渲染的相应视图之间的误差。通过多个视角最小化这个误差鼓励网络通过为包含真实场景内容的位置分配高体积密度和准确颜色来预测场景的连贯模型。图2展示了这个整体流程。

我们发现，在复杂场景中优化神经辐射场表示的基本实现无法收敛到足够高分辨率的表示，并且所需的每个相机射线样本数量低效。我们通过使用位置编码来转换输入的5D坐标，使MLP能够表示更高频率的函数，并提出了分层采样过程来减少所需的查询数量，以充分采样这个高频率的场景表示。

我们的方法继承了体积表示的优点：两者都可以表示复杂的真实世界几何形状和外观，并且非常适合使用投影图像进行基于梯度的优化。重要的是，我们的方法克服了对离散化体素网格进行建模时的存储成本限制，可以高分辨率地建模复杂场景。

总之，我们的技术贡献包括：

- 一种将复杂几何形状和材料表示为5D神经辐射场的方法，其参数化为基本的MLP网络。
- 基于经典的体积渲染技术的可微分渲染过程，我们使用标准RGB图像对其进行优化。这包括一种分层采样策略，以将MLP的容量分配给具有可见场景内容的空间。

- 一种位置编码，将每个输入的5D坐标映射到更高维空间，使我们能够成功地优化神经辐射场以表示高频率的场景内容。

我们证明了，我们的神经辐射场方法在定量和定性上都优于最先进的视图合成方法，包括将神经3D表示拟合到场景的作品，以及训练深度卷积网络来预测采样体积表示的作品。据我们所知，本文首次提出了连续神经场景表示，能够从自然环境中捕获的RGB图像中渲染出高分辨率逼真的新视图，用于真实物体和场景。

2 Related Work

最近在计算机视觉领域中有一个很有前途的方向，就是使用多层感知机（MLP）的权重来编码物体和场景，直接从一个3D空间位置映射到该位置上的形状的隐式表示，例如该位置处的有符号距离[6]。然而，这些方法迄今为止无法像使用三角形网格或体素网格等离散表示的技术那样以相同的保真度再现具有复杂几何形状的逼真场景。在本节中，我们回顾了这两条工作线，并将它们与我们的方法进行对比，通过增强神经场景表示的能力，我们实现了用于渲染复杂逼真场景的最先进结果。使用MLP将低维坐标映射到颜色的类似方法也被用于表示其他图形函数，如图像[44]、贴图材料[12,31,36,37]和间接光照值[38]。

Neural 3D shape representations

最近的研究探索了将连续的三维形状作为等值集的隐式表示，通过优化将xyz坐标映射到有符号距离函数[15,32]或占据场[11,27]的深度网络。然而，这些模型的局限性在于它们需要访问真实的三维几何形状，通常从ShapeNet等合成的三维形状数据集中获得。随后的研究通过制定可微分渲染函数来放松真实三维形状的要求，从而使神经隐式形状表示可以仅使用二维图像进行优化。Niemeyer等人[29]将表面表示为三维占用场，并使用数值方法找到每个光线的表面交点，然后使用隐式微分计算精确导数。每个光线交点位置作为输入提供给神经三维纹理场，该场预测该点的漫反射颜色。Sitzmann等人[42]使用较少直接的神经三维表示，该表示仅在每个连续的三维坐标处输出特征向量和RGB颜色，并提出了一个可微分渲染函数，其中包含一个递归神经网络，沿着每个光线行进以决定表面的位置。虽然这些技术可以潜在地表示复杂和高分辨率的几何形状，但迄今为止它们仅限于低几何复杂度的简单形状，导致过度平滑的渲染。我们展示了一种优化网络以编码5D辐射场（具有2D视角相关外观的三维体积）的替代策略，可以表示更高分辨率的几何和外观，以呈现复杂场景的逼真新视图。

View synthesis and image-based rendering

对于密集采样的视角，可以通过简单的光场采样插值技术重建出逼真的新视角。对于稀疏视角采样的新视角合成，计算机视觉和图形学界已经通过从观察到的图像预测传统几何和外观表示取得了重大进展。其中一类流行的方法使用基于网格的场景表示，包括漫反射[48]或视角相关[2,8,49]外观。可微栅格化器[4,10,23,25]或路径追踪器[22,30]可以直接通过梯度下降优化网格表示以重现一组输入图像。然而，基于图像重投影的基于梯度的网格优化通常很困难，可能是由于局部最小值或损失景观的不良条件。此外，这种策略需要在优化之前提供具有固定拓扑结构的模板网格[22]，这在通常情况下对于无约束的现实世界场景是不可用的。

还有另一类方法使用体素表示法来解决从一组输入RGB图像合成高质量的逼真视图的任务。体素方法能够逼真地表示复杂的形状和材质，非常适合基于梯度的优化，并且倾向于产生比基于网格的方法更少的视觉干扰。早期的体素方法使用观察到的图像直接对体素网格进行着色。最近，一些方法使用大量多个场景的数据集来训练深度网络，从一组输入图像中预测采样的体积表示，然后在测试时使用alpha合成或沿光线学习合成来渲染新视图。其他作品针对每个特定场景优化卷积网络和采样的体素网格的组合，使得CNN可以补偿低分辨率体素网格的离散化伪影，或者允许根据输入时间或动画控制来预测体素网格的变化。虽然这些体素技术在新视图合成方面取得了令人印象深刻的结果，但是它们的时间和空间复杂度由于离散采样而受到根本性的限制，从而在更高分辨率的图像上进行渲染需要更细致的3D空间采样。我们通过在深度全连接神经网络的参数中编码连续的体积来规避这个问题，这不仅比以前的体素方法产生了显著更高质量的渲染结果，而且还需要比那些采样的体积表示法仅仅只有一小部分的存储成本。

3 Neural Radiance Field Scene Representation

我们将连续场景表示为一个5D向量值函数，其输入为3D位置x=(x，y，z)和2D视线方向（θ，φ），其输出为发射颜色c=(r，g，b)和体积密度σ。实际上，我们将方向表示为一个3D笛卡尔单位向量d。我们使用MLP网络FΘ:（x，d）→（c，σ）来近似这个连续的5D场景表示，并优化它的权重Θ，使其将每个输入5D坐标映射到其相应的体积密度和方向发射颜色。

我们通过限制网络仅将体积密度σ预测为仅与位置x有关的函数来鼓励表示具有多视角一致性，同时允许RGB颜色c作为位置和视线方向的函数进行预测。为此，MLP FΘ首先使用8个完全连接层（每层使用ReLU激活和256个通道）处理输入的3D坐标x，并输出σ和一个256维特征向量。然后将该特征向量与相机光线的视线方向进行串联，并传递到一个额外的完全连接层（使用ReLU激活和128个通道），以输出视角相关的RGB颜色。

请参见图3，了解我们的方法如何使用输入的视线方向表示非Lambertian效果的示例。如图4所示，仅使用x作为输入进行训练的模型难以表示镜面反射。

4 Volume Rendering with Radiance Fields

我们的5D神经辐射场将场景表示为空间中任意点的体密度和方向性辐射强度。我们使用经典体渲染原理[16]来渲染穿过场景的任何光线的颜色。体密度σ(x)可以被解释为光线在位置x处终止于无穷小粒子的微分概率。相机光线r(t) = o + td的预期颜色C(r)，其近和远端边界为tn和tf，可以表示为:

5 Optimizing a Neural Radiance Field

6 Results

7 Conclusion

$$\begin{bmatrix} z \\ \dots \\ z^N \end{bmatrix} = \begin{bmatrix} x_1^1 & \dots & x_8^1 \\ \dots & \dots & \dots \\ x_1^N & \dots & x_8^N \end{bmatrix} \begin{bmatrix} w_1 \\ \dots \\ w_8 \end{bmatrix} + \begin{bmatrix} b \\ \dots \\ b \end{bmatrix}$$