



GAMES 003 科研素养课

第七周：论文图表的设计



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为什么要做好论文图表

- 图表让读者更能理解清楚文章的要点
- 论文图表的目的是什么？
 - “把读者当作来你家的客人”
 - 清晰：让读者能够看明白你论文的方法，实验结果
 - 切中要点：让读者能够直接看出来你的核心想法及提升的点
 - 简洁：让读者不被多余的信息干扰，从而变得困惑

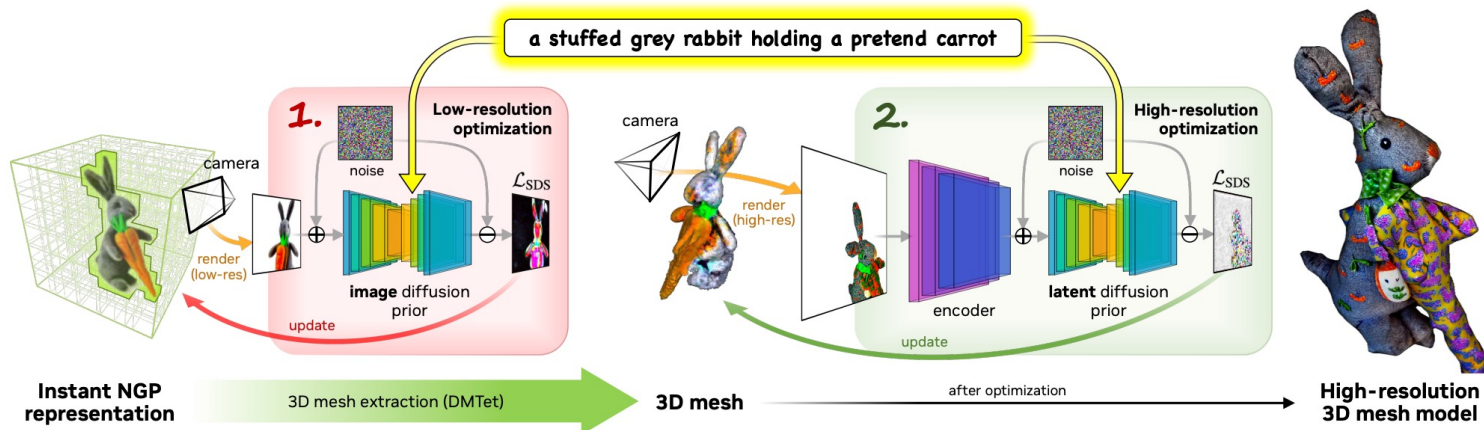


课程内容

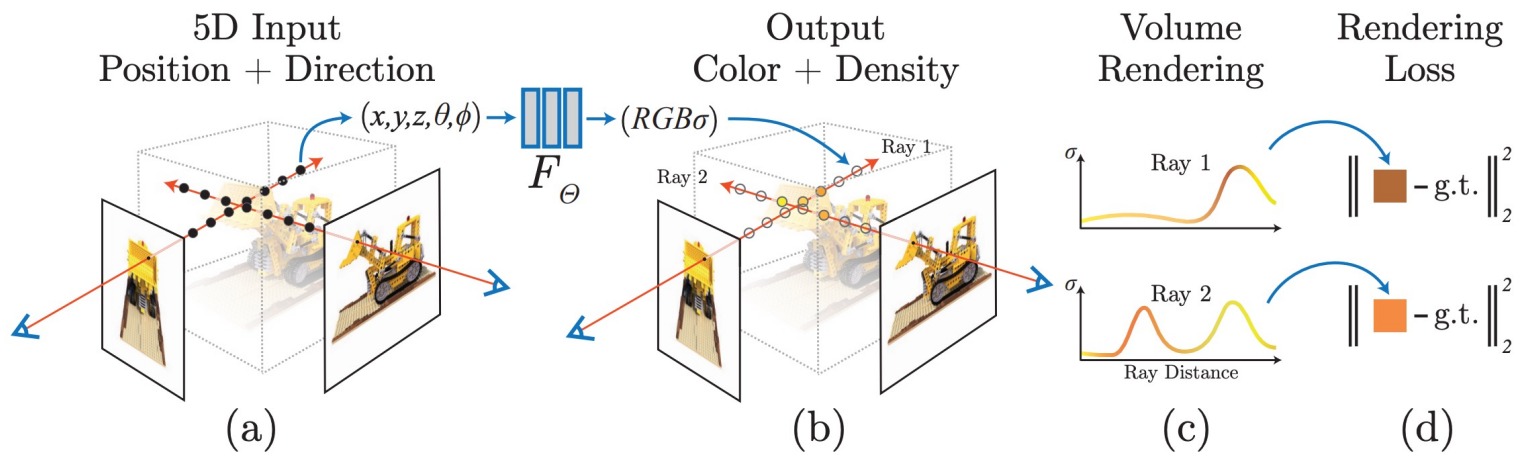
- 图片设计
 - 技术方案流程图
 - 片头Teaser图
 - 实验结果图
 - Quantitative 图
 - Qualitative 图
- 表格设计
 - 实验方法的表格
 - 实验结果的表格
- 视频设计
 - 实验结果的视频

技术方案流程图

- 什么需要被放到流程图里面?
 - 论文的核心贡献需要被突出
 - 着重介绍的内容



2-stage generation pipeline

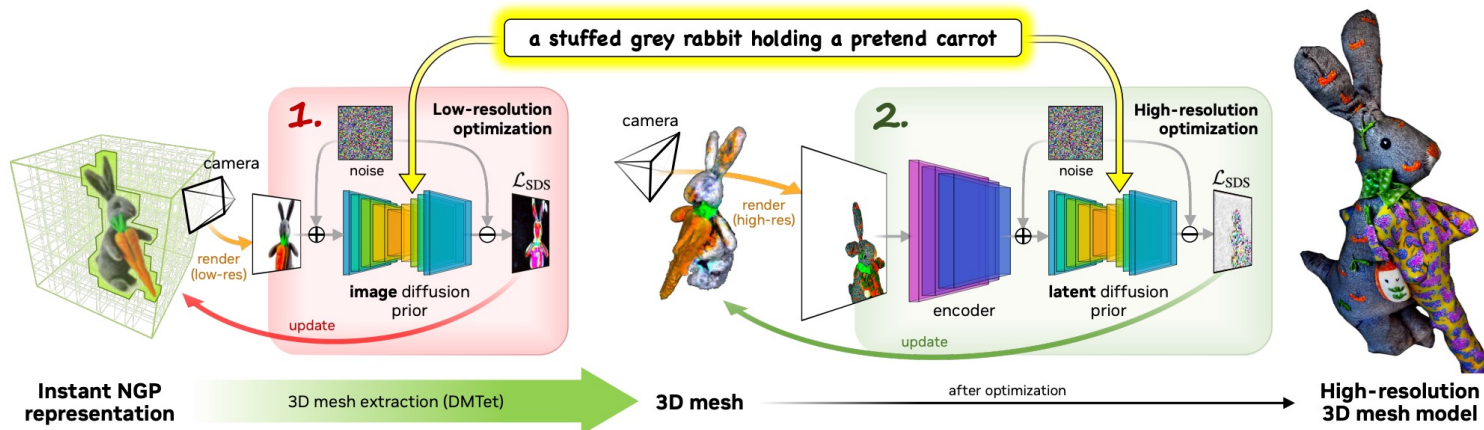


Neural radiance field

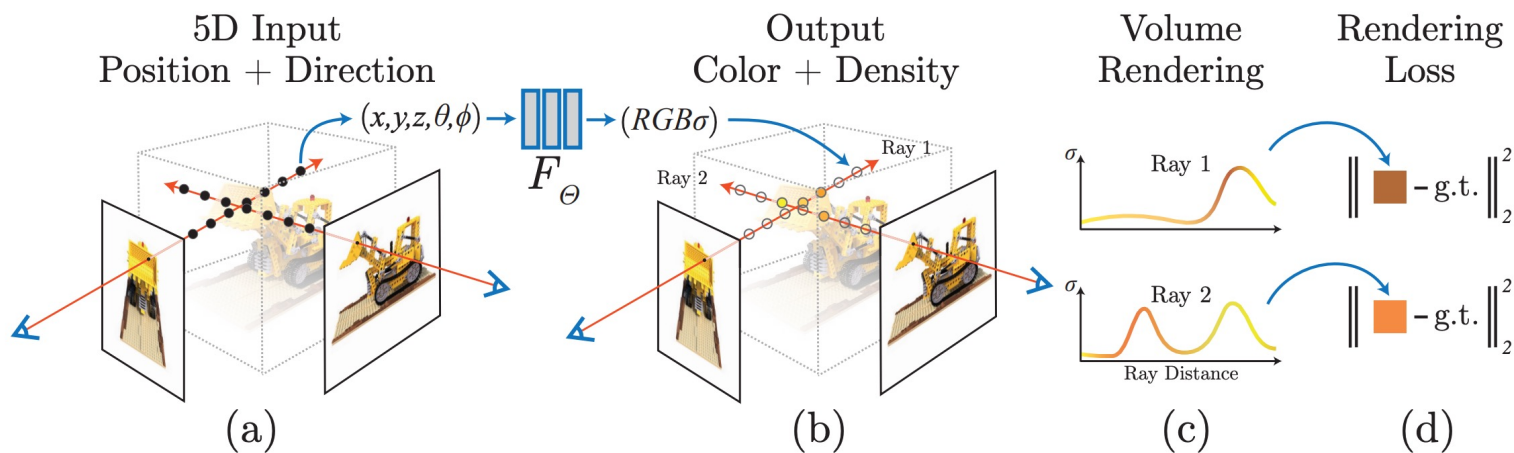
Tips: 写intro的时候就会确定方法的核心贡献

技术方案流程图

- 什么需要被放到流程图里面?
 - 论文的核心贡献需要被突出
 - 方法的核心步骤
 - 输入输出的对应关系
 - 让读者看明白方法的整体流程



2-stage generation pipeline

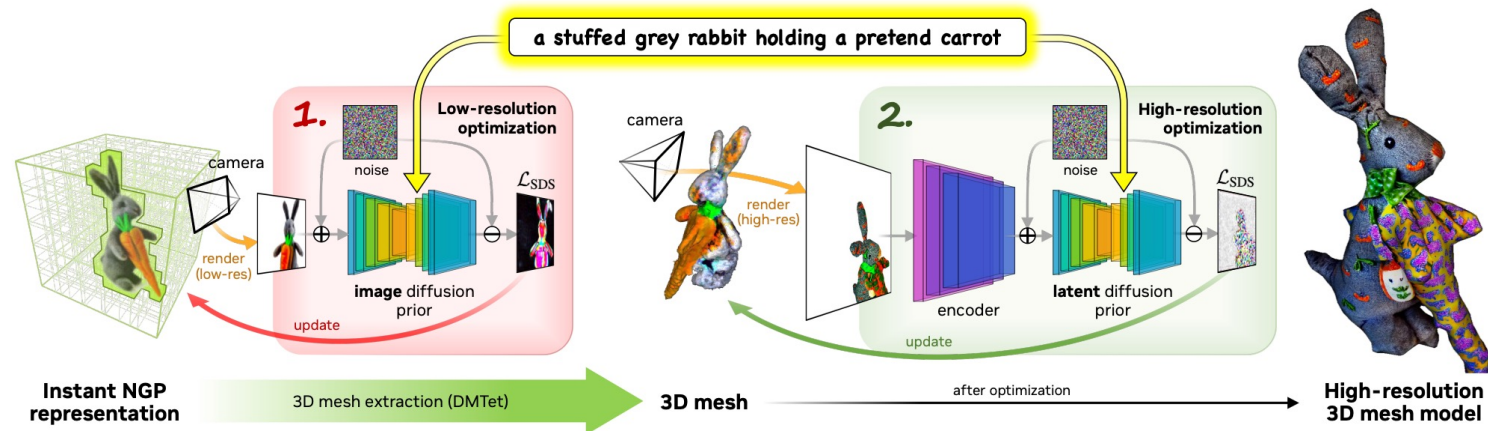


Neural radiance field

Tips: 利用箭头表明输入输出的对应关系

技术方案流程图

- 什么需要被放到流程图里面?
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 - 方法的核心步骤
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 - 让读者看明白方法的整体流程
 - 与论文的Method section对应
 - 帮助读者理解方法



4. High-Resolution 3D Generation

Magic3D is a two-stage coarse-to-fine framework that uses efficient scene models that enable high-resolution text-to-3D synthesis (Fig. 2). We describe our method and key differences from DreamFusion [33] in this section.

4.1. Coarse-to-fine Diffusion Priors

4.2. Scene Models

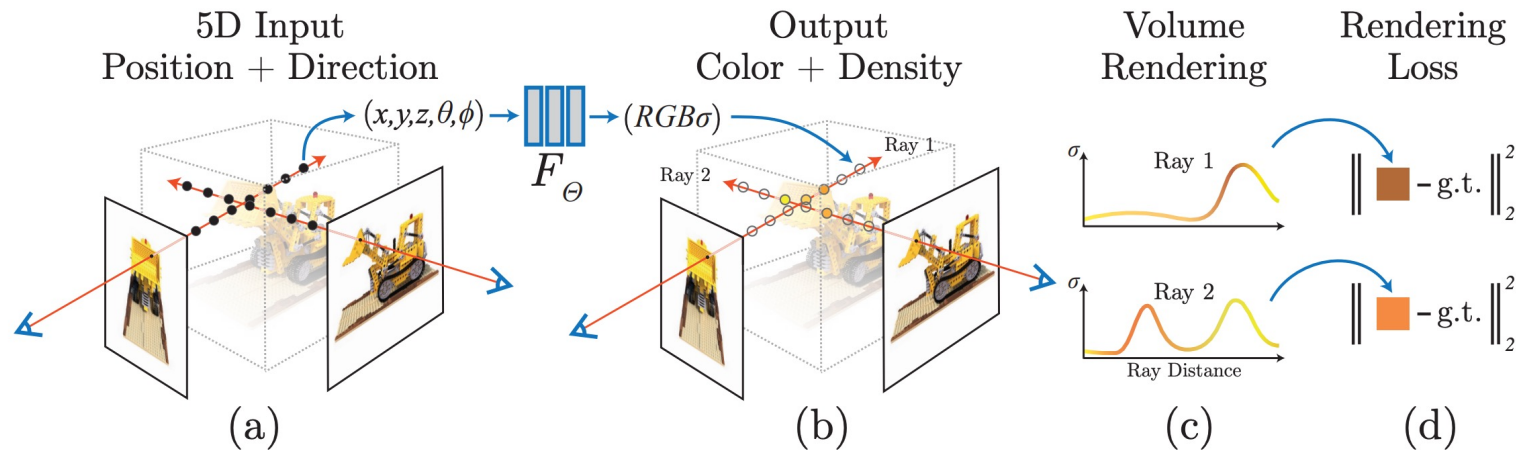
4.3. Coarse-to-fine Optimization

We describe our coarse-to-fine optimization procedure, which first operates on a coarse neural field representation and subsequently a high-resolution textured mesh.

Tips: 图片中的每个小模块对应着论文中解释方法时候每一个模块

技术方案流程图

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3 Neural Radiance Field Scene Representation

We represent a continuous scene as a 5D vector-valued function whose input is

4 Volume Rendering with Radiance Fields

Our 5D neural radiance field represents a scene as the volume density and directional emitted radiance at any point in space. We render the color of any ray

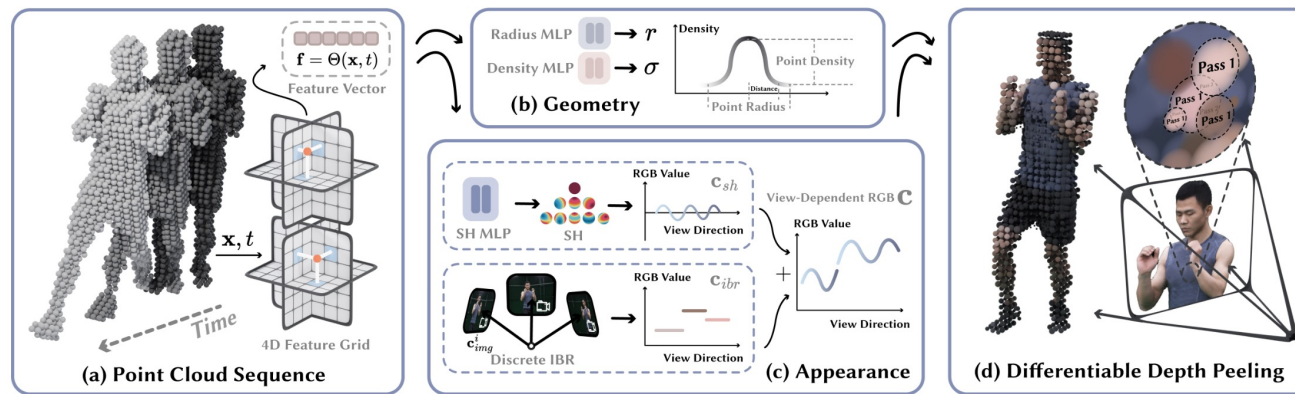
5 Optimizing a Neural Radiance Field

In the previous section we have described the core components necessary for modeling a scene as a neural radiance field and rendering novel views from this

Tips: 图片中的每个小模块对应着论文中解释方法时候每一个模块

技术方案流程图

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 - 方法的核心步骤
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3.1. Modeling Dynamic Scenes with Point Clouds

4D embedding. Given the coarse point clouds of the target scene, we represent its dynamic geometry and appearance using neural networks and feature grids. Specifically, our method first defines six feature planes $\theta_{xy}, \theta_{xz}, \theta_{yz}, \theta_{tx}, \theta_{ty}$, and θ_{tz} . To assign a feature vector \mathbf{f} to any point \mathbf{x} at frame t , we adopt the strategy of K-Planes [19] to model a 4D feature field $\Theta(\mathbf{x}, t)$ using these six planes:

$$\mathbf{f} = \Theta(\mathbf{x}, t) = \theta_{xy}(x, y) \oplus \theta_{xz}(x, z) \oplus \theta_{yz}(y, z) \oplus \theta_{tx}(t, x) \oplus \theta_{ty}(t, y) \oplus \theta_{tz}(t, z), \quad (1)$$

where $\mathbf{x} = (x, y, z)$ is the input point, and \oplus indicates the concatenation operator. Please refer to K-Planes [19] for more implementation details.

Geometry model. Based on coarse point clouds, the dynamic scene geometry is represented by learning three entries on each point: position $\mathbf{p} \in R^3$, radius $r \in R$, and density $\sigma \in R$. Using these point entries, we calculate the volume density of space point \mathbf{x} with respect to an image pixel \mathbf{u} for the volume rendering, which will be described in Sec. 3.2. The point position \mathbf{p} is modeled as an optimizable vector. The radius r and density σ are predicted by feeding the feature vector \mathbf{f} in Eq. (1) to an MLP network.

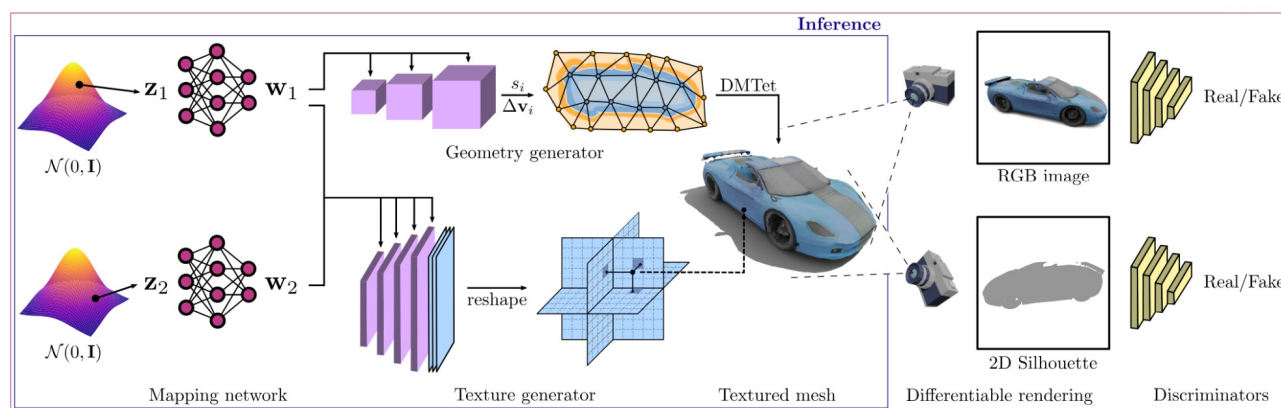
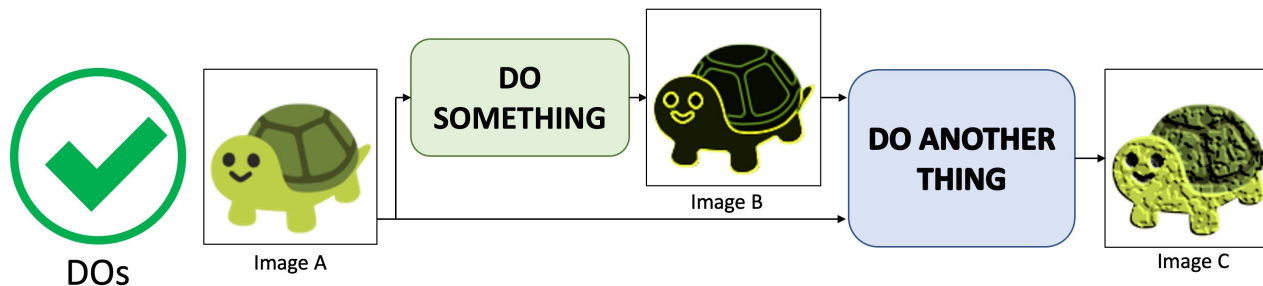
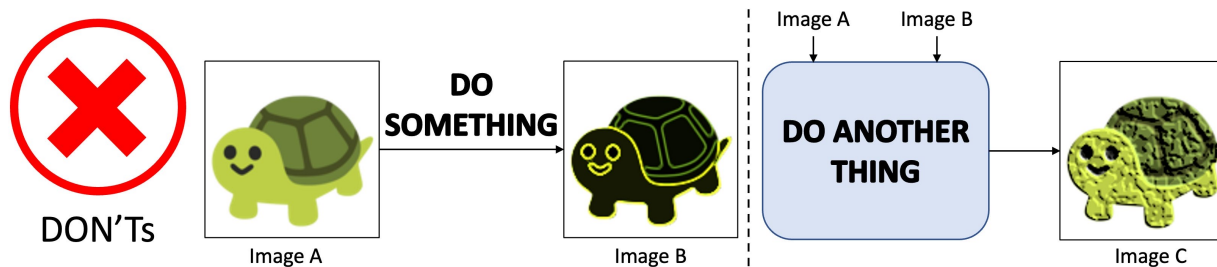
Appearance model. As illustrated in Fig. 2c, we use the image blending technique and the spherical harmonics (SH)

3.2. Differentiable Depth Peeling

Tips: 图片中的每个小模块对应着论文中解释方法时候每一个模块

技术方案流程图 – Tips

- 把技术方案想象成一个流程图



Tips: 通过箭头来表示输入与输出在每一个模块之间的连接关系

Credit: Jiabin Huang

<https://x.com/jbhuang0604/status/1665738070002483201>

技术方案流程图 – Tips

- 把技术方案想象成一个流程图
- 选择适当细节进行展示



DON'Ts



image

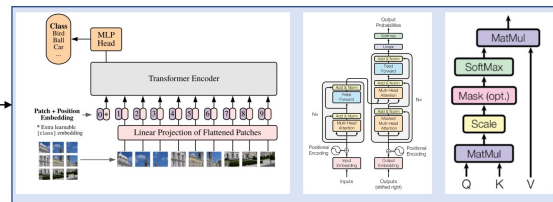


image encoder



image embedding



DOs



image

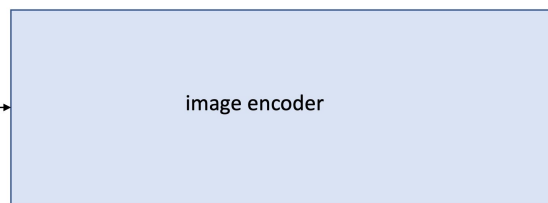
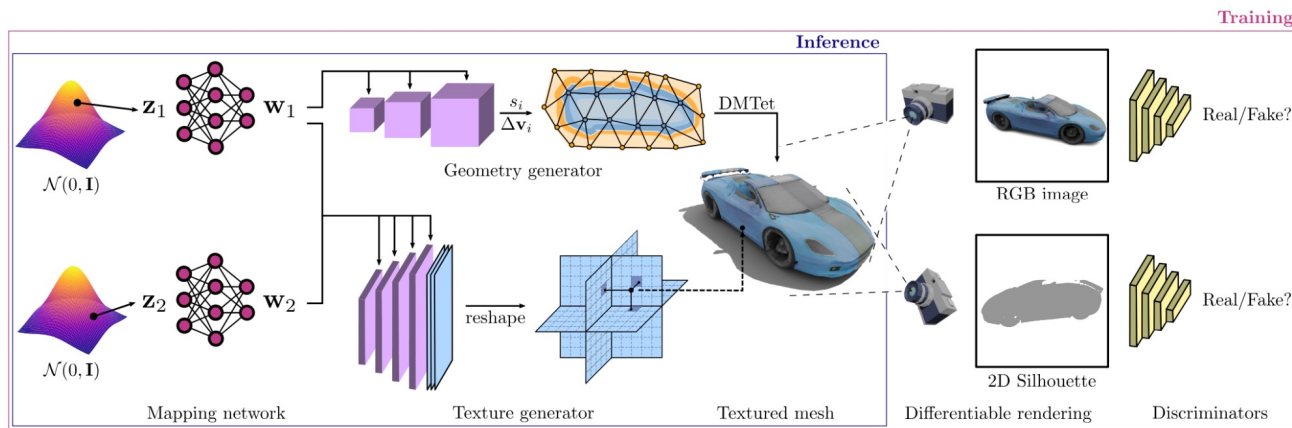


image encoder



image embedding



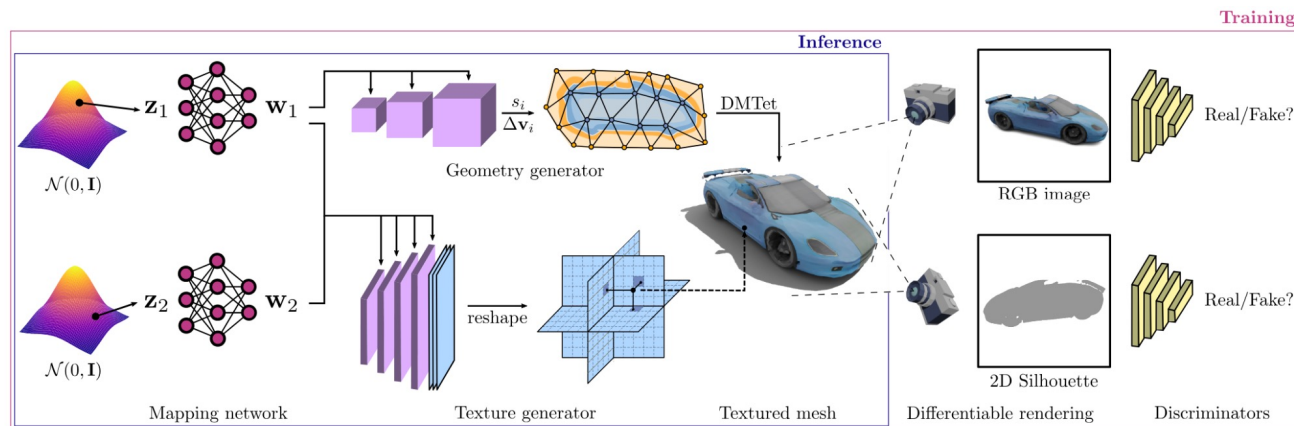
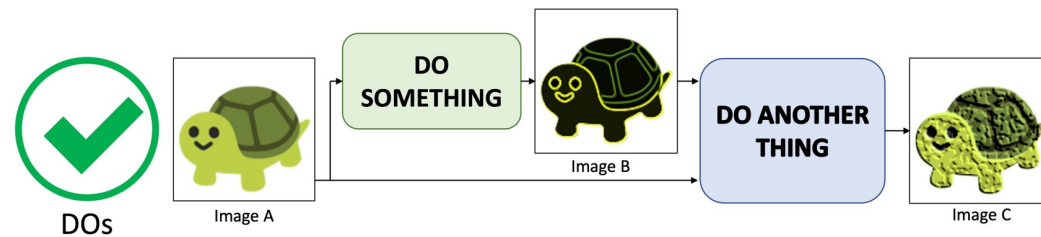
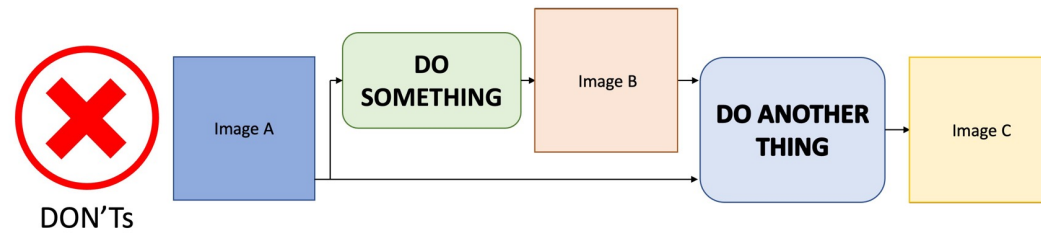
Tips: 想想如果这个简化了会不会影响别人理解你的方法
少即是多 ☺

Credit: Jiabin Huang

<https://x.com/jbhuang0604/status/1665738070002483201>

技术方案流程图 – Tips

- 把技术方案想象成一个流程图
- 选择适当细节进行展示
- 用图片去展示每一部分内容
 - 文字只是附带的解释
 - 图片胜似千言



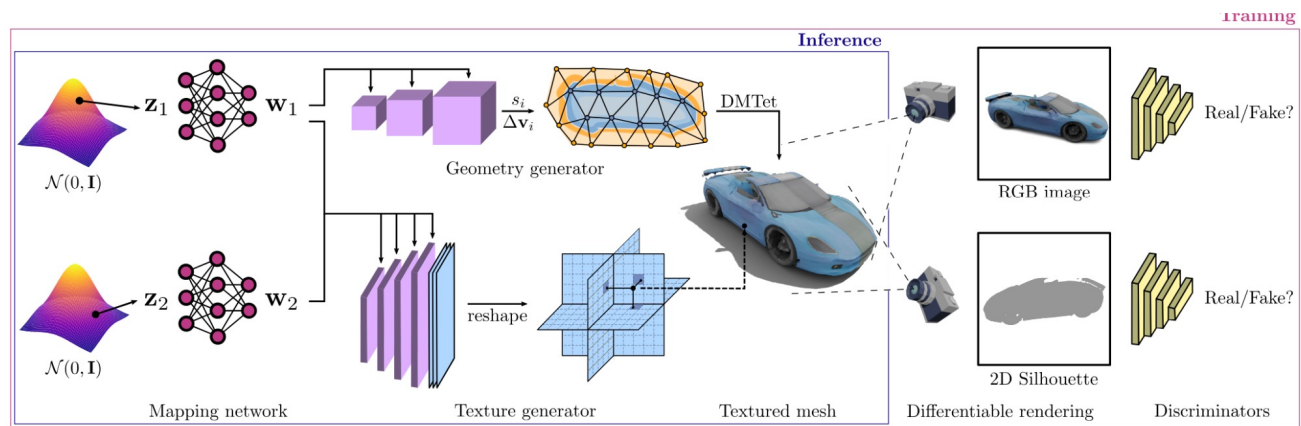
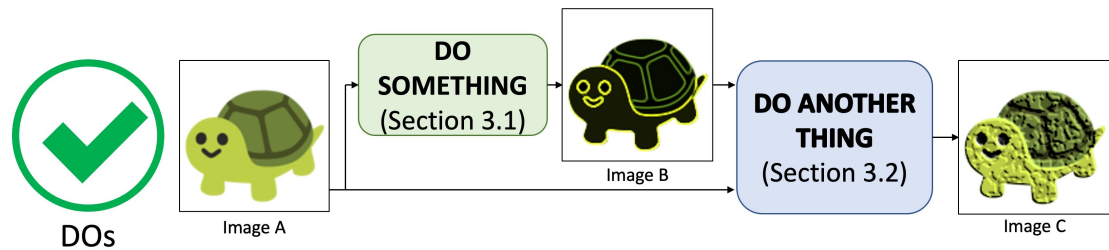
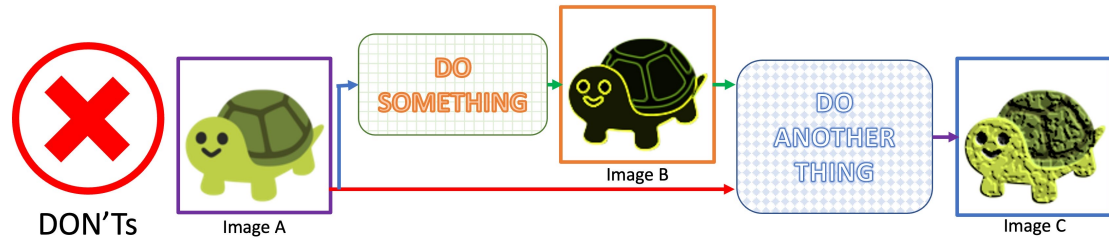
Tips: 图片胜过文字

Credit: Jiabin Huang

<https://x.com/jbhuang0604/status/1665738070002483201>

技术方案流程图 – Tips

- 把技术方案想象成一个流程图
- 选择适当细节进行展示
- 用图片去展示每一部分内容
 - 文字只是附带的解释
- 流程图和论文相呼应
- 不要用过多的色彩



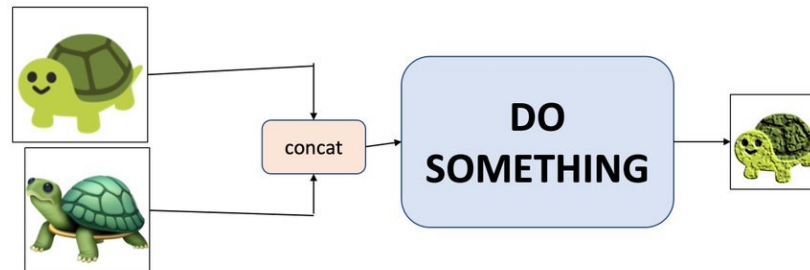
Tips: 一张图里面不要有超过三种色调
(这个图片是特地挑了一个蓝色的车)

技术方案流程图 – Tips

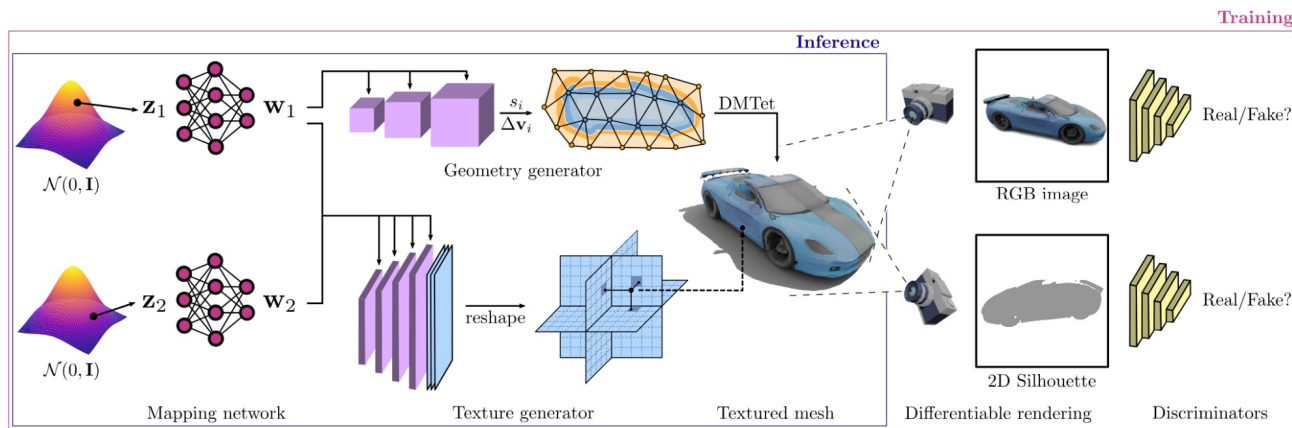
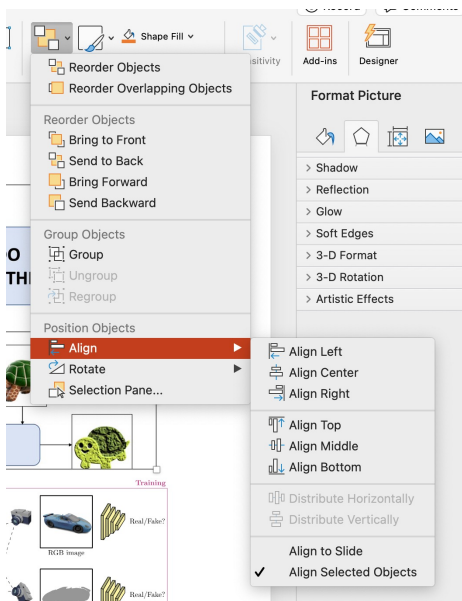
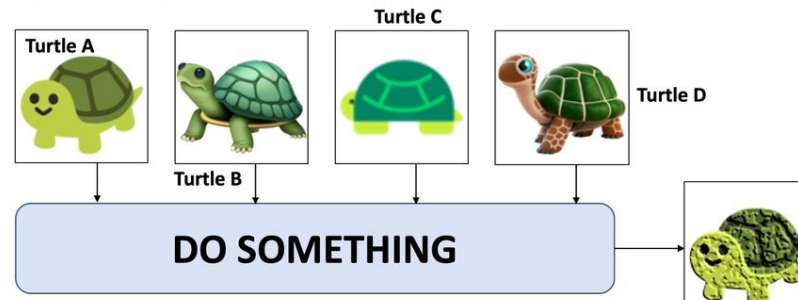
- 把技术方案想象成一个流程图
- 选择适当细节进行展示
- 用图片去展示每一部分内容
 - 文字只是附带的解释
- 流程图和论文相呼应
- 不要用过多的色彩
- 对齐文字，图片，线段



DON'Ts



DON'Ts



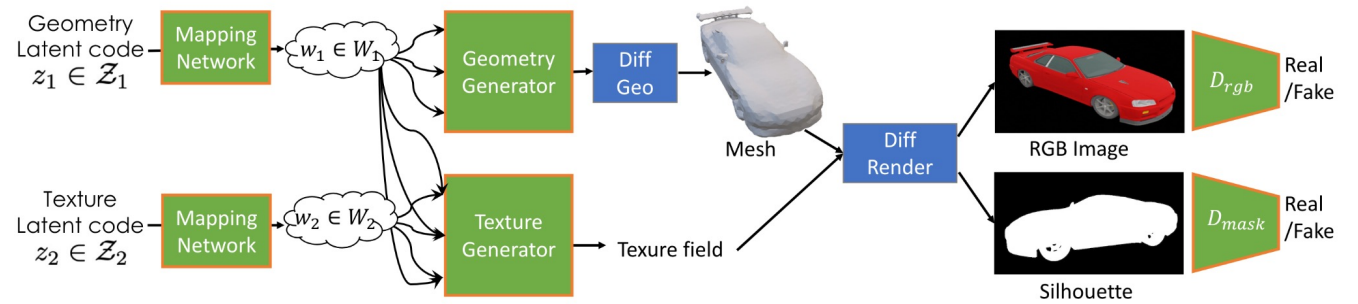
Tips: PPT有一个很好的tool

Credit: Jiabin Huang

<https://x.com/jbhuang0604/status/1665738070002483201>

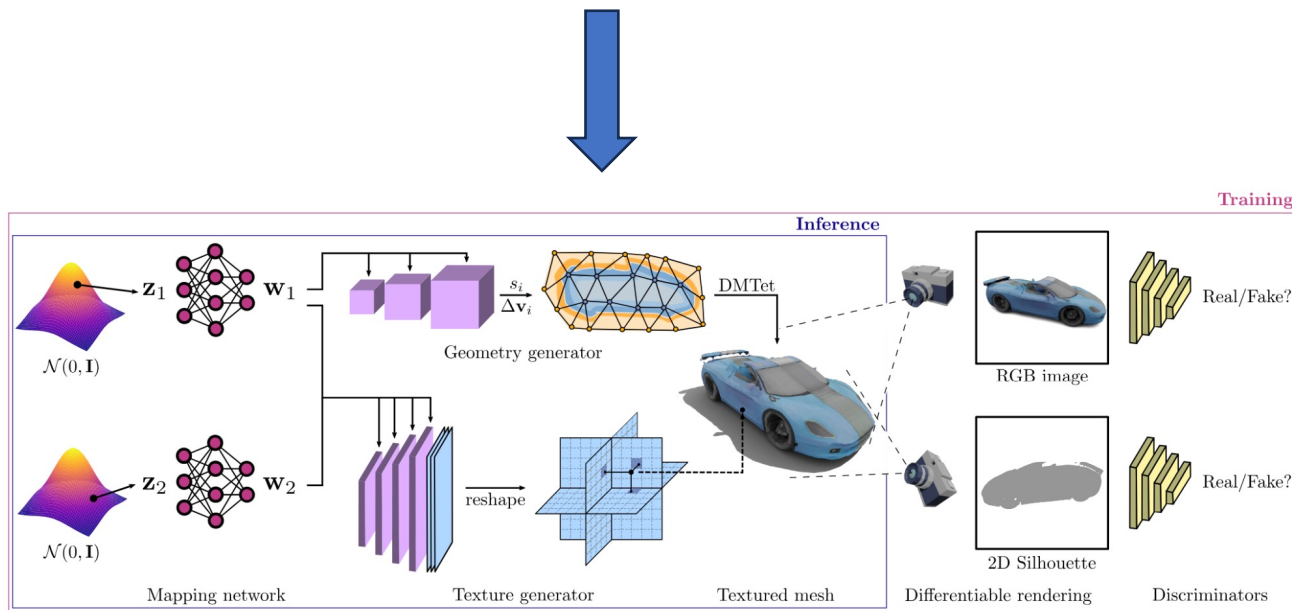
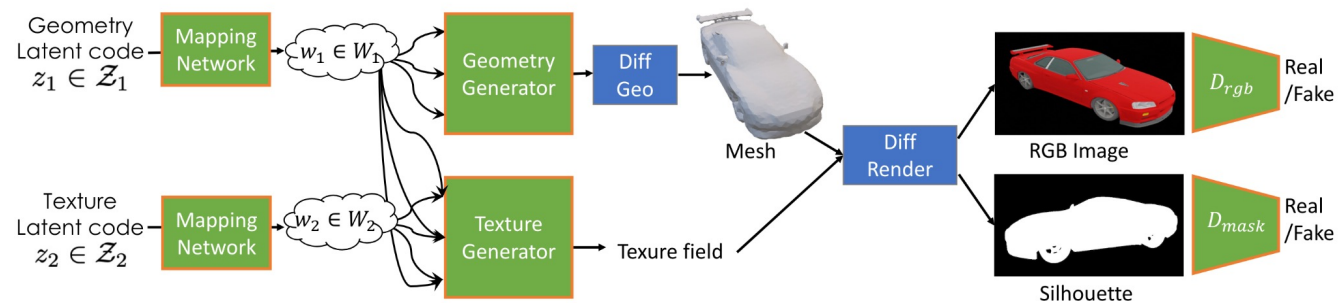
怎么画技术方案流程图

- 从最简单的流程图开始
 - 先画出来轮廓



怎么画技术方案流程图

- 从最简单的流程图开始
 - 先画出来轮廓
- 提升细节
 - 能用图片的就不用文字
 - Diff geo, diff render,
 - Geometry generator
 - Texture generator
 - Drgb, Dmask
 - 能删掉的就删掉
 - Texture latent code
 - Geometry latent code
 - 换更好看的图片
 - 背景从黑色变成白色
 - 三维的示意图表示网络结构
 - 字体, 线段, 图片对齐



怎么画技术方案流程图

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 - 字体, 线段, 图片对齐
- 写Caption!!!
 - 解释图片
 - 读者能够只看这张图+caption理解我们的方法

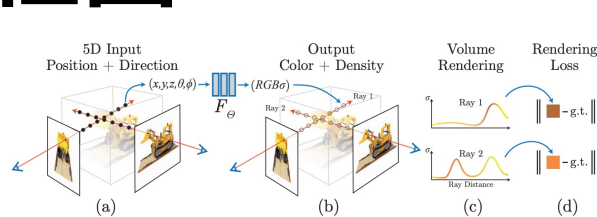


Fig. 2: An overview of our neural radiance field scene representation and differentiable rendering procedure. We synthesize images by sampling 5D coordinates (location and viewing direction) along camera rays (a), feeding those locations into an MLP to produce a color and volume density (b), and using volume rendering techniques to composite these values into an image (c). This rendering function is differentiable, so we can optimize our scene representation by minimizing the residual between synthesized and ground truth observed images (d).

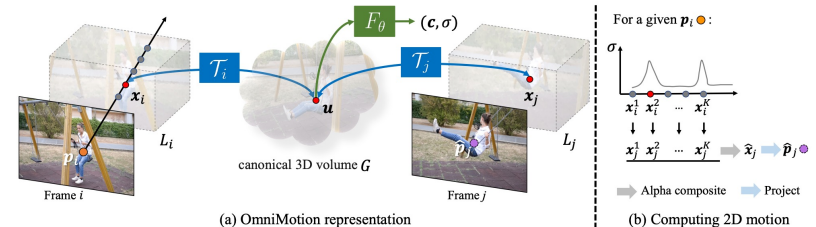


Figure 2: *Method overview.* (a) Our OmniMotion representation is comprised of a canonical 3D volume G and a set of bijections T_i that map between each frame's local volume L_i and the canonical volume G . Any local 3D location x_i in frame i can be mapped to its corresponding canonical location u through T_i , and then mapped back to another frame j as x_j through the inverse mapping T_j^{-1} . Each location u in G is associated with a color c and density σ , computed using a coordinate-based MLP F_θ . (b) To compute the corresponding 2D location for a given query point p_i , mapped from frame i to j , we shoot a ray into L_i and sample a set of points $\{x_j^k\}_{k=1}^K$, which are then mapped first to the canonical space to obtain their densities, and then to frame j to compute their corresponding local 3D locations $\{x_j^k\}_{k=1}^K$. These points $\{x_j^k\}_{k=1}^K$ are then alpha-composited and projected to obtain the 2D corresponding location β_j .

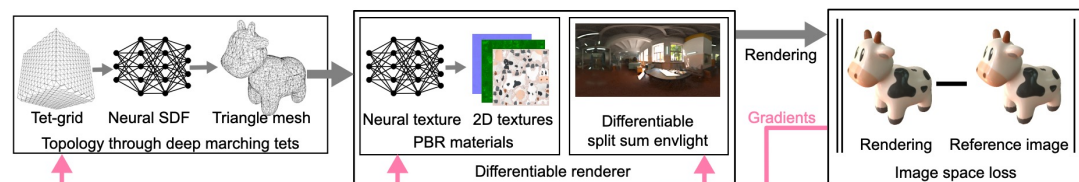


Figure 2. **Overview of our approach.** We learn topology, materials, and environment map lighting jointly from 2D supervision. We leverage differentiable marching tetrahedrons to directly optimize topology of a triangle mesh. While the topology is drastically changing, we learn materials through volumetric texturing, efficiently encoded using an MLP with positional encoding. Finally, we introduce a differentiable version of the split sum approximation for environment lighting. Our output representation is a triangle mesh with spatially varying 2D textures and a high dynamic range environment map, which can be used unmodified in standard game engines. The system is trained end-to-end, supervised by loss in image space, with gradient-based optimization of all stages. Spot model by Keenan Crane.

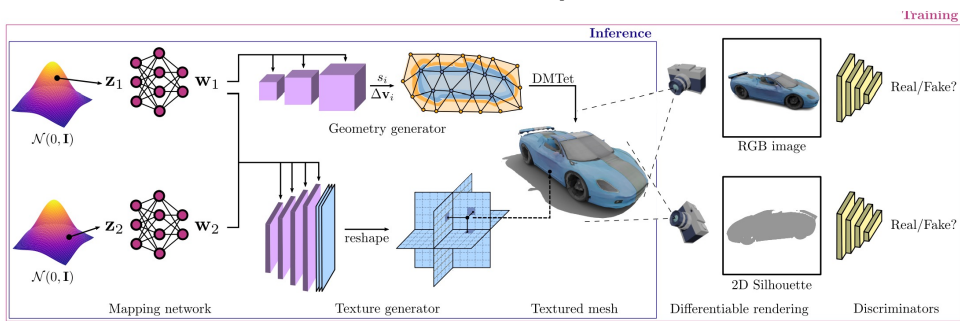


Figure 2: Overview of GET3D: We generate a 3D SDF and a texture field via two latent codes. We utilize DMtet [60] to extract a 3D surface mesh from the SDF, and query the texture field at surface points to get colors. We train with adversarial losses defined on 2D images. In particular, we use a rasterization-based differentiable renderer [37] to obtain RGB images and silhouettes. We utilize two 2D discriminators, each on RGB image, and silhouette, respectively, to classify whether the inputs are real or fake. The whole model is end-to-end trainable. Note that we additionally provide an improved version of our Generator in Appendix A.5 and Fig. C.

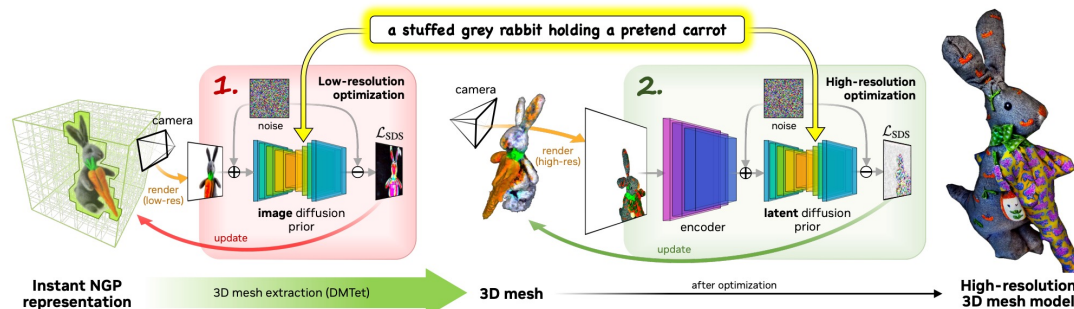


Figure 2. **Overview of Magic3D.** We generate high-resolution 3D content from an input text prompt in a coarse-to-fine manner. In the first stage, we utilize a low-resolution diffusion prior and optimize neural field representations (color, density, and normal fields) to obtain the coarse model. We further differentially extract textured 3D mesh from the density and color fields of the coarse model. Then we fine-tune it using a high-resolution latent diffusion model. After optimization, our model generates high-quality 3D meshes with detailed textures.

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 - 解释图片
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Fig. 2: The overview of our proposed approach.

反面示例



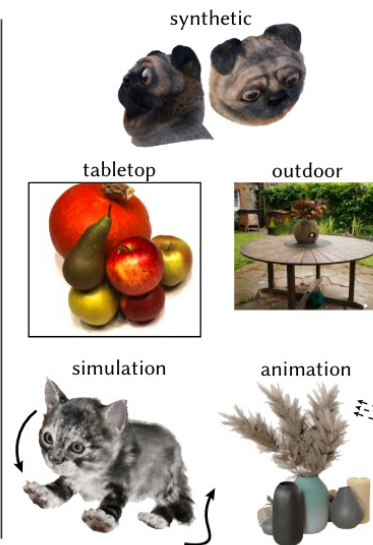
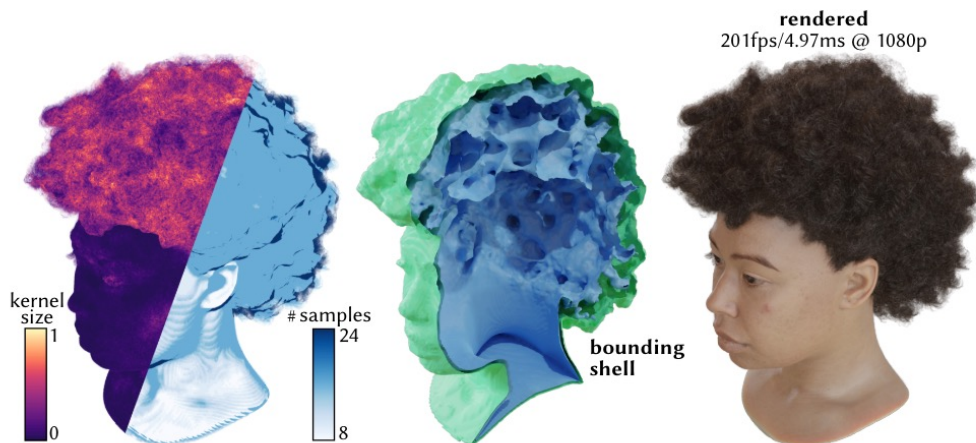
课程内容

- 图片设计
 - 技术方案流程图
 - **片头Teaser图**
 - 实验结果图
 - Quantitative 图
 - Qualitative 图
- 表格设计
 - 实验方法的表格
 - 实验结果的表格
- 视频设计
 - 实验结果的视频

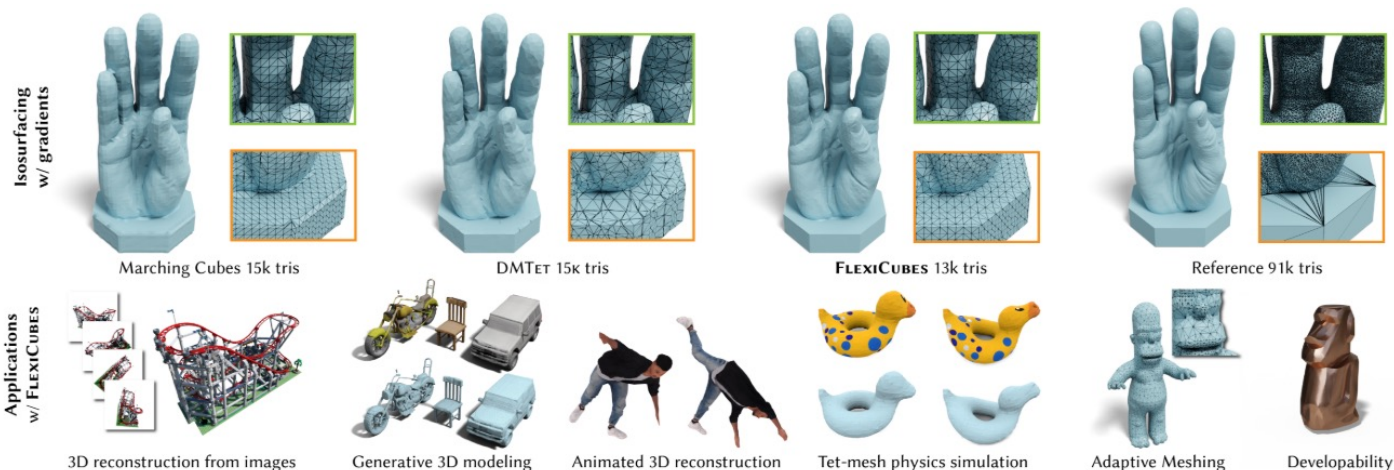
片头Teaser图

SRINIVAS DEBILAKAR, NVIDIA, University of Toronto, Vector Institute, Canada
THOMAS MÜLLER, NVIDIA, Switzerland
ZAN GOJCIC, NVIDIA, Switzerland

- Teaser是大家第一眼看到的图片
- 核心是需要突出重点
 - 方法最核心的贡献
 - 更好的performance?



Improving inference speed and quality



Improving triangle quality

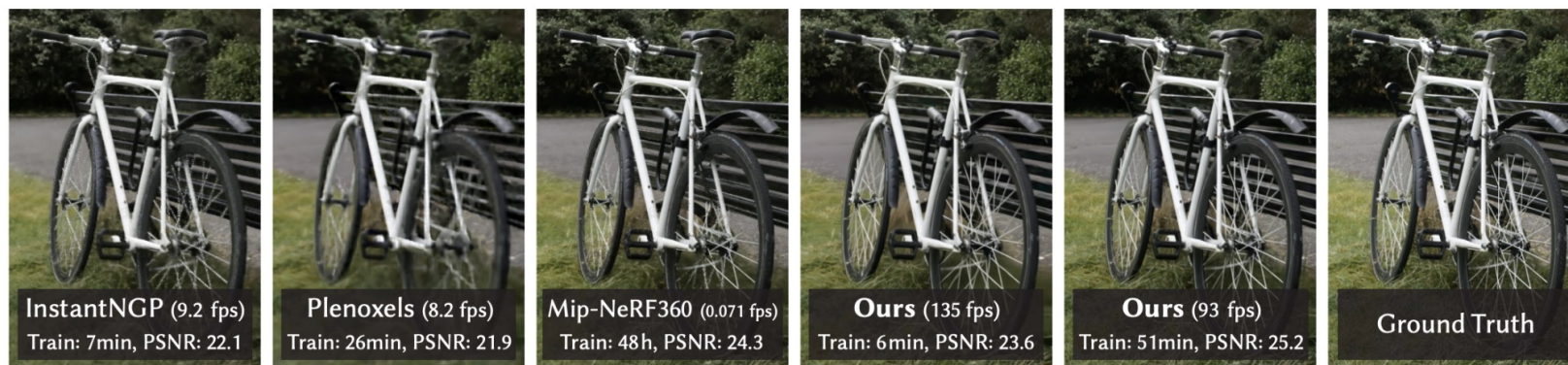
Tips: 想想文章最核心的贡献是什么

片头Teaser图

- Teaser是大家第一眼看到的图片
- 核心是需要突出重点
 - 方法最核心的贡献
 - 更难的（新的）任务？



Tracking every pixel in every frame

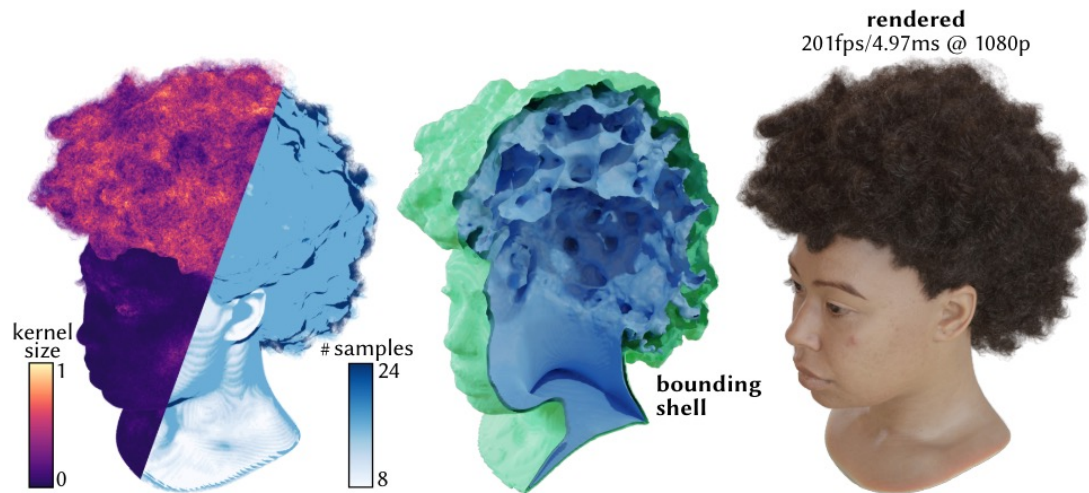


Improving training speed and quality

Tips: 想想文章最核心的贡献是什么

片头Teaser图

- Teaser是大家第一眼看到的图片
- 核心是需要突出重点
 - 方法最核心的贡献
 - 新的方法能被用到更多的场景?
 - 别人不能做的任务?



Tips: 实验章节展示了哪些让人眼前一亮的结果?

片头Teaser图

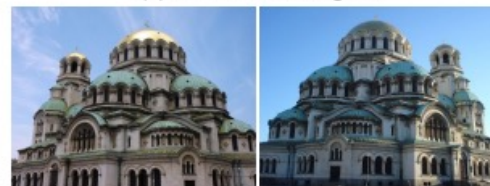
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 - 方法最核心的贡献
 - 新的方法能被用到更多的场景?
 - 别人不能做的任务?
 - 能不能引起别人思考?



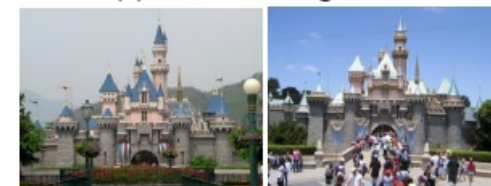
(a) Arc de Triomphe



(b) Charlottenburg Palace

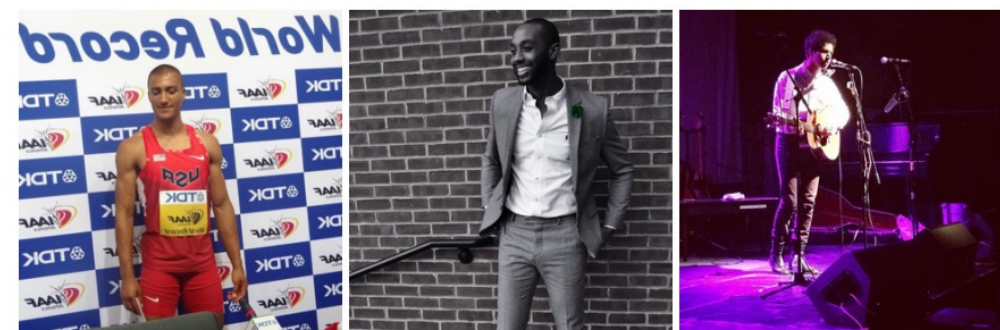


(c) Alexander Nevsky Cathedral



(d) Sleeping Beauty Castles

Figure 1. These image pairs observe distinct but visually similar 3D surfaces. Can you spot the differences and distinguish between the two images in each pair? Hints in the footnote.¹ Such illusory image matches can fool humans, and also fool 3D reconstruction algorithms into thinking they share 3D correspondence. We propose



(a)

(b)

(c)

Figure 1. **Which images have been mirrored?** Our goal is to understand how distributions of natural images differ from their

Tips: 文章的motivation能不能用一个图片来展示? 实验那个章节展示了哪些让人眼前一亮的结果?

片头Teaser图

- Teaser是大家第一眼看到的图片
- 核心是需要突出重点
 - 方法最核心的贡献
 - 新的方法能被用到更多的场景?
 - 别人不能做的任务?
 - 能不能引起别人思考?
 - 也可以是解释具体的任务是什么

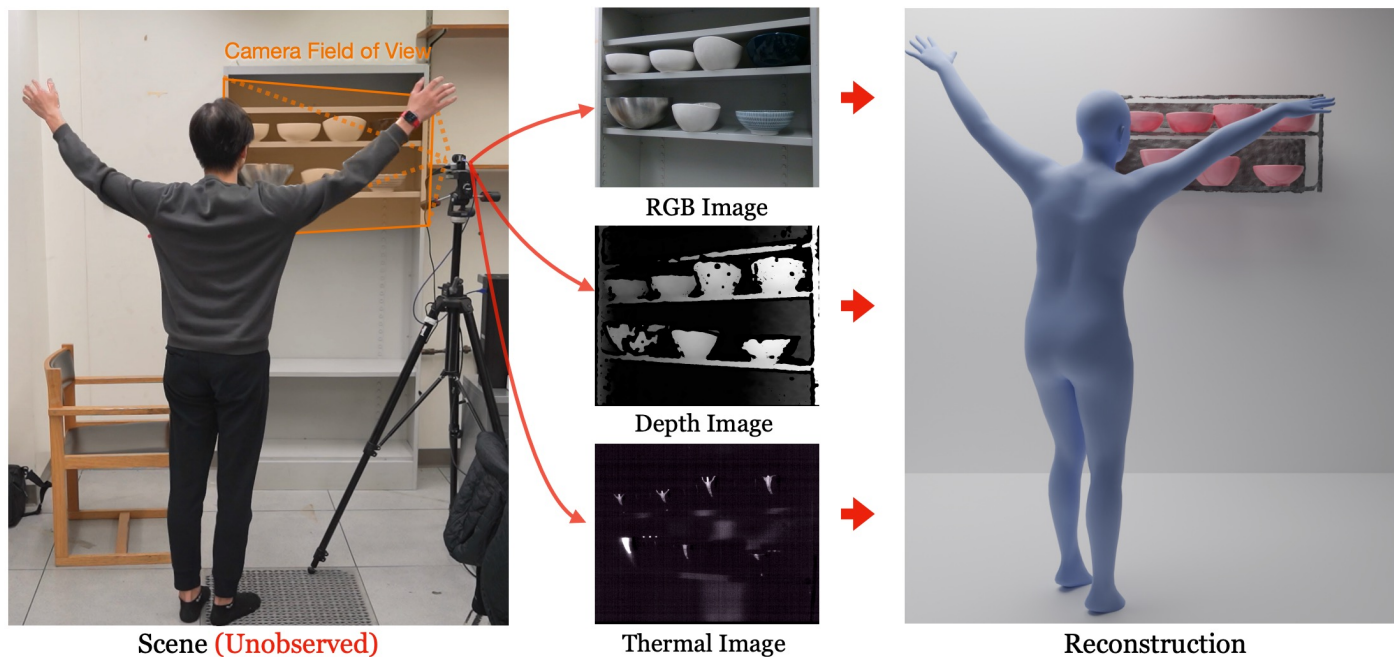


Figure 1. We introduce a method to reconstruct the 3D position and pose of a person from their thermal reflections in everyday objects with non-planar surfaces. Given an RGBD image and a thermal image in the middle of the figure, our method is able to recover the 3D mesh of the person (blue) as well as the objects (pink), even though they are not within the field of view of the camera system. Our system **never sees the scene on the left**, which is only shown for visualization purposes.

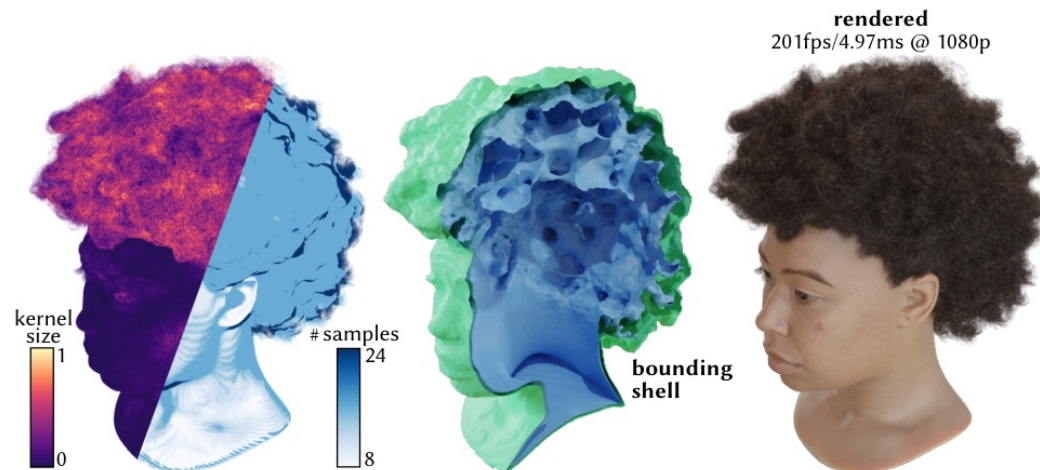
Tips: 把任务的输入输出解释清楚

片头Teaser图

- Teaser是大家第一眼看到的图片
- 核心是需要突出重点
 - 方法最核心的贡献
 - 新的方法能被用到更多的场景?
 - 别人不能做的任务?
 - 能不能引起别人思考?
 - 也可以是解释具体的任务是什么
- 合适的Teaser – Tips
 - 与Method很类似
 - 简洁, 清晰, 切中要害

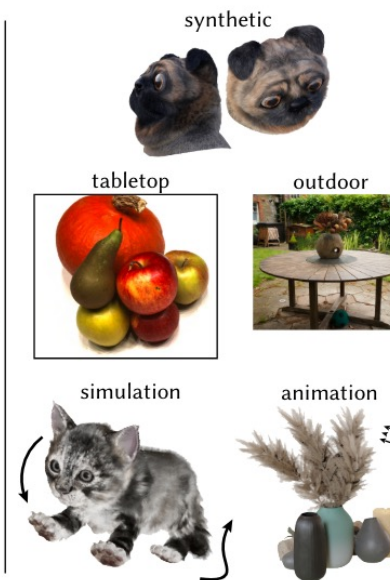


SANJAY VIDLER, NVIDIA, University of Toronto, Vector Institute, Canada
THOMAS MÜLLER, NVIDIA, Switzerland
ZAN GOJCIC, NVIDIA, Switzerland



Tips: 参照method部分

- 多用图片, 而不是文字
- 去掉不必要的部分
- 对齐与色彩



片头Teaser图

- Teaser是大家第一眼看到的图片
- 核心是需要突出重点
 - 方法最核心的贡献
 - 新的方法能被用到更多的场景?
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 - 能不能引起别人思考?
 - 也可以是解释具体的任务是什么
- 合适的Teaser
 - 与Method很类似
 - 简洁, 清晰, 切中要害
 - 写Caption!!!

Tips: 参照method部分

- 多用图片, 而不是文字
- 去掉不必要的部分
- 对齐与色彩

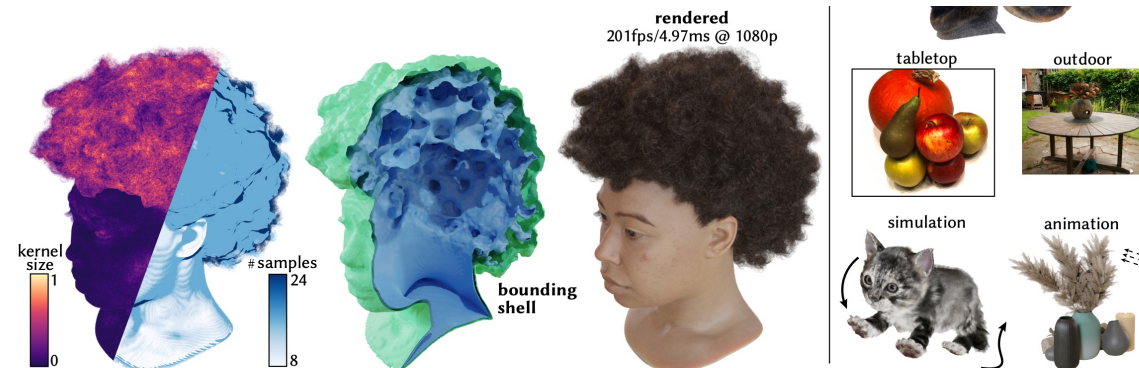


Fig. 1. This work presents an approach for efficiently rendering neural radiance fields by restricting volumetric rendering to a narrow band around the object. *Left:* We first fit a dense neural volume using a new spatially-varying kernel that automatically adapts to be large in volumetric regions such as hair or grass, and small in sharp-surface regions such as skin or furniture. We then extract an explicit bounding mesh of the region to be rendered whose width is determined by the kernel, and render at real-time rates. *Right:* the proposed method is general and effective across a wide range of data and well-suited for downstream applications such as simulation and animation. The face model of the Khady synthetic human shown *left* is courtesy of [texturing.xyz](#).



Figure 1: We present a new method for estimating full-length motion trajectories for every pixel in every frame of a video, as illustrated by the motion paths shown above. For clarity, we only show sparse trajectories for foreground objects, though our method computes motion for *all* pixels. Our method yields accurate, coherent long-range motion even for fast-moving objects, and robustly tracks through occlusions as shown in the *dog* and *swing* examples. For context, in the second row we depict the moving object at different moments in time.

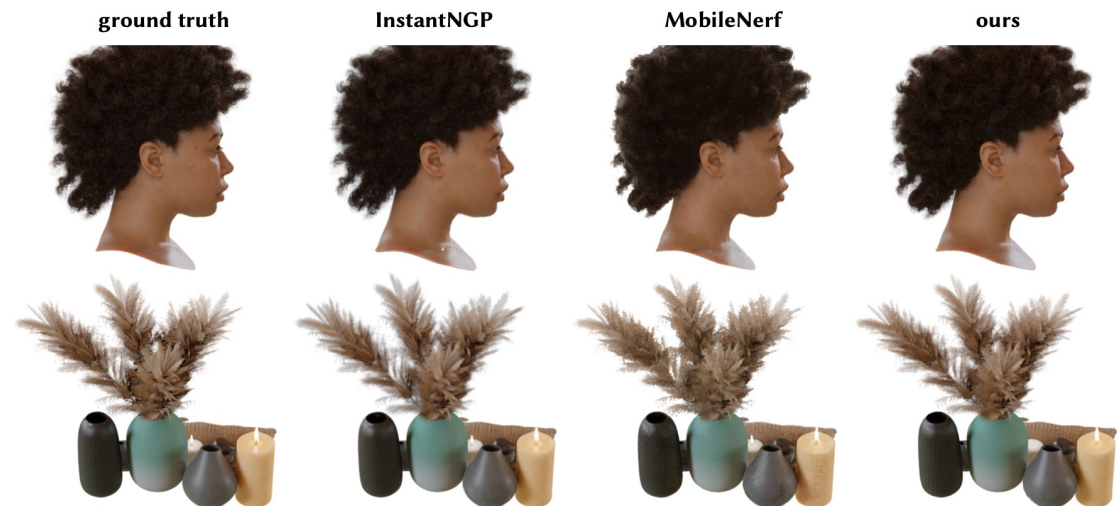


课程内容

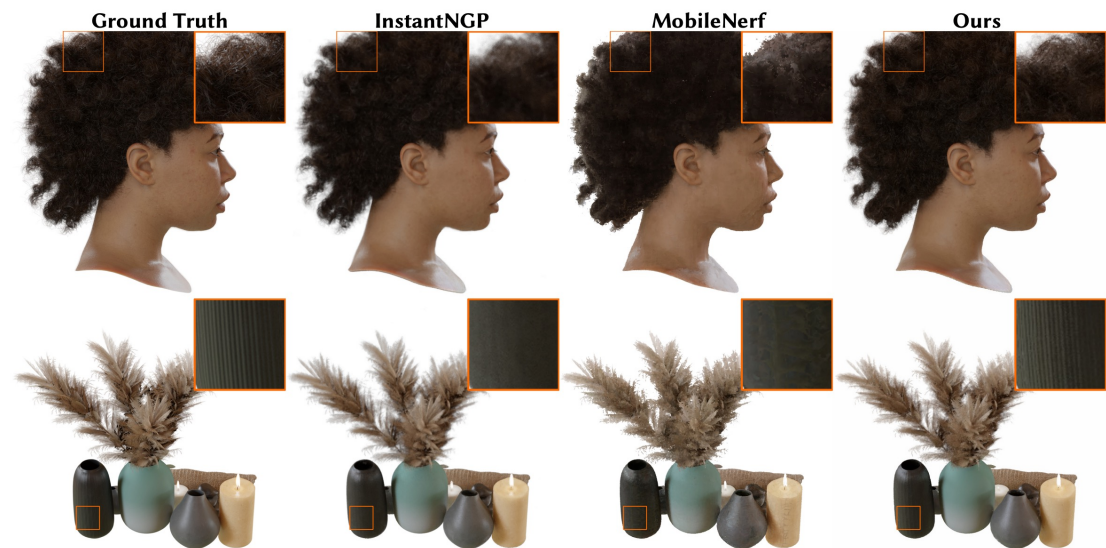
- 图片设计
 - 技术方案流程图
 - 片头Teaser图
 - **实验结果图**
 - **Quantitative 图**
 - Qualitative 图
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 - 实验方法的表格
 - 实验结果的表格
- 视频设计
 - 实验结果的视频

实验结果图 — Qualitative figure

- 核心依然是需要突出重点
 - 如果比别人好，好在什么地方？



Submission一天之前的图

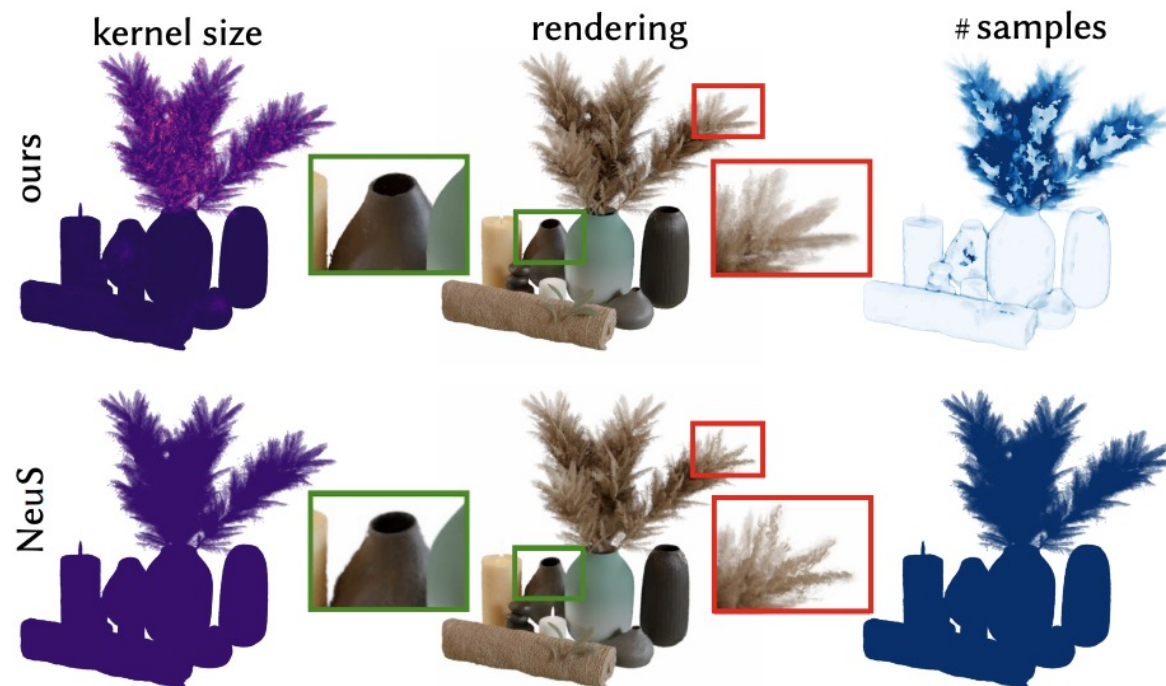
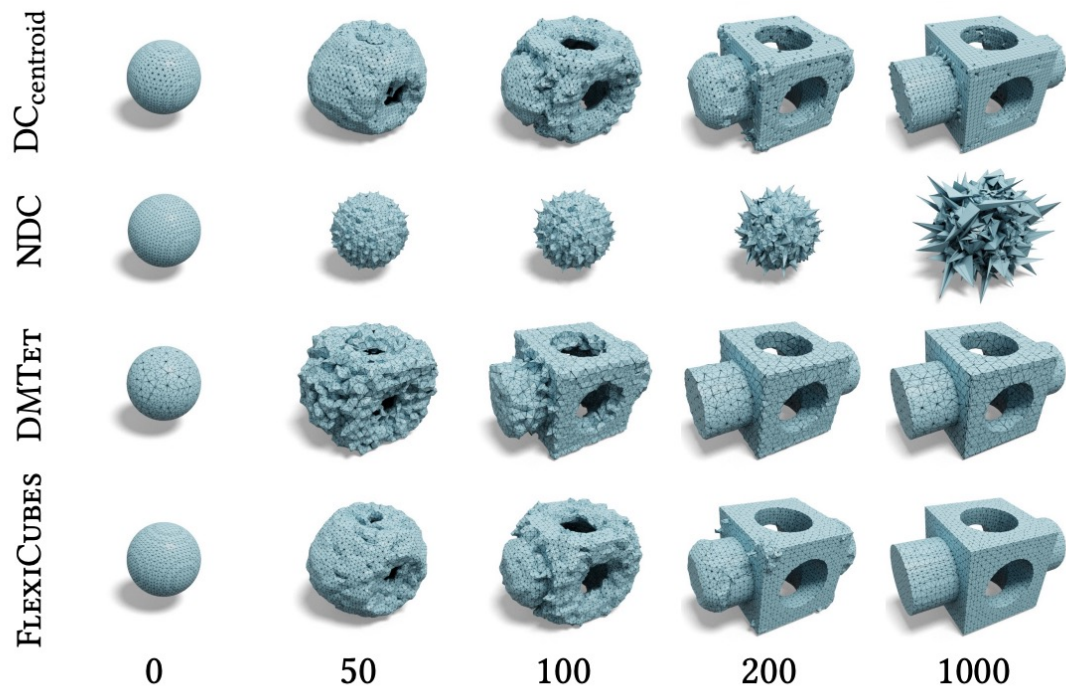


最终的submission

Tips: 突出有提升的地方，对它进行标亮

实验结果图 — Qualitative figure

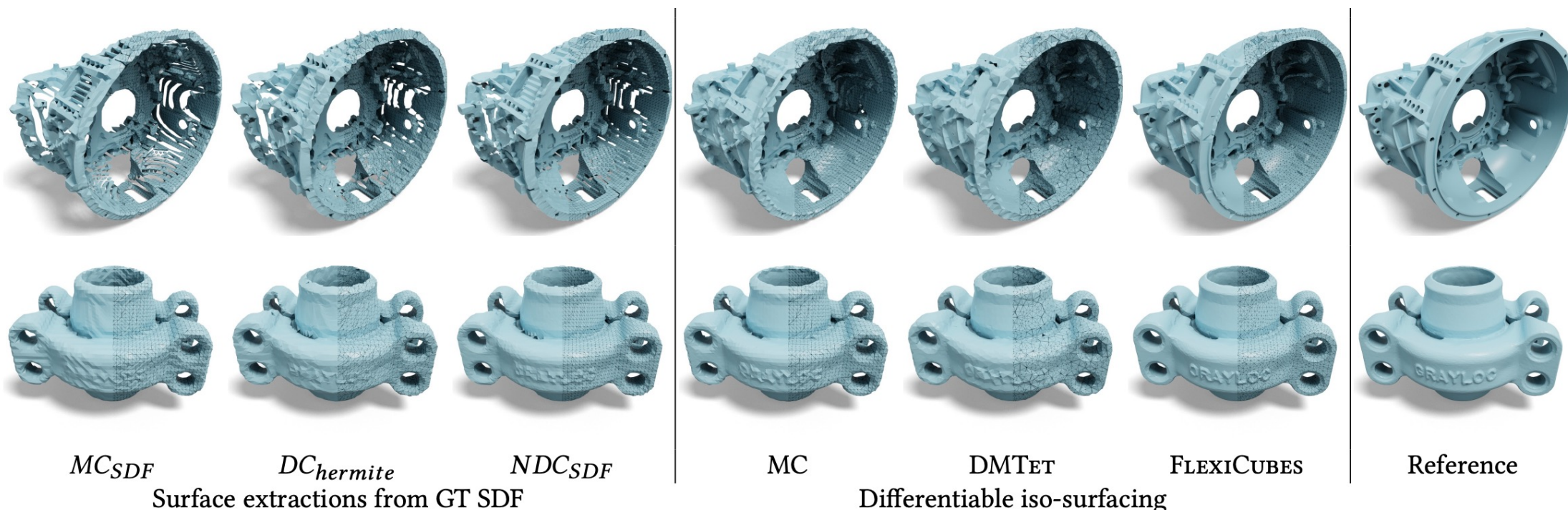
- 核心依然是需要突出重点
 - 如果比别人好，好在什么地方？
 - 方法上与别人不一样，不一样的地方在哪？



Tips: 有没有一个例子能说明我们跟baseline 方法上的不一样？

实验结果图 — Qualitative figure

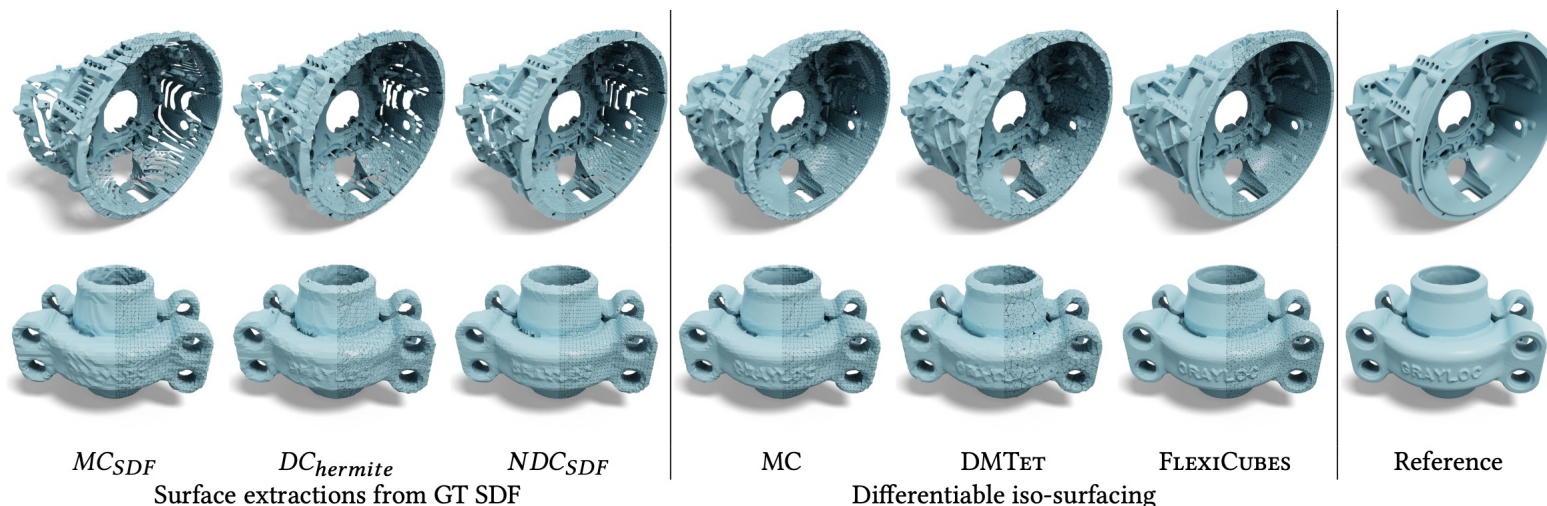
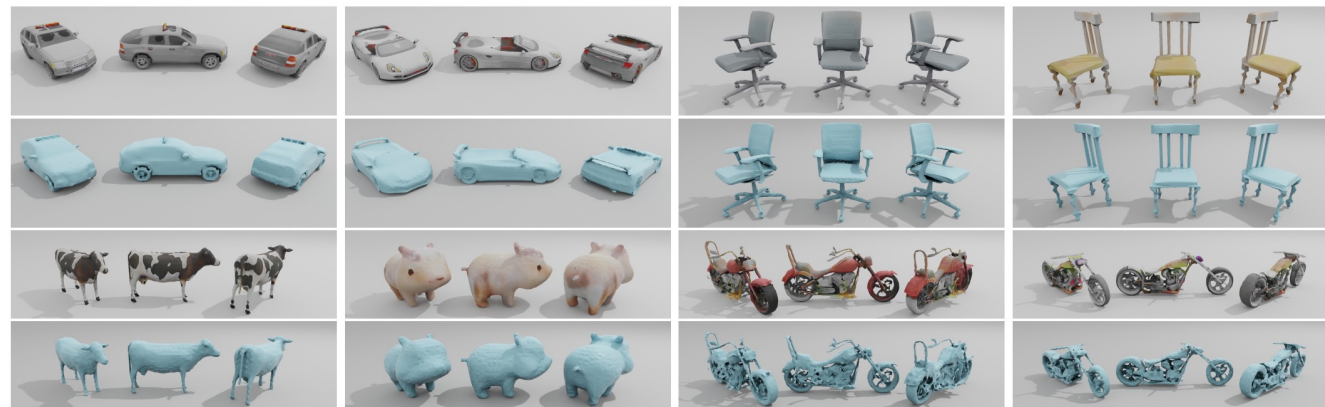
- 核心依然是需要突出重点
 - 如果比别人好，好在什么地方？
 - 方法上与别人不一样，不一样的地方在哪？
 - 把实验结果分类处理（有条理）



Tips: 对比的Baseline是不是可以分成两个类别?

实验结果图 — Qualitative figure

- 核心依然是需要突出重点
 - 如果比别人好，好在什么地方？
 - 方法上与别人不一样的地方在哪？
 - 把实验结果分类处理（有条理）
- 让图片变得好看
 - 用Blender渲染
 - <https://github.com/HTDerekLiu/BlenderToolbox>
 - 加阴影（三维效果）
 - 加光（三维效果）
 - 调一个自己喜欢的颜色
 - 不要用超过三种颜色



Tips: 学习使用Blender -> Blender的python接口 -> 批量渲染

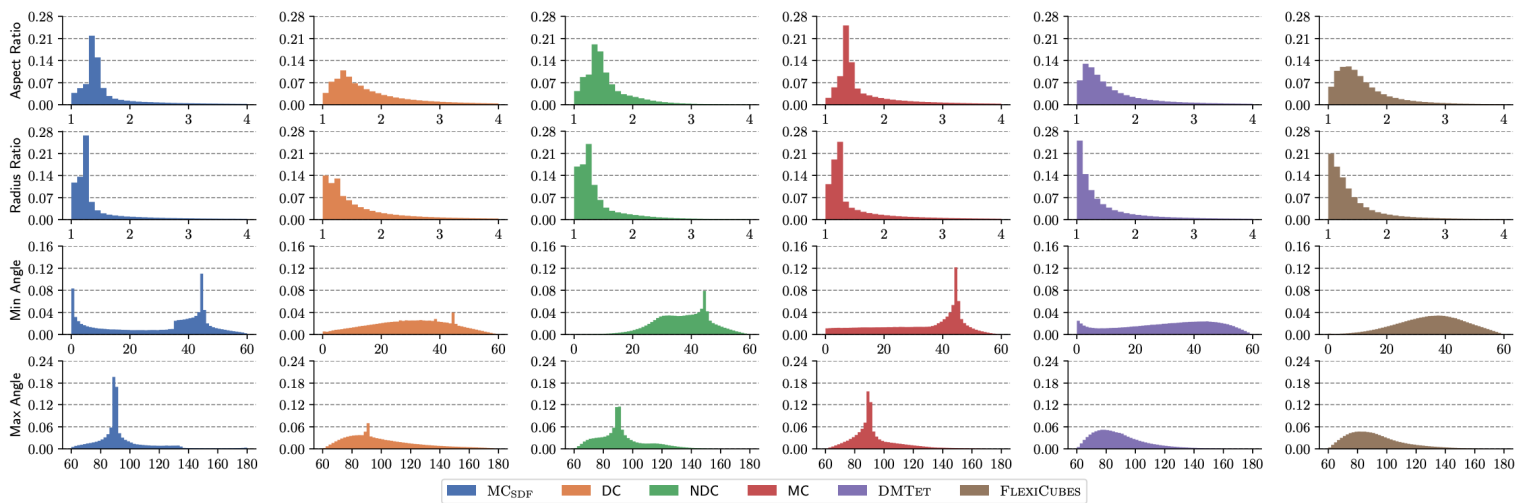
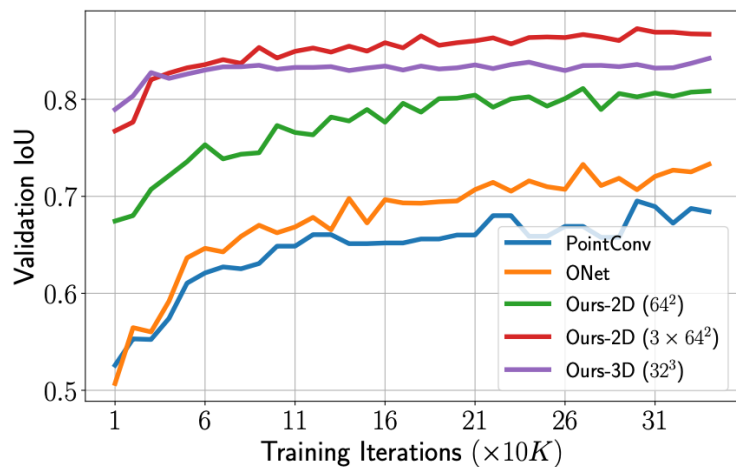
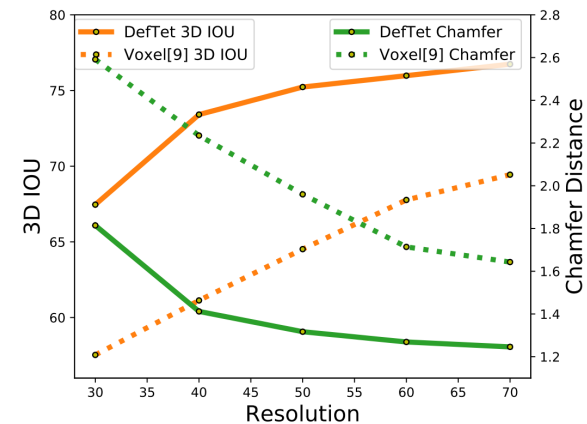
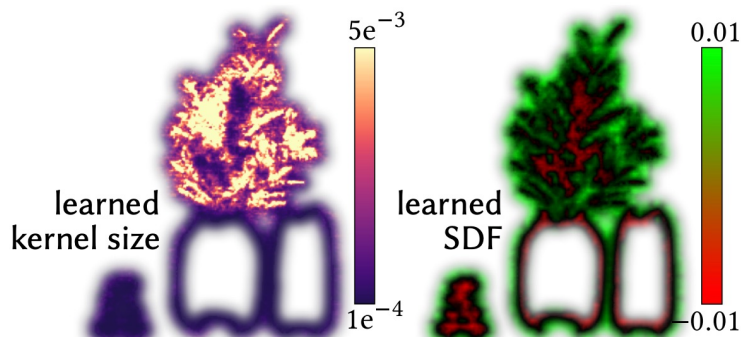


课程内容

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 - 实验结果的表格
- 视频设计
 - 实验结果的视频

实验结果图 – Quantitative figure

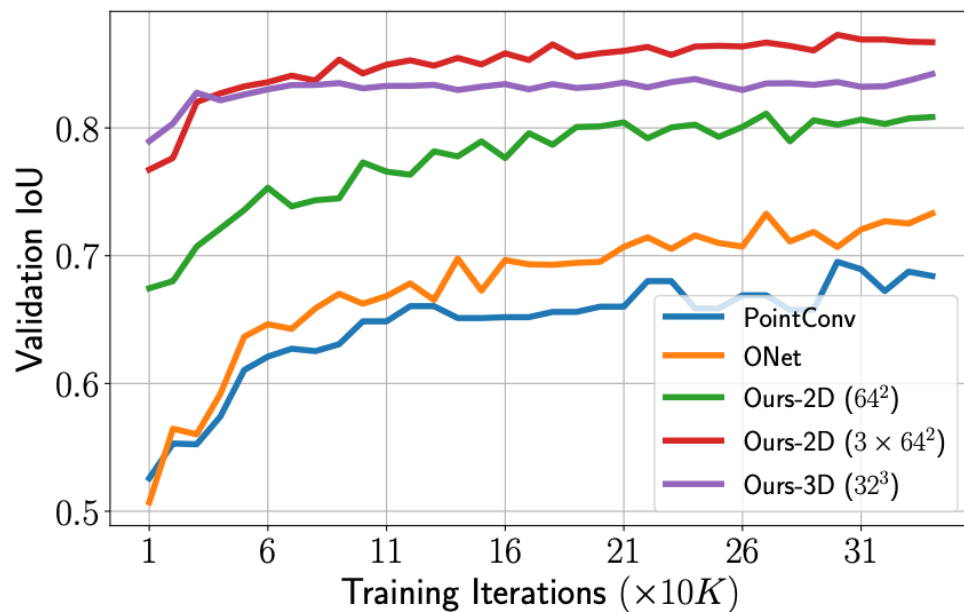
- 让读者看明白要展示的内容
 - 坐标轴的意义标清楚
 - 如果是热量图，记得带上color-bar



Tips: Python画图的时候都带上坐标轴

实验结果图 — Quantitative figure

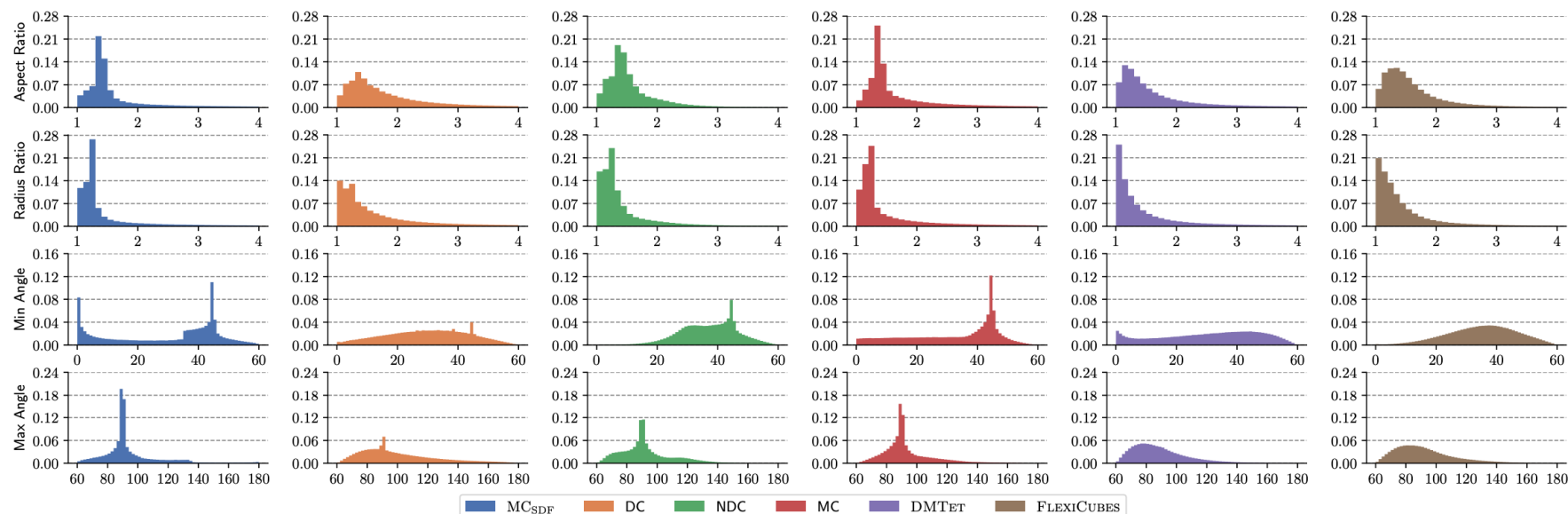
- 让读者看明白要展示的内容
 - 坐标轴的意义标清楚
 - 如果是热量图，记得带上color-bar
 - 不同的方法标出来legend



Tips: Python画图的时候都带上

实验结果图 — Quantitative figure

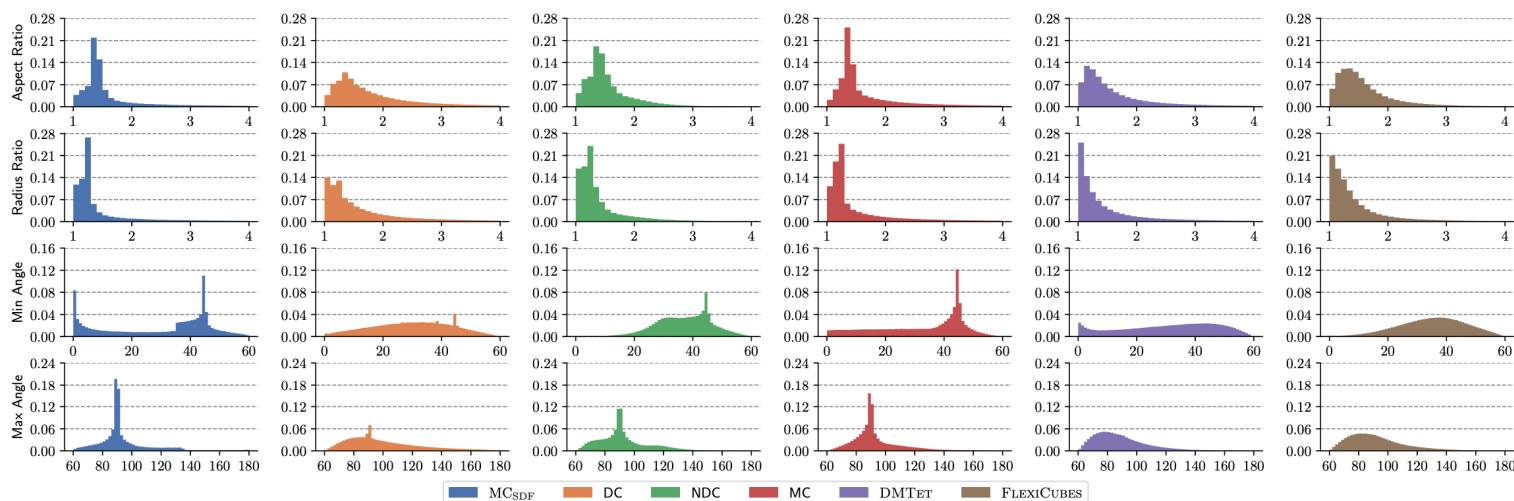
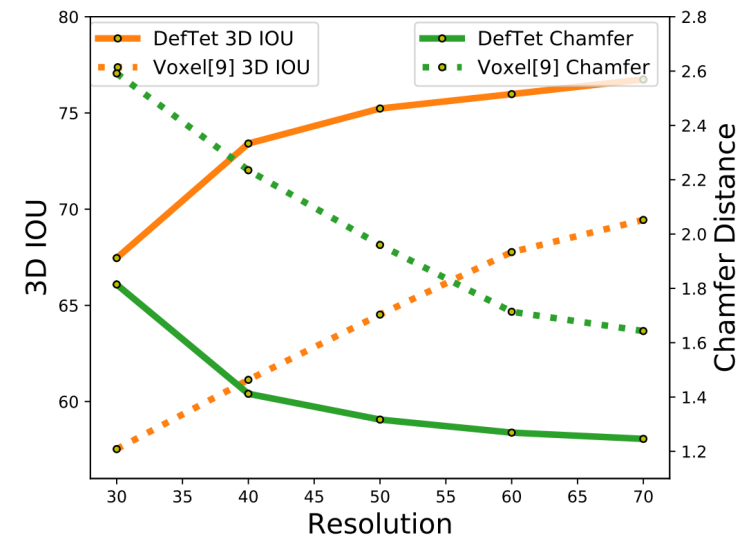
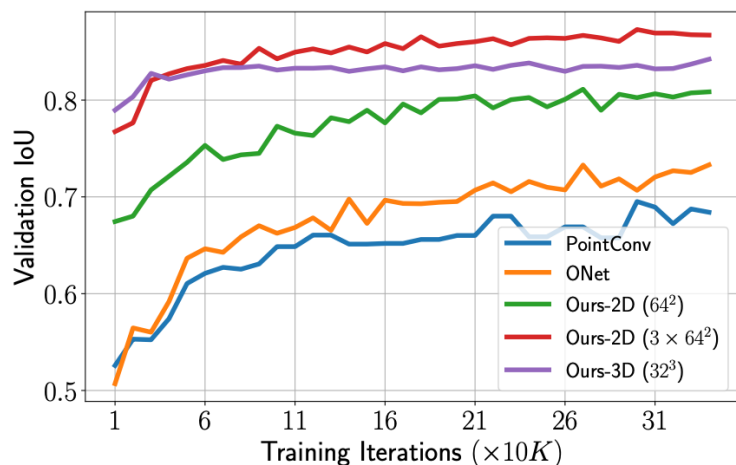
- 让读者看明白要展示的内容
 - 坐标轴的意义标清楚
 - 如果是热量图，记得带上color-bar
 - 不同的方法标出来legend
 - 去掉多余的空白的地方



Tips: 图片可以扣掉最顶上的跟下面的空白 (不需要占文章的空间)

实验结果图 — Quantitative figure

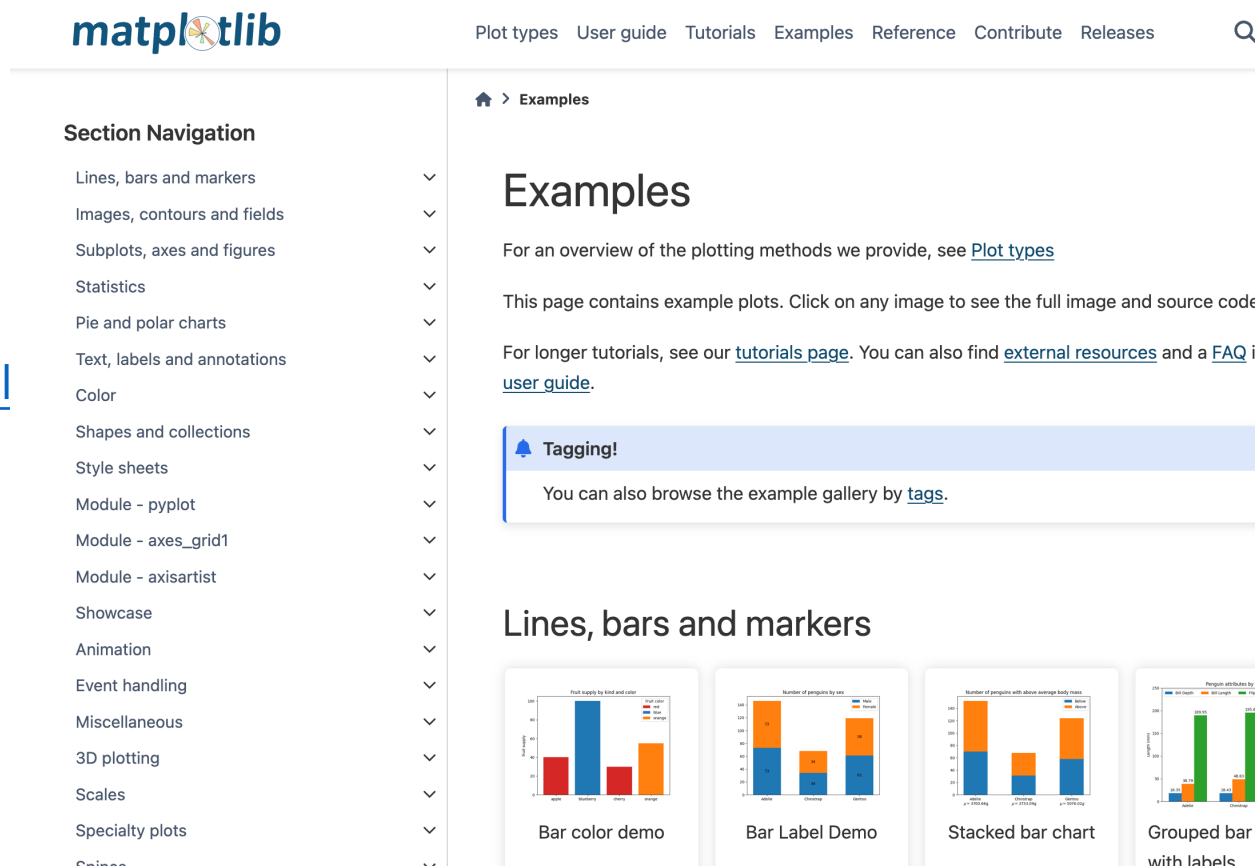
- 让读者看明白要展示的内容
 - 坐标轴的意义标清楚
 - 如果是热量图，记得带上color-bar
 - 不同的方法标出来legend
 - 去掉多余的空白的地方
 - 字体弄大一点 (matplotlib default比较小)



Tips: Python 调大

实验结果图 — Quantitative figure

- 让读者看明白要展示的内容
 - 坐标轴的意义标清楚
 - 如果是热量图，记得带上color-bar
 - 不同的方法标出来legend
 - 去掉多余的空白的地方
 - 字体弄大一点 (matplotlib default比较小)
 - <https://matplotlib.org/stable/gallery/index.html>



The screenshot shows the Matplotlib website's gallery page. The top navigation bar includes links for Plot types, User guide, Tutorials, Examples, Reference, Contribute, and Releases. The main content area is titled 'Examples' and contains a 'Tagging!' notification box. Below this, there are several plot thumbnails under the heading 'Lines, bars and markers'. The thumbnails include: 'Bar color demo', 'Bar Label Demo', 'Stacked bar chart', and 'Grouped bar with labels'. A left-hand navigation menu lists various plot types and modules, such as 'Lines, bars and markers', 'Images, contours and fields', 'Subplots, axes and figures', 'Statistics', 'Pie and polar charts', 'Text, labels and annotations', 'Color', 'Shapes and collections', 'Style sheets', 'Module - pyplot', 'Module - axes_grid1', 'Module - axisartist', 'Showcase', 'Animation', 'Event handling', 'Miscellaneous', '3D plotting', 'Scales', 'Specialty plots', and 'Science'.

Tips: 需要用的时候浏览一下，找到适合自己的



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 - 实验结果的视频

表格设计 — 实验方法表格

- 跟不同方法对比突出自己的优势
 - Position自己的方法
 - 让读者了解背景
 - 切忌漏掉了相关工作
 - 让更多的人了解这个领域

Method	Grad.	Sharp Features	Uniform	Intersection-Free	2-Manifold
MC [Lorensen and Cline 1987]	✓	✗	✗	✓	✗
DC [Ju et al. 2002]	✗	✓	✗	✗	✗
NDC [Chen et al. 2022b]	✗	✓	✓	✓	✗
DMC [Nielson 2004] Centroid	✓	✗	✓	✓	✓
DMC [Schaefer et al. 2007] QEF	✗	✓	✓	✓	✓
Template Mesh [Liu et al. 2019]	✗	✗	✓	✗	✓
DMTet [Shen et al. 2021]	✓	✓	✗	✓	✓
FLEXICUBES	✓	✓	✓	✗	✓

Method	Geometry	Factorize	Training	Inference
NeRF [45]	NV		day	seconds
NGP-NeRF [47]	NV		minutes	ms
NeRD [5]	NV	✓	days	seconds
NerFactor [79]	NV	✓	days	seconds
PhySG [77]	NS	✓	day	seconds
NeuS [67]	NS		day	seconds
Our	Mesh	✓	hour	ms

Table 1. Taxonomy of methods. NV: Neural volume, NS: Neural surface. Factorize indicates if the method supports some decom-

Method	Application	Representation	Supervision	Textured mesh	Arbitrary topo
OccNet [43]	3D generation	Implicit	3D	✗	✓
PointFlow [68]	3D generation	Point cloud	3D	✗	✓
Texture3D [53]	3D generation	Mesh	2D	✓	✗
StyleNerf [25]	3D-aware NV	Neural field	2D	✗	✓
EG3D [8]	3D-aware NV	Neural field	2D	✗	✓
PiGAN [7]	3D-aware NV	Neural field	2D	✗	✓
GRAF [57]	3D-aware NV	Neural field	2D	✗	✓
Ours	3D generation	Mesh	2D	✓	✓

Table 1: Comparison with prior works. (NV: Novel view synthesis.)



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表格设计 — 实验结果表格

- 让读者看明白表格
 - 把最好的结果标亮
 - <https://github.com/jonbarron/tabilize/blob/main/tabilize.ipynb>

Scale Factor: Error Metric:	1×			2×			4×			8×			Time (hrs)
	PSNR ↑	SSIM ↑	LPIPS ↓	PSNR ↑	SSIM ↑	LPIPS ↓	PSNR ↑	SSIM ↑	LPIPS ↓	PSNR ↑	SSIM ↑	LPIPS ↓	
Instant NGP [21, 32]	24.36	0.642	0.366	25.23	0.712	0.251	26.84	0.809	0.142	28.42	0.877	0.092	0.15
mip-NeRF 360 [3, 20]	27.51	0.779	0.254	29.19	0.864	0.136	30.45	0.912	0.077	30.86	0.931	0.058	21.86
mip-NeRF 360 + iNGP	26.46	0.773	0.253	27.92	0.855	0.141	27.67	0.866	0.116	25.58	0.804	0.160	0.31
Our Model	28.25	0.822	0.198	30.00	0.892	0.099	31.57	0.933	0.056	32.52	0.954	0.037	0.90
A) Naive Sampling	27.93	0.797	0.233	29.70	0.880	0.114	29.24	0.887	0.094	26.53	0.820	0.144	0.53
B) Naive Supersampling (6×)	27.48	0.803	0.224	29.03	0.881	0.109	28.42	0.881	0.097	25.97	0.810	0.151	2.54
C) Jittered	27.91	0.797	0.233	29.60	0.879	0.116	29.45	0.893	0.090	27.58	0.855	0.120	0.55
D) Jittered Supersampling (6×)	27.50	0.810	0.212	28.99	0.884	0.105	28.91	0.896	0.086	27.65	0.870	0.109	3.04
E) No Multisampling	28.15	0.817	0.208	29.87	0.886	0.105	31.33	0.927	0.061	32.12	0.948	0.043	0.54
F) No Downweighting	28.22	0.818	0.205	29.94	0.889	0.102	31.25	0.928	0.060	31.67	0.944	0.046	0.88
G) No Appended Scale ω	28.23	0.820	0.200	29.98	0.890	0.101	31.48	0.931	0.057	32.19	0.951	0.041	0.89
H) Random Multisampling	28.09	0.816	0.207	29.75	0.886	0.106	31.18	0.928	0.061	32.03	0.950	0.042	0.95
I) Unscented Multisampling	28.27	0.822	0.198	30.03	0.891	0.100	31.57	0.933	0.056	32.46	0.954	0.038	1.11
J) No New Interlevel Loss	28.12	0.824	0.196	29.82	0.892	0.098	31.31	0.932	0.056	32.23	0.953	0.039	0.86
K) No Weight Decay	27.34	0.814	0.203	28.91	0.881	0.109	30.29	0.921	0.067	31.23	0.941	0.050	0.90
L) Un-Normalized Weight Decay	27.99	0.821	0.196	29.65	0.889	0.100	31.10	0.930	0.058	32.09	0.951	0.040	0.91
M) Small View-Dependent MLP	27.41	0.811	0.207	28.98	0.882	0.109	30.32	0.924	0.065	31.11	0.944	0.047	0.63

Tips: 用一些pre-define好的脚本

表格设计 — 实验结果表格

- 让读者看明白表格
 - 把最好的结果标亮
 - 自己先对实验结果进行整理

		<i>Shelly</i>			<i>DTU</i>			<i>NeRFSynthetic</i>		
		PSNR ↑	SSIM ↑	LPIPS ↓	PSNR ↑	SSIM ↑	LPIPS ↓	PSNR ↑	SSIM ↑	LPIPS ↓
<i>offline</i>	NeRF [Mildenhall et al. 2020]	31.27	0.893	0.157	28.51	0.894	0.183	31.01	0.947	0.081
	NeuS [Wang et al. 2021]	29.98	0.893	0.158	28.92	0.913 ●	0.168	/	/	/
	Mip-NeRF [Barron et al. 2021]	32.59	0.899	0.148	28.90	0.900	0.179	33.09 ●	0.961 ●	0.043 ●
	Ours (full ray)	34.26 ●	0.932 ●	0.104 ●	33.51 ●	0.901	0.081 ●	32.51 ●	0.962 ●	0.048 ●
<i>real-time</i>	I-NGP [Müller et al. 2022]	33.22 ●	0.922 ●	0.125 ●	31.37 ●	0.932 ●	0.139 ●	33.18 ●	/	/
	MobileNeRF [Chen et al. 2023]	31.62	0.911	0.129	/	/	/	30.90	0.947	0.062
	VMesh [Guo et al. 2023]	/	/	/	/	/	/	30.70	0.947	0.060
	Ours	36.02 ●	0.954 ●	0.079 ●	33.37 ●	0.964 ●	0.077 ●	31.84	0.957 ●	0.056 ●

Category	Method	COV (% , ↑)		MMD (↓)		FID (↓)	
		LFD	CD	LFD	CD	Ori	3D
Car	PointFlow [68]	51.91	57.16	1971	0.82	-	-
	OccNet [43]	27.29	42.63	1717	0.61	-	-
	Pi-GAN [7]	0.82	0.55	6626	25.54	52.82	104.29
	GRAF [57]	1.57	1.57	6012	10.63	49.95	52.85
	EG3D [8]	60.16	49.52	1527	0.72	15.52	21.89
	Ours	66.78	58.39	1491	0.71	10.25	10.25
	Ours+Subdiv.	62.48	55.93	1553	0.72	12.14	12.14
	Ours (improved G)	59.00	47.95	1473	0.81	10.60	10.60
Chair	PointFlow [68]	49.58	71.87	3755	3.03	-	-
	OccNet [43]	61.10	67.13	3494	3.98	-	-
	Pi-GAN [7]	53.76	39.65	4092	6.65	65.70	120.53
	GRAF [57]	50.23	39.28	4055	6.80	43.82	61.63
	EG3D [8]	58.31	50.14	3444	4.72	38.87	46.06
	Ours	69.08	69.91	3167	3.72	23.28	23.28
	Ours+Subdiv.	71.59	70.84	3163	3.95	23.17	23.17
	Ours (improved G)	71.96	71.96	3125	3.96	22.41	22.41

Category	Method	COV (% , ↑)		MMD (↓)		FID (↓)	
		LFD	CD	LFD	CD	Ori	3D
Mbike	PointFlow [68]	50.68	63.01	4023	1.38	-	-
	OccNet [43]	30.14	47.95	4551	2.04	-	-
	Pi-GAN [7]	2.74	6.85	8864	21.08	72.67	131.38
	GRAF [57]	43.84	50.68	4528	2.40	83.20	113.39
	EG3D [8]	38.36	34.25	4199	2.21	66.38	89.97
	Ours	67.12	67.12	3631	1.72	65.60	65.60
	Ours+Subdiv.	63.01	61.64	3440	1.79	54.12	54.12
	Ours (improved G)	69.86	65.75	3393	1.79	48.90	48.90
Animal	PointFlow [68]	42.70	74.16	4885	1.68	-	-
	OccNet [43]	56.18	75.28	4418	2.39	-	-
	Pi-GAN [7]	31.46	30.34	6084	8.37	36.26	150.86
	GRAF [57]	60.67	61.80	5083	4.81	42.07	52.48
	EG3D [8]	74.16	58.43	4889	3.42	40.03	83.47
	Ours	79.77	78.65	3798	2.02	28.33	28.33
	Ours+Subdiv.	66.29	74.16	3864	2.03	28.49	28.49
	Ours (improved G)	74.16	82.02	3767	1.97	27.18	27.18

Tips: 可以分开多个表, 或者是用竖线分开, 把类似的baseline分类到一块

表格设计 — 实验结果表格

- 让读者看明白表格
 - 把最好的结果标亮
 - 自己先对实验结果进行整理
- 让表格美观?
 - \toprule, \midrule
 - 尽量不要太多竖线
 - 表格整理分类

		<i>Shelly</i>			<i>DTU</i>			<i>NeRFSynthetic</i>		
		PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow	PSNR \uparrow	SSIM \uparrow	LPIPS \downarrow
<i>offline</i>	NeRF [Mildenhall et al. 2020]	31.27	0.893	0.157	28.51	0.894	0.183	31.01	0.947	0.081
	NeuS [Wang et al. 2021]	29.98	0.893	0.158	28.92	0.913	0.168	/	/	/
	Mip-NeRF [Barron et al. 2021]	32.59	0.899	0.148	28.90	0.900	0.179	33.09	0.961	0.043
	Ours (full ray)	34.26	0.932	0.104	33.51	0.901	0.081	32.51	0.962	0.048
<i>real-time</i>	I-NGP [Müller et al. 2022]	33.22	0.922	0.125	31.37	0.932	0.139	33.18	/	/
	MobileNeRF [Chen et al. 2023]	31.62	0.911	0.129	/	/	/	30.90	0.947	0.062
	VMesh [Guo et al. 2023]	/	/	/	/	/	/	30.70	0.947	0.060
	Ours	36.02	0.954	0.079	33.37	0.964	0.077	31.84	0.957	0.056

Category	Method	COV (% \uparrow)		MMD (\downarrow)		FID (\downarrow)	
		LFD	CD	LFD	CD	Ori	3D
Car	PointFlow [68]	51.91	57.16	1971	0.82	-	-
	OccNet [43]	27.29	42.63	1717	0.61	-	-
	Pi-GAN [7]	0.82	0.55	6626	25.54	52.82	104.29
	GRAF [57]	1.57	1.57	6012	10.63	49.95	52.85
	EG3D [8]	60.16	49.52	1527	0.72	15.52	21.89
	Ours	66.78	58.39	1491	0.71	10.25	10.25
	Ours+Subdiv.	62.48	55.93	1553	0.72	12.14	12.14
	Ours (improved G)	59.00	47.95	1473	0.81	10.60	10.60
Chair	PointFlow [68]	49.58	71.87	3755	3.03	-	-
	OccNet [43]	61.10	67.13	3494	3.98	-	-
	Pi-GAN [7]	53.76	39.65	4092	6.65	65.70	120.53
	GRAF [57]	50.23	39.28	4055	6.80	43.82	61.63
	EG3D [8]	58.31	50.14	3444	4.72	38.87	46.06
	Ours	69.08	69.91	3167	3.72	23.28	23.28
	Ours+Subdiv.	71.59	70.84	3163	3.95	23.17	23.17
	Ours (improved G)	71.96	71.96	3125	3.96	22.41	22.41

Category	Method	COV (% \uparrow)		MMD (\downarrow)		FID (\downarrow)	
		LFD	CD	LFD	CD	Ori	3D
Mbike	PointFlow [68]	50.68	63.01	4023	1.38	-	-
	OccNet [43]	30.14	47.95	4551	2.04	-	-
	Pi-GAN [7]	2.74	6.85	8864	21.08	72.67	131.38
	GRAF [57]	43.84	50.68	4528	2.40	83.20	113.39
	EG3D [8]	38.36	34.25	4199	2.21	66.38	89.97
	Ours	67.12	67.12	3631	1.72	65.60	65.60
	Ours+Subdiv.	63.01	61.64	3440	1.79	54.12	54.12
	Ours (improved G)	69.86	65.75	3393	1.79	48.90	48.90
Animal	PointFlow [68]	42.70	74.16	4885	1.68	-	-
	OccNet [43]	56.18	75.28	4418	2.39	-	-
	Pi-GAN [7]	31.46	30.34	6084	8.37	36.26	150.86
	GRAF [57]	60.67	61.80	5083	4.81	42.07	52.48
	EG3D [8]	74.16	58.43	4889	3.42	40.03	83.47
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Tips: 可以分开多个表, 或者用竖线分开, 把类似的baseline分类到一块

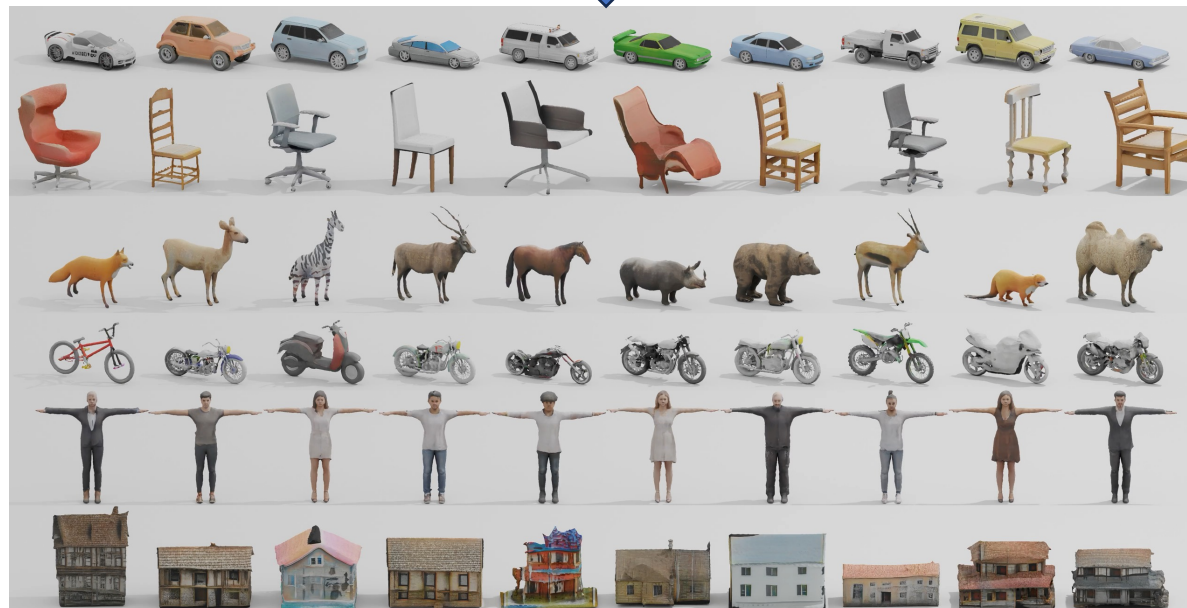
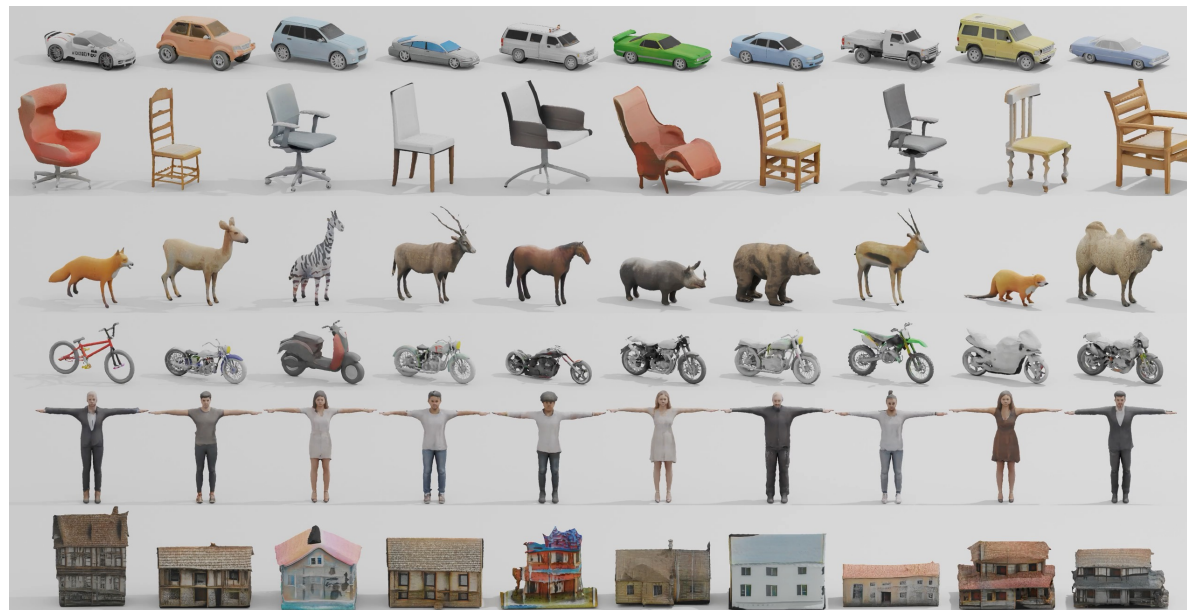


课程内容

- 图片设计
 - 技术方案流程图
 - 片头Teaser图
 - 实验结果图
 - Quantitative 图
 - Qualitative 图
- 表格设计
 - 实验方法的表格
 - 实验结果的表格
- 视频设计
 - 实验结果的视频

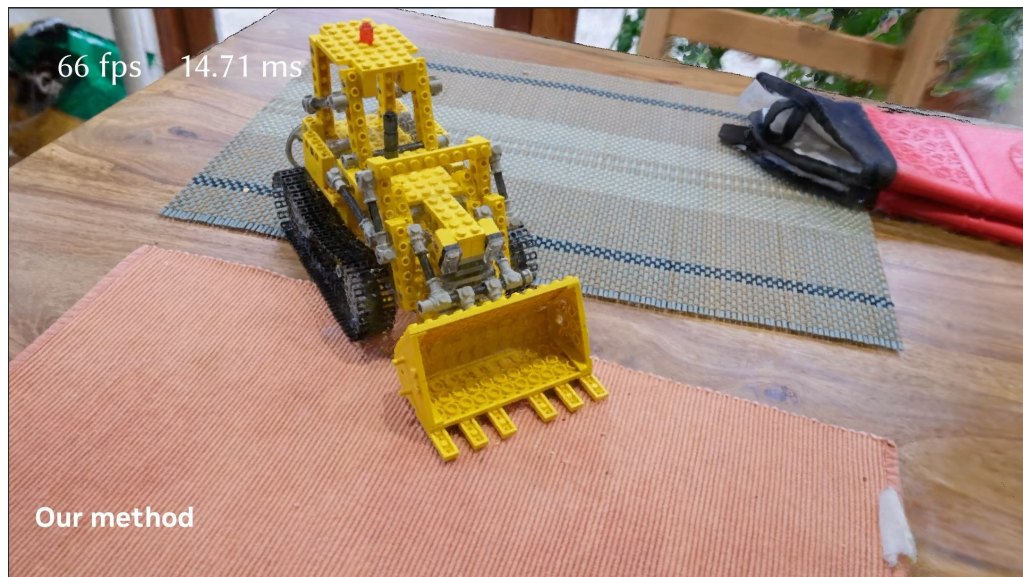
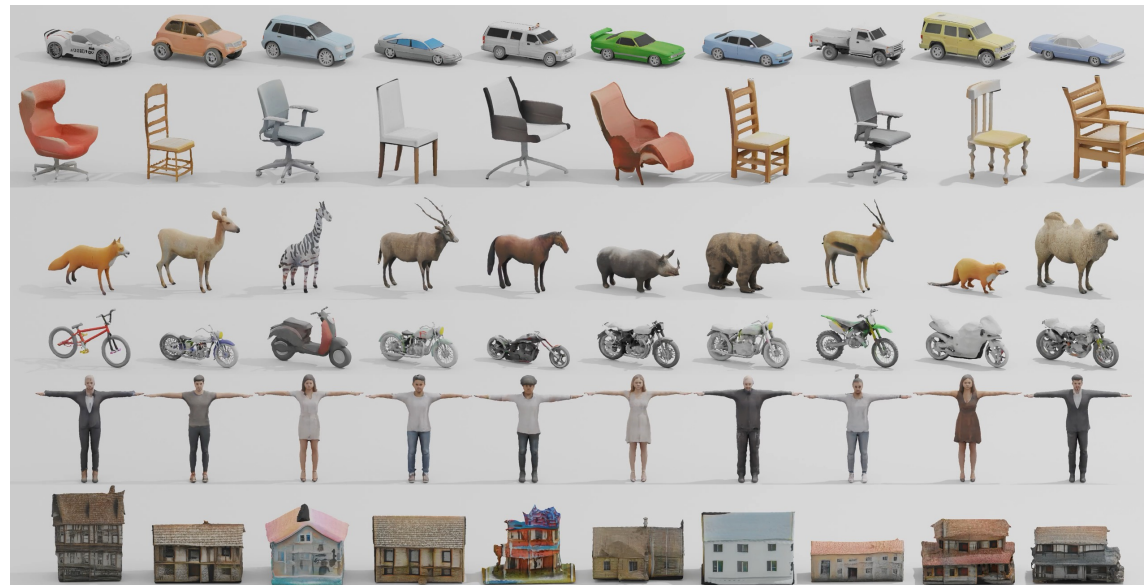
Demo-视频设计

- 为什么要做好一个视频?
 - 2D图片没法完全展示我们的结果
 - 做3D相关的只能通过视频来展示
 - 视频生成也只能通过视频来展示
 - Graphics的demo video很重要



Demo-视频设计

- 突出你想突出的重点
 - 3D重建/生成效果好:
 - 把所有的结果360旋转一遍
 - Swipe between geometry&RGB



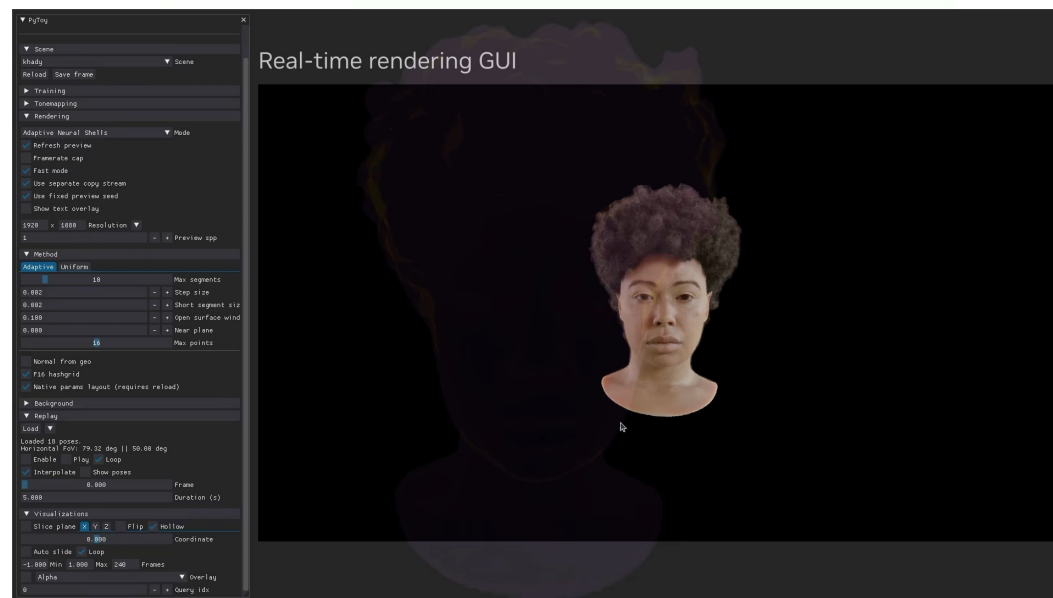
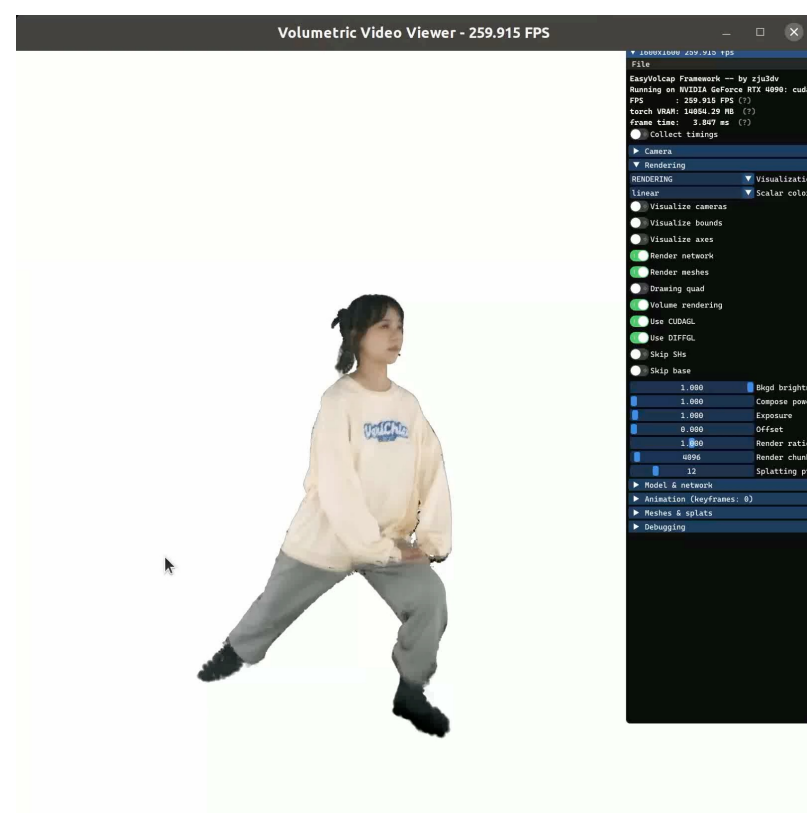
Demo-视频设计

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 - 旋转lighting, re-lighting



Demo-视频设计

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 - 实时渲染：
 - 录制一个视频



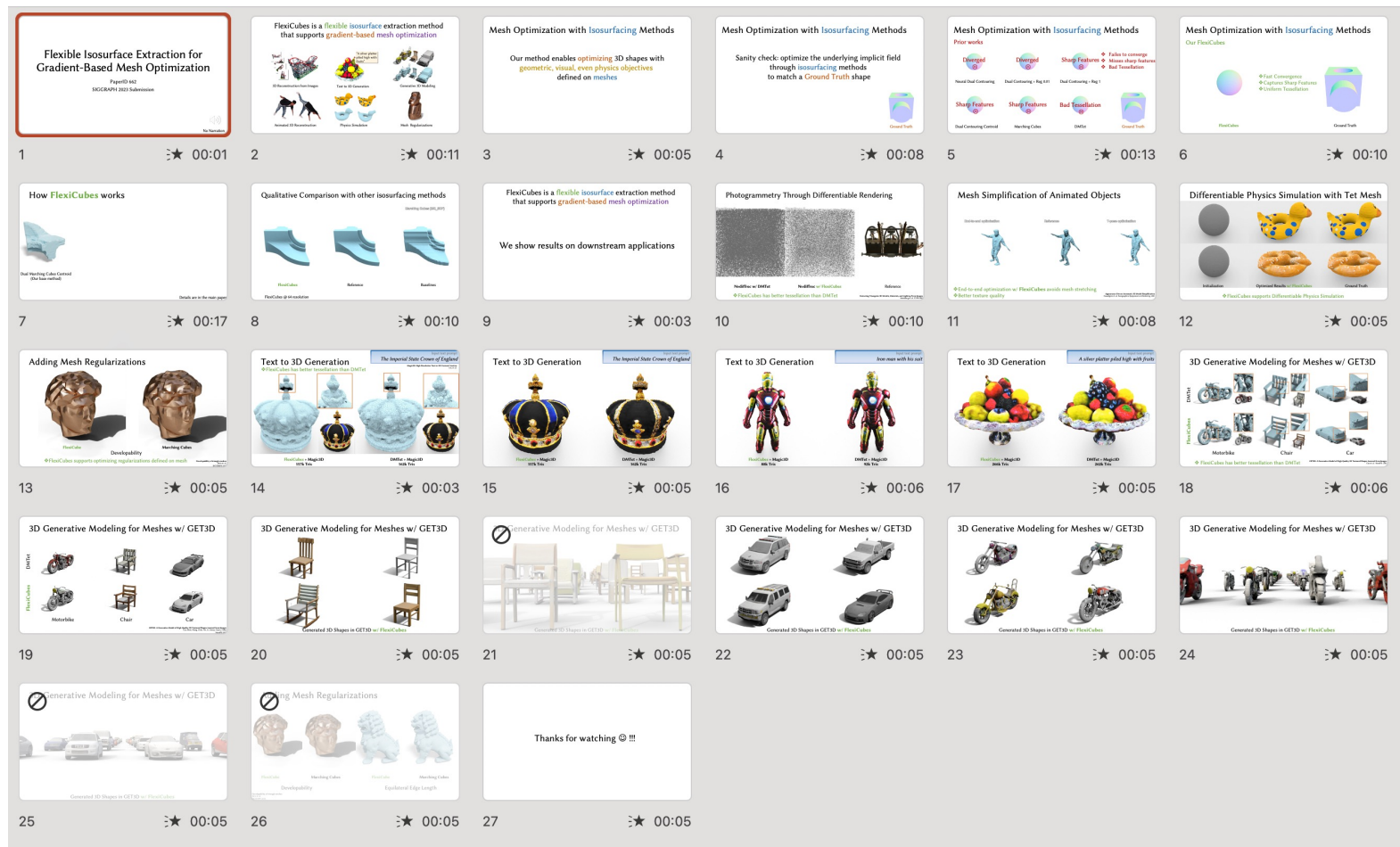
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 - 3D重建/生成效果好：
 - 把所有的结果360旋转一遍
 - Swipe between geometry&RGB
 - 光照材质预测：
 - 旋转lighting, re-lighting
 - 实时渲染：
 - 录制一个视频
 - 把结果在时序上展现



视频设计

- 用什么做视频?
 - Disclaim: 我目前只会用PPT + iMovie 😊





Q&A

- Q: 哪些平时积累会对论文画图、实验表格、demo等呈现环节有帮助? 您会有收集论文插图或arxiv代码的习惯吗
- A: 积累画图的代码模板 (Blender, matplotlib)

- Q: 论文中好看的插图一般是使用什么工具画出来的? 是否有设计素材及模板推荐或分享
- A: 我的主要是PPT 😊

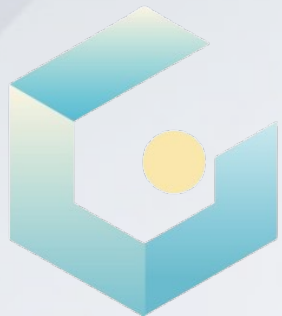
- Q: 请问能分享一些论文配色吗? 如何控制颜色的个数
 - From Songyou Peng:
 - <https://colorhunt.co/>
 - https://jrnold.github.io/ggthemes/reference/tableau_color_pal.html
 - <https://colors.co/palettes/trending>



Q&A

- Q: 图中什么时候用粗体 什么时候用斜体 什么时候用正常体
- A: 大部分都是正常体, 粗体/斜体只是为了highlight

- Q: 如果想要做一个像magic3d那样的demo, 一般需要预留多少时间? 很多时候感觉自己没有精力在supplementary 的一周时间内做完非常完善的demo。
- A: demo video花了一整天, 在准备paper的时候已经有初步素材 (360旋转)



谢谢



Sida Peng



Jun Gao



Songyou Peng



Qianqian Wang