
LLaNA: Large Language and NeRF Assistant

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Abstract

Multimodal Large Language Models (MLLMs) have demonstrated an excellent understanding of images and 3D data. However, both modalities have shortcomings in holistically capturing the appearance and geometry of objects. Meanwhile, Neural Radiance Fields (NeRFs), which encode information within the weights of a simple Multi-Layer Perceptron (MLP), have emerged as an increasingly widespread modality that simultaneously encodes the geometry and photorealistic appearance of objects. This paper investigates the feasibility and effectiveness of ingesting NeRF into MLLM. We create LLaNA, the first general-purpose NeRF-language assistant capable of performing new tasks such as NeRF captioning and Q&A. Notably, our method directly processes the weights of the NeRF’s MLP to extract information about the represented objects without the need to render images or materialize 3D data structures. Moreover, we build a dataset of NeRFs with text annotations for various NeRF-language tasks with no human intervention. Based on this dataset, we develop a benchmark to evaluate the NeRF understanding capability of our method. Results show that processing NeRF weights performs favourably against extracting 2D or 3D representations from NeRFs.

1 Introduction

Large Language Models (LLMs) [70, 1] have revolutionized the field of Natural Language Processing, demonstrating incredible text comprehension and generation capabilities. These results have fostered the development of Multimodal LLMs (MLLMs) [14, 81, 44, 11, 10], which can ingest various modalities such as images, videos, and audio, to generate then text describing and reasoning about the content of such modalities. Recently, MLLMs have also been extended to 3D data [58, 77], primarily represented through colored point clouds, yielding remarkable results even in this scenario.

Beyond images and 3D data, another paradigm is emerging to represent objects and scenes: Neural Radiance Fields (NeRFs) [50]. NeRFs are coordinate-based neural networks, typically Multi-Layer Perceptrons (MLPs), designed to capture both the geometry and the photorealistic appearance of an object by learning a continuous radiance field at each 3D spatial location. After training, a NeRF model can be queried to render realistic images or to reconstruct the 3D surface of the encoded object.

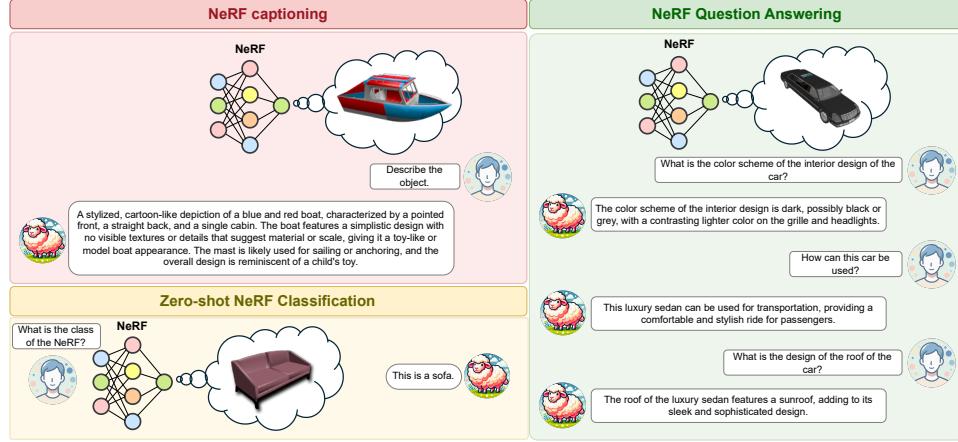


Figure 1: **LLaNA.** A new Multimodal Large Language Model that understands and reasons on an input NeRF. Notably, our framework processes directly the NeRF weights and performs tasks such as captioning, Q&A, and zero-shot classification of NeRFs.

Therefore, capturing an object as a NeRF provides an interesting alternative to create a digital twin with respect to standard representations such as multi-view images or point clouds. For instance, thanks to its continuous formulation, from a single NeRF, one can generate an infinite number of photorealistic images at any resolution while storing only the weights of an MLP instead of the entire image set. See Appendix A.4 for more on the memory advantages of using NeRFs. Due to their advantages, NeRFs are effectively becoming a new modality stored and communicated independently, with datasets of NeRFs being made publicly available [25, 61] and companies providing digital twins of objects represented as NeRFs (e.g., <https://lumalabs.ai/>).

The increasing adoption of NeRFs and their appealing characteristics prompted us to the following research question: is it possible to build an MLLM able to ingest directly NeRFs? Inspired by recent studies on meta-networks that can process neural fields [80, 42], we answer this question in the positive by showing that it is possible to process the weights of a given NeRF with a meta-network encoder that projects the NeRF weights into the embedding space of a pre-trained LLM such as LLaMA 2 [70]. By doing so, we create the first MLLM for NeRFs, dubbed Large Language and NeRF Assistant (LLaNA), which can solve NeRF-language tasks such as NeRF captioning, Q&A and zero-shot NeRF classification (see Fig. 1).

We also introduce a new NeRF–language dataset, that we will make publicly available, to train LLaNA and test the capabilities of our assistant. To collect this dataset, we designed an automated annotation framework that leverages MLLMs to produce text annotations for NeRFs trained on Shapenet [8]. Using this dataset alongside an additional split containing manually curated textual descriptions [2], we establish a benchmark for NeRF textual assistants.

Since a straightforward way to create an assistant for NeRFs would be to render images or extract 3D point clouds out of it and provide them as input to existing MLLMs specifically designed to handle such modalities, we thoroughly compare LLaNA against these baselines on the proposed benchmark. We show how the resolution of the extracted 3D geometry or images, and for images also the vantage point used for rendering, negatively impact the quality of the MLLM’s output. Important details might be lost by rendering from the wrong angle, or the extracted geometry might not be detailed enough. Vice versa, by operating directly on the MLP weights, we extract all the information they hold about the object without any other design decision. Our approach turns out to be the most effective way to create a NeRF assistant as it consistently outperforms MLLMs processing images or 3D geometries extracted by querying NeRFs. Our contributions can be summarized as follows:

- LLaNA, the first MLLM capable of performing tasks such as captioning and Q&A on NeRFs.
- We show that it is possible to build such an assistant by directly processing the NeRFs weights with a meta-encoder, which is faster and captures more information than rendering images or extracting 3D data.

- We automatically create a NeRF-language benchmark based on ShapeNet, and we thoroughly evaluate LLaNA on it, showing that it performs better than applying popular MLLMs on discrete representations obtained from NeRFs.

2 Related work

Multi-modal Large Language Models (MLLMs). Significant advancements have been made by Large Language Models (LLMs) in language understanding, reasoning, and generalization capabilities [62, 1, 54, 70, 75, 60]. These models have been extended into Multimodal Large Language Models (MLLMs), which broaden their reasoning abilities by including other modalities like images [14, 81, 17, 19], audio [26], and videos [47, 10]. MLLMs generally align target features with textual ones and then integrate them into LLMs for various text inference tasks. Some MLLMs are trained entirely from scratch [27, 56], others utilize pretrained LLMs [37, 4, 44, 38, 11]. 3D MLLMs focus on understanding the 3D world typically represented as colored point clouds [58, 24, 85, 20, 77] or multi-view images [23]. Some of these models are trained using 2D images [24, 85, 23] while others directly align textual phrases with points [20, 77, 58].

Neural radiance fields. NeRF [50] have been applied in several visual tasks such as novel view synthesis [48], generative media [57], and robotics [78]. The base formulation employs MLPs to convert spatial coordinates into colors and densities. Recent advancements substitute or enhance MLPs with explicit data structures [9, 68, 16, 52] for faster training and inference.

Neural radiance fields and language. The interaction between NeRF and language has been recently investigated for several practical applications. Many works address the problem of generating geometrically consistent views of objects or scenes described by textual prompts [66, 49, 31, 65, 40, 36, 57]. Other approaches focus on editing the scene represented by a NeRF from text, e.g., by changing the appearance and shape of objects [73, 28, 67, 74, 69, 21, 79, 86], or by inserting/removing objects in the scene [3, 51]. Some techniques investigate new types of radiance fields that predict language features for each spatial location alongside density and color [32, 34]. In particular, by distilling knowledge from vision-language models into these models, the neural fields can be queried by textual prompts. Unlike all previous methods, Ballerini et al. [5] is the first to utilize NeRFs as an input modality. They aim to learn a mapping between the NeRF and CLIP [59] embedding spaces to perform tasks such as NeRF retrieval from textual or image queries. Differently, our goal is to develop an MLLM capable of reasoning about NeRFs.

Deep learning on neural networks. Several studies have explored using meta-networks, i.e. neural networks that analyze other neural networks. Initially, researchers concentrated on predicting network characteristics, such as accuracy and hyperparameters, by processing their weights [71, 64, 33, 30, 45]. Several recent works focus on processing networks implicitly representing data (Implicit Neural Representations or Neural Fields). These methods perform tasks such as classifying or segmenting the data by processing solely the weights of the input neural networks. Among these works, Functa [15] trains a shared network on the entire dataset and then learns a compact embedding for each sample for downstream tasks. Later works concentrate on processing networks representing individual data samples, e.g., a specific object. By leveraging a novel encoder architecture for MLP weights, inr2vec [12] extracts compact embeddings from INRs of 3D shapes, which are employed as inputs for downstream tasks. nf2vec [61] extends inr2vec to ingest the NeRF’s network weights to classify, segment, or retrieve similar NeRFs. Cardace et al. [7] develop a strategy to process neural fields represented by a hybrid tri-plane structure. Other approaches [53, 83, 82, 84] develop equivariant architectures to handle MLPs by exploiting weight space symmetries [22] as an inductive bias. Also, Graph Neural Networks have been investigated to compute a network representation [35, 42]. Since we aim to process NeRFs directly from the network weights, we employ nf2vec as our meta-encoder due to its efficient and scalable architecture.

3 Methodology

This section describes the proposed Large Language and NeRF Assistant (LLaNA). We provide an overview of NeRFs and the meta-encoder that maps NeRF weights into a global embedding. Then, we present the overall LLaNA framework and discuss our training protocol.

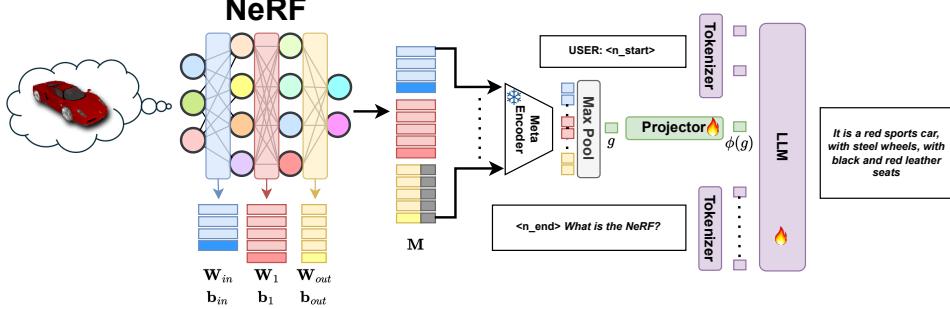


Figure 2: Framework overview. Example of NeRF captioning.

Neural Radiance Fields (NeRF) Neural Radiance Field (NeRF) [50] is a framework that employs coordinate-based neural networks, typically MultiLayer Perceptrons (MLP) and is trained on a collection of images of an object or scene taken from various vantage points. The main application of NeRFs is the task of novel views synthesis, i.e., photorealistic rendering of images from viewpoints unseen at training time. In its base formulation, the MLP is a function of continuous 3D coordinates $\mathbf{p} = (x, y, z) \in \mathbb{R}^3$, that yields four-dimensional outputs, $RGB\sigma \in [0, 1]^4$. This output encodes the RGB color and the volume density σ of each 3D location in the scene. The volume density σ can be interpreted as the differential probability of a ray terminating at point \mathbf{p} . After training, a NeRF can render images from any desired viewpoints at arbitrary resolution by querying it for the values of RGB and σ at several points along the ray corresponding to each pixel and applying the volumetric rendering equation [50].

In this work, we realize NeRFs as MLPs composed of L hidden layers, an input layer, and an output layer. An example of MLP with 1 input, 1 output, and 1 hidden layer is shown in Fig. 2(left). A layer is parameterized by a weight matrix plus a bias vector. More in detail, the hidden layers in our architecture have the same number of input and output neurons, H , thus having squared weight matrices $\mathbf{W}_l \in \mathbb{R}^{H \times H}$ for $l = 1, \dots, L$ and H -dimensional biases $\mathbf{b}_l \in \mathbb{R}^H$. As input \mathbf{p} goes through a 24-frequency encoding [50], the first layer has $\mathbf{W}_{in} \in \mathbb{R}^{144 \times H}$ and $\mathbf{b}_{in} \in \mathbb{R}^H$. The final one has $\mathbf{W}_{out} \in \mathbb{R}^{H \times 4}$ and $\mathbf{b}_{out} \in \mathbb{R}^4$. Refer to Appendix A for more details on NeRFs.

Meta-encoder In this work, we explore how a NeRF assistant can be realized by processing the NeRF weights directly. We expect the NeRF weights to contain comprehensive information about the represented object, such as its geometry and appearance. Thus, an encoder processing them might extract all the necessary information for downstream language tasks such as captioning and Q&A.

Inspired by the recent development of meta-networks capable of processing neural fields [42, 80], we employ as our meta-encoder architecture nf2vec [80]. It takes as input the weights of a NeRF and yields a global embedding that distills the content of the input NeRF. In particular, the weight matrices and biases of the input NeRF are stacked along the row dimension to form a matrix $\mathbf{M} \in \mathbb{R}^{S \times H}$, where $S = 144 + 1 + L * (H + 1) + H + 1 = L * H + L + H + 146$. Before stacking, we pad the output layer weights \mathbf{W}_{out} and biases \mathbf{b}_{out} with zeros to obtain H columns (see Fig. 2, center).

The meta-encoder is parametrized as an MLP with batch normalization layers [29] and ReLU nonlinearities. To scale gracefully with the input MLP dimensions, the encoder processes each row of \mathbf{M} independently, extracting a total of S tokens, each of length G , from an input NeRF. They are then max-pooled to obtain a global representation $g \in \mathbb{R}^G$ of the NeRF, with $G = 1024$ in our experiments. The encoder is pre-trained using the self-training protocol of nf2vec [80], i.e., jointly with a decoder architecture that, given as input the NeRF global embedding, reconstructs the same images as the input NeRF from arbitrary viewpoints. More details in Appendix B.

Large language and NeRF assistant Inspired by recent approaches that created effective Multimodal Large Language Models, we build LLANNA by leveraging on a pre-trained LLM with a Transformer backbone [72], in our experiments LLaMA 2 [70], and injecting the NeRF modality into its embedding input space, as proposed for images and 3D data [44, 77] (see Fig. 2, right). Thanks to the self-attention mechanism, the transformer can understand the contextual relationships between text and NeRF tokens, enabling it to generate responses based on both text and NeRF inputs.

We employ a trainable linear projection layer, ϕ , to project the embedding of the input NeRF computed by the meta-encoder into the LLaMA 2 embedding space. The projection layer has weights $\mathbf{W}_{proj} \in \mathbb{R}^{G \times T}$, where T is the word embedding dimension of the employed LLaMA model. This embedding is encapsulated between two special tokens, whose embeddings are learned end-to-end while training, namely $\langle n_start \rangle$ and $\langle n_end \rangle$.

Then, given an input sequence of mixed NeRF and word tokens, $(\langle n_start \rangle, \phi(g), \langle n_end \rangle, w_1, w_2, \dots, w_k)$, where k is the number of word tokens, the large language model returns a sequence of predicted word tokens $(\hat{w}_{k+1}, \hat{w}_{k+2}, \dots, \hat{w}_{eos})$.

Training protocol To train our framework, we hold multi-turn conversations about each NeRF available in the ShapeNeRF–Text dataset that we created (see Sec. 4). These conversations are organized into a set of prompts from the user and expected ground-truth answers that are used to optimize the original auto-regressive objective of the LLM. For the meta-encoder, we employ the nf2vec encoder pre-trained on ShapeNet released by the authors [80], and we keep it frozen during training. We follow the two-stage training protocol delineated in Liu et al. [44]:

Stage1: projector training. In the first stage, we train the projector network ϕ to align the NeRF and the word embedding spaces while keeping the LLM weights fixed. We train on an instruction dataset of brief descriptions to learn the projection layer efficiently. We also train the embeddings of the special tokens used to encapsulate the NeRF one. We optimize the projector weights and the embeddings for 3 epochs with a learning rate of 0.002 and batch size of 64.

Stage2: instruction tuning. During the second stage, we train on complex instructions to help the model understand and reason about NeRF data. In this phase, we optimize both the projector and the LLM for 3 epochs on the detailed descriptions, single-round and multi-round Q&A conversations available in our dataset. For this phase, we employ a learning rate of 0.0002 and a batch size of 16.

Our model is implemented in PyTorch and trained on 4 NVIDIA A100 with 64GB of VRAM each. Completing both stages requires ~ 1 day of training. When fine-tuning LLaMA 2 for our specific applications, we strictly use a dataset that does not come from scraped web data. This approach should ensure that the integrity and effectiveness of the pre-existing safeguards are maintained.

4 Benchmark

4.1 ShapeNeRF–Text dataset

To train and validate our NeRF assistant, we automatically created a dataset of conversations about NeRFs, the ShapeNeRF–Text dataset. It features paired NeRFs and language annotations for ShapeNet objects [8], in particular for all the 40K NeRFs available in the nf2vec dataset [61]. We followed the structure defined in PointLLM [77] to create the textual annotations. More in detail, we generated a *brief description*, a *detailed description*, 3 *single-round Q&As*, and one *multi-round Q&A* for each object. The brief descriptions are concise captions of the object, taking into account its global structure and appearance. The detailed descriptions are longer sentences that describe all the details of the object. The single-round Q&As consist of a question about the object and the corresponding ground-truth answer. Finally, the multi-round Q&As are longer conversations formed by 3 questions and the relative answers. The automatic data annotation pipeline is inspired by Cap3D [46] and is shown in Fig. 3. First, multiple views of each ShapeNet object have been rendered from different perspectives. Then, each view has been provided as input to LLaVA (LLaVA2-13b) [44] to get a detailed description of the object from that point of view. Afterward, starting from the captions generated by LLaVA, LLaMA 3 (LLaMA3-8B-chat) was used to generate the final ground-truth text data (brief and detailed descriptions, single and multi-round Q&As). Both the frozen LLMs employed to create our benchmark (LLaVA2-13b, LLaMA3-8b-chat) are equipped with safeguards.

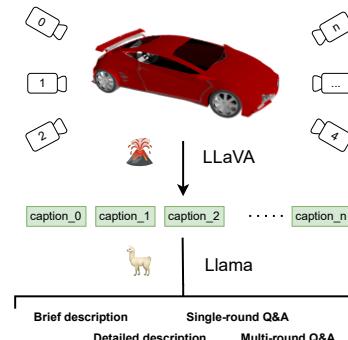


Figure 3: **Automatic annotation pipeline.**

When building the ground-truth data, to ensure diversity in the language annotations, each brief and detailed description has been associated with a question randomly sampled from 30 instructions for each kind of description. Such instructions, together with the carefully engineered request prompts for LLaVA and LLaMA, are reported in the supplementary material in Appendix C. ShapeNeRF–Text comprises 40K objects, with 240K textual annotations: 40K brief captions, 40K detailed descriptions, 120K single-round Q&A, and 40K three-round Q&A. The supplementary material shows an example of the resulting texts in Fig. 8. We split the dataset into train, validation, and test sets, stratified on the ShapeNet classes, containing distinct objects in proportions of 80%, 10%, and 10% of the total number of shapes, respectively.

4.2 Language tasks and metrics

We evaluate NeRF assistants on three different language tasks, given an input NeRF: brief captioning, detailed captioning, and single-round Q&A. We evaluate all tasks on the objects from the ShapeNeRF–Text test set. For brief captioning, we additionally evaluate the methods on the GPT2Shape Human Shape Text (HST) dataset [2], a subset of ShapeNet for which human-curated brief descriptions are publicly available. To generate the dialogues for HST, we randomly pair each of its shapes with one of the 30 instructions requesting a brief description. We employ standard language similarity metrics to evaluate these methods. We compute the cosine similarity between the global embeddings of the generated and ground-truth sentences provided by the pre-trained encoders Sentence-BERT [63] and SimCSE [18]. These metrics based on learned networks are the most effective at measuring the quality of the generated output. We also include standard handcrafted metrics based on n-gram statistics, like BLEU-1 [55], ROUGE-L [43], and METEOR [6].

5 Experiment results

5.1 Baselines

As our method is the first to investigate language tasks on NeRF, there are no baselines in the literature. However, given a NeRF, a straightforward way to create an assistant for it could be to render an image and use an MLLM capable of ingesting images. Alternatively, we could extract the 3D shape from the NeRF and use one of the recent 3D MLLMs. Hence, we use MLLMs as off-the-shelf foundation models, trained on hundreds of thousands of shapes or millions of images, without performing any fine-tuning on the training set of ShapeNeRF–Text, and consider such pipelines as natural baselines. Specifically, we use LLaVA (v1.6) [44], and BLIP-2 [39] for images, as well as PointLLM [77] and GPT4Point [58] for colored point clouds. We employ the official codes and pre-trained models released by the respective authors for such evaluations.¹. We note that the only official GPT4Point weights available at submission time were those obtained from fine-tuning OPT-2.7B on Cap3D [46]. In the main paper, we present the performance of all methods under the more realistic scenario where NeRFs are treated as the only input data to the assistant. Hence, images and point clouds can only be extracted from NeRFs. Details on the extraction procedure are provided in Appendix A.3. Moreover, in Appendix D, we report the results dealing with the images used to train the NeRF or the original 3D point cloud from ShapeNet, which confirms the methods’ ranking. When rendering an image, a non-obvious design decision for the pipeline is from which vantage point to render it. ShapeNet artificially simplifies this task since all objects have been canonically aligned to a common reference frame, but this may not be the case in a general setting. To show the vantage point’s effect on the assistant’s results, we report results processing a frontal or back view.

5.2 NeRF captioning

In the captioning experiments, we test the assistants’ ability to describe the NeRF content. We prompt them with the NeRF, or the image/cloud extracted from it, followed by the question which has been paired with its ground-truth description, as detailed in section 4.2, e.g. “*What’s the content of this NeRF/image/cloud?*”. We then collect the answers generated by the models and compare them with the ground-truth description according to the selected metrics.

¹LLaVA: <https://github.com/haotian-liu/LLaVA> BLIP-2: <https://github.com/salesforce/LAVIS/tree/main/projects/blip2> PointLLM: <https://github.com/OpenRobotLab/PointLLM> GPT4Point: <https://github.com/Pointcept/GPT4Point>.

Model	Modality	Sentence-BERT	SimCSE	BLEU-1	ROUGE-L	METEOR
LLaVA-vicuna-13b	Image (Front View)	61.00	61.16	14.30	20.00	23.31
LLaVA-vicuna-13b	Image (Back View)	54.35	56.09	21.94	21.67	22.09
LLaVA-vicuna-7b	Image (Front View)	59.85	<u>62.35</u>	22.67	<u>23.24</u>	<u>23.35</u>
LLaVA-vicuna-7b	Image (Back View)	55.68	58.46	<u>21.97</u>	22.46	22.50
BLIP-2 FlanT5-xxl	Image (Front View)	56.13	58.21	5.46	18.69	9.67
BLIP-2 FlanT5-xxl	Image (Back View)	52.48	54.05	5.67	18.20	9.50
PointLLM-7b	Point cloud	49.59	48.84	16.74	17.92	14.56
GPT4Point-Opt-2.7b	Point cloud	41.85	40.22	11.76	16.54	11.63
LLaNA-7b	NeRF	68.63	70.54	20.64	28.33	31.76

Table 1: **NeRF captioning - brief description on ShapeNeRF-Text.** Baseline results obtained on data extracted from NeRFs. Best results in **bold**. Runner-up underlined.

Model	Modality	Sentence-BERT	SimCSE	BLEU-1	ROUGE-L	METEOR
LLaVA-vicuna-13b	Image (Front View)	55.62	55.56	6.56	11.81	14.52
LLaVA-vicuna-13b	Image (Back View)	50.00	50.79	9.39	12.76	14.46
LLaVA-vicuna-7b	Image (Front View)	54.31	56.28	10.08	14.71	14.53
LLaVA-vicuna-7b	Image (Back View)	51.75	52.29	8.13	13.96	14.18
BLIP-2 FlanT5-xxl	Image (Front View)	<u>57.11</u>	<u>59.43</u>	8.21	<u>18.02</u>	12.14
BLIP-2 FlanT5-xxl	Image (Back View)	54.11	56.37	9.09	17.38	11.79
PointLLM-7b	Point cloud	43.40	44.50	8.53	11.64	9.97
GPT4Point-Opt-2.7B	Point cloud	43.15	42.22	12.02	18.73	13.69
LLaNA-7b	NeRF	59.20	61.66	9.47	14.94	17.06

Table 2: **NeRF captioning - brief description on the HST dataset.** Baseline results obtained on data extracted from NeRFs. Best results in **bold**. Runner-up underlined.

Brief description. We report the results for the brief description tasks on ShapeNeRF-Text and the HST dataset in Tab. 1 and Tab. 2 respectively. Comparing LLaNA with the baselines described in Sec. 5.1, we appreciate how LLaNA achieves the best performance in most metrics, often by large margins against runner-ups. For instance, for the Sentence-BERT similarity on the ShapeNeRF-Text dataset, LLaNA achieves 68.63, 7.63 points more than LLaVA-vicuna13b, even if LLaNA uses a smaller LLM. Results on the HST dataset, which provides ground-truth descriptions validated by humans, are generally lower for all methods. Yet, LLaNA provides again the best performance according to most metrics. The difference in the quality of the brief description provided by LLaNA compared to the baselines is showcased by the qualitative result reported in the first row of Fig. 4, where the description provided by LLaNA is the most accurate.

A clear trend in both tables and qualitative results is that image-based models tend to perform better than models processing point clouds. This is likely due to the larger amount of data used during training of the modality encoder, i.e. millions of images versus hundreds of thousands of shapes, which enhances their generalization ability, as well as the capability of images to capture more details than point clouds at the input resolutions required by image-based MLLMs versus 3D MLLMs. Nonetheless, our method, which operates on NeRFs, benefits from a holistic view of the object and provides the most accurate descriptions. Remarkably, in LLaNA, all the necessary information for this language task can be extracted from a single global embedding obtained by directly processing the NeRF weights. It is also worth pointing out that, while LLaNA directly processes weights and thus is independent by design from spatial resolution, the baselines face a computational overhead growing with the desired resolution due to the necessity of extracting spatial data from NeRF (Appendix A.3). Finally, comparing the results of image-based MLLMs when processing front versus back views, we can see that the vantage point has a non-negligible effect on the performance of such baselines, with SentenceBERT and SimCSE metrics diminishing by about 4 points in all baselines. In a dataset without canonical poses for objects, this would be a relevant limitation that processing NeRF weights seamlessly sidesteps.

Detailed description. We evaluate the performance for the detailed description tasks on the proposed ShapeNeRF-Text, reporting the results in Tab. 3 and the second row of Fig. 4. For this task, the point-based model PointLLM [77] performs similarly to the image-based one LLaVA [44]. However, we appreciate that LLaNA achieves the best performance in all metrics by large margins. For instance, for the Sentence-BERT metric, LLaNA achieves 77.43, notably 18.35 points more than LLaVA-vicuna-13b. These large improvements indicate that, while individual images may be

Model	Modality	Sentence-BERT	SimCSE	BLEU-1	ROUGE-L	METEOR
LLaVA-vicuna-13b	Image (Front View)	59.08	58.87	23.63	23.55	22.55
LLaVA-vicuna-13b	Image (Back View)	50.09	50.33	13.77	21.36	13.18
LLaVA-vicuna-7b	Image (Front View)	57.55	57.68	14.99	22.82	14.36
LLaVA-vicuna-7b	Image (Back View)	53.11	54.46	14.73	22.47	14.05
BLIP-2 FlanT5-xxl	Image (Front View)	41.27	40.69	0.18	7.83	2.60
BLIP-2 FlanT5-xxl	Image (Back View)	38.49	37.89	0.19	7.72	2.58
PointLLM-7b	Point cloud	59.02	58.30	10.28	19.26	10.55
GPT4Point-Opt-2.7b	Point cloud	42.44	38.33	3.72	9.21	5.13
LLaNA-7b	NeRF	77.43	79.81	41.32	36.18	32.39

Table 3: **NeRF captioning - detailed description on ShapeNeRF-Text.** Baseline results obtained on data extracted from NeRFs. Best results in **bold**. Runner-up underlined.

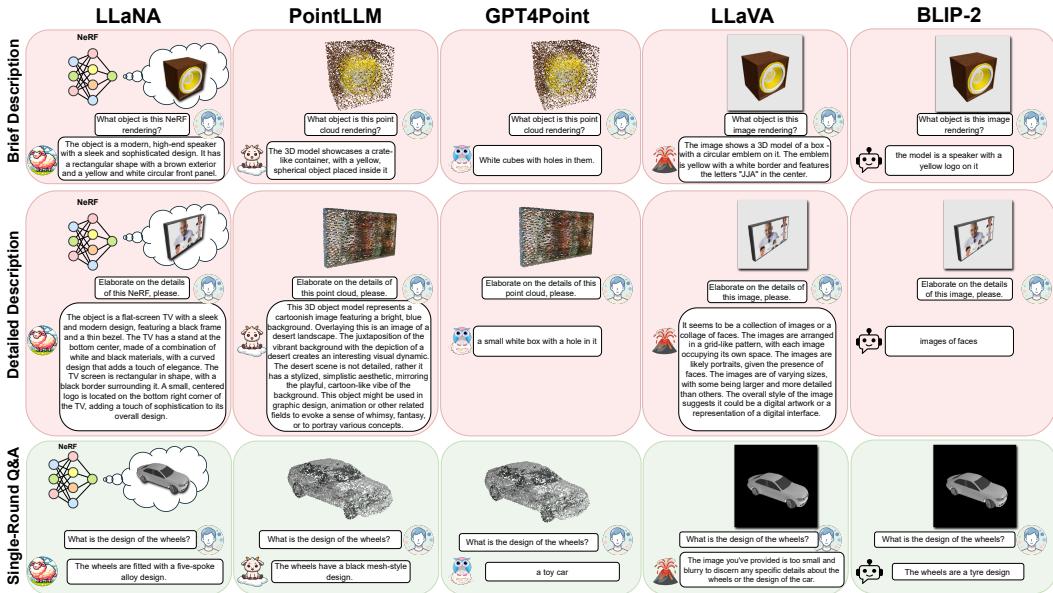


Figure 4: **Qualitative results of NeRF captioning and Q&A.** Results on ShapeNeRF-Text. From top to bottom: brief and detailed descriptions, single-round Q&A

sufficient for brief descriptions, they may lack all the details needed to provide a comprehensive description. Moreover, the dependency of the output quality on the selected vantage point remains strong. Contrarily, the NeRF weights contain detailed and complete information about the object, which is fundamental for more granular description tasks, with the additional advantage of not requiring tuning such hyperparameters. The ability of NeRF to capture holistic information about the object is also shown in the second row of Fig. 4, where only the direct processing of NeRF weights lets LLaNA understand that the object is a TV. PointLLM and LLaVA provide detailed but wrong descriptions, likely because of the need to extract the intermediate discrete representation as a point cloud or an image, losing information. Indeed, in both cases, it is hard even for a human observer to provide the right description from the intermediate modalities shown in the figure.

5.3 NeRF single-round Q&A

In the single-round Q&A experiment, we test the ability of the assistants to provide precise answers to specific questions about the object instead of open-ended general descriptions. We prompt the models with the NeRF, or the image/cloud extracted from it, followed by one of the questions in the single-round Q&A annotations associated with the NeRF. We then collect the answer generated by the model and compare it against the ground-truth answer with the selected metrics. Results are reported in Tab. 4. Interestingly, PointLLM [77] performs better than LLaVA [44] in this task, likely because it has been specifically trained to answer detailed questions about objects represented as point clouds. Nevertheless, similarly to the detailed description results, LLaNA is the top-performing method across all metrics, again by large margins. This result suggests that the meta-encoder and the

Model	Modality	Sentence-BERT	SimCSE	BLEU-1	ROUGE-L	METEOR
LLaVA-vicuna-13b	Image (Front View)	71.61	70.98	20.19	30.42	32.53
LLaVA-vicuna-13b	Image (Back View)	68.25	69.06	20.03	29.84	32.27
LLaVA-vicuna-7b	Image (Front View)	71.79	71.96	25.79	34.04	34.86
LLaVA-vicuna-7b	Image (Back View)	70.88	70.93	25.17	33.30	34.22
BLIP-2 FlanT5-xxl	Image (Front View)	45.20	47.92	11.50	20.16	13.49
BLIP-2 FlanT5-xxl	Image (Back View)	45.06	47.66	11.50	19.98	13.44
PointLLM-7b	Point cloud	<u>74.70</u>	<u>74.40</u>	<u>36.81</u>	<u>44.41</u>	<u>39.76</u>
GPT4Point-Opt-2.7b	Point cloud	27.62	31.41	6.26	9.38	5.41
LLaNA-7b	NeRF	81.03	81.56	46.16	53.17	50.15

Table 4: **NeRF Q&A - single round conversation on ShapeNeRF–Text.** Baseline results obtained on data extracted from NeRFs. Best results in **bold**. Runner-up underlined.

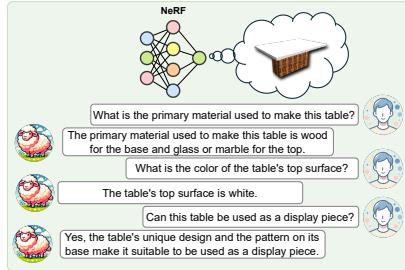


Figure 5: **NeRF multi-round Q&A example.**

Model	Modality	Accuracy (%)
LLaVA-vicuna-13b	Image (Front View)	66.13
LLaVA-vicuna-13b	Image (Hard View)	63.90
LLaVA-vicuna-7b	Image (Front View)	60.25
LLaVA-vicuna-7b	Image (Hard View)	57.00
BLIP-2 FlanT5-xxl	Image (Front View)	63.67
BLIP-2 FlanT5-xxl	Image (Hard View)	61.47
PointLLM-7b	Point cloud	50.14
GPT4Point-Opt-2.7b	Point cloud	41.93
LLaNA-7b	NeRF	67.14

Table 5: **NeRF zero-shot classification.**

projector can extract fine-grained information from the NeRF, even if they are processing directly NeRF weights. Remarkably, the amount of information they can extract lets LLaNA answer more precisely than when images or point clouds are extracted from the NeRF. Indeed, as shown in the third row of Fig. 4 which reports a qualitative example, the only assistant able to answer correctly to a precise question about the appearance of the tyres of the car is LLaNA. Another qualitative result confirming the ability of LLaNA to provide high-quality answers to specific questions, in this case in a multi-round Q&A experiment, is reported in Fig. 5.

5.4 Zero-shot NeRF classification

Finally, we compare assistants on the task of zero-shot classification. We query the models with the sentence “*What is the class of the NeRF/image/cloud? Choose among these: <Shapenet_classes>*” where *<Shapenet_classes>* are the 10 ShapeNet classes available in our dataset. We consider the answer correct only if the ground truth class appears in the response. We report results in Tab. 5 on the ShapeNeRF–Text dataset. Notably, LLaNA achieves the best performance, demonstrating the effectiveness of the proposed architecture in realizing a NeRF assistant.

6 Limitations and future directions

Despite the promising results of our framework, it is the first study in this direction and several limitations are yet to be addressed. First, the pre-trained nf2vec encoder, having been trained exclusively on synthetic data from ShapeNet, may not generalize well to real-world objects. To address this, future work should create a NeRF–Text dataset including a more diverse set of objects, like the ones provided by Objaverse [13]. Another limitation is that nf2vec currently processes only MLPs, restricting our model to MLP-only NeRFs. However, with the rapid advancements in meta-networks, it may become very soon possible to extend LLaNA to more complex NeRF architectures, such as InstantNGP [52]. For instance, the approach by Lim et al. [42] suggests the feasibility of processing various input network architectures, although it is currently limited to small networks. Finally, our framework has been tested solely on object-centric NeRFs. Expanding its application to NeRFs representing entire scenes would be a compelling direction for future research.

7 Concluding remarks

This paper addressed the novel task of creating a language assistant for NeRF. We have tackled this problem by leveraging recent advances in MLLMs and meta-networks processing neural fields. We have shown that it is feasible and effective to process directly the weights of a NeRF to project it into the embedding space of tokens of the selected LLM. We have built and made publicly available a dataset of textual annotations of NeRFs and have shown that our approach compares favourably on its test set with respect to several foundational MLLMs used as baselines for the novel tasks of brief and detailed captioning, question answering, and zero-shot classification of NeRFs.

Acknowledgements

We acknowledge the CINECA award under the ISCRA initiative, for the availability of high-performance computing resources and support.

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A Details on NeRFs

We report here some details regarding the NeRFs of the ShapeNeRF–Text dataset, which were trained by Zama Ramirez et al. [80]. The NeRF code is implemented leveraging the `NerfAcc` library [41].

A.1 Architecture

An instance of the employed NeRFs consists of a multi-layer perceptron (MLP) that contains three hidden layers, each with 64 neurons. The ReLU activation function is applied between all layers except for the last one, which calculates the density and RGB values directly without any activation function. A frequency encoding [50] is applied to input 3D coordinates to improve the NeRF reconstruction quality. NeRFs do not take in input the view direction. The MLP processes an input coordinate $\mathbf{p} \in \mathbb{R}^3$, to produce a 4-dimensional vector containing the $RGB\sigma$.

A.2 Training

Training a NeRF consists of minimizing the error between the rendered images from the NeRF and the ground truth images. Our NeRFs were trained using an L_1 loss between the predicted and ground truth RGB pixel intensities, weighting background pixels less than foreground pixels (0.8 foregrounds vs. 0.2 background). Image rendering involves querying the neural network by feeding it 3D coordinates to obtain RGB color values and density estimates. By integrating these outputs along camera rays using volumetric rendering techniques [50], colors and opacities have been accumulated to produce the final rendered image. Each NeRF is trained until it reaches a good reconstruction quality, approximately for 2000 steps.

A.3 Generating images and point clouds from NeRFs

To compare with 2D and 3D MLLMs on the new tasks of NeRF captioning and NeRF Q&A, we need to render images or reconstruct point clouds from the NeRF. To render images, we employ the same volumetric rendering procedure used during the NeRF’s training. To convert NeRF into a point cloud, the marching cubes algorithm is first applied to the volumetric density field derived from the NeRF. This process generates a mesh by identifying isosurfaces within the density field. The mesh is then converted into a point cloud by considering only the mesh vertices, uniformly distributed in the 3D space. We sample RGB values from NeRF for each point coordinate to approximate point cloud colors. An example of data extracted from NeRF is depicted in Fig. 6.

Generating images and point clouds requires the user to make some decisions, the effects of which on the assistant’s performance are not easy to anticipate. In the case of images, it is first of all difficult to decide the rendering viewpoint. It might happen that the object is not clearly visible in the picked viewpoint or that important elements are missing. Another decision is the resolution of the generated image, which, if too coarse, may prevent the identification of fine-grained details. The same concerns regarding the resolution also apply to point clouds. Yet, the modality encoder may not handle large resolutions or may greatly increase the processing time. Another important point is the additional computational time required to extract data from NeRF. For instance, extracting point clouds from NeRF with only 8192 points requires approximately 620ms. Moreover, the time for sampling the MLP and running a marching cube algorithm scales cubically with the desired spatial resolution. On the other hand, the time required to process the MLP weights is independent of the spatial resolution.

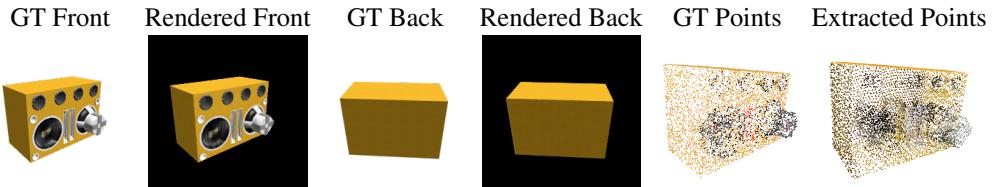


Figure 6: **Example of data extracted from NeRF.** From left to right: GT front view, rendered front view, GT back view, rendered back view, GT point cloud, extracted point cloud.

A.4 NeRF memory occupation compared to images or point clouds

An important benefit of using NeRF to represent objects is that memory consumption is decoupled from spatial resolution. In Fig. 7, we analyze the number of parameters needed for point clouds and images compared to neural fields by altering the spatial resolution of the data. We account for all variables required by an explicit representation in their parameter count. For instance, each point in a point cloud has six parameters corresponding to its coordinates (x, y, z) and color (R, G, B), while each pixel has only three channels (R, G, B). The orange line represents the parameters of the NeRF MLP, while the blue lines indicate the parameters for 3D points (Fig. 7-left) and image pixels (Fig. 7-right).

We observe that the space occupied by the NeRF MLP is comparable to that used by point clouds in our experiments (i.e., 8192 points, the data size used in GPT4Point [58] and PointLLM [77]). However, NeRF becomes advantageous for representing data as soon as the point cloud size is greater than 8621 points. This is crucial, considering real datasets may contain point clouds or meshes with significantly more points or faces; for example, Objaverse [13] features meshes with over 10^7 polygons.

The advantages are even more pronounced for images, where a single NeRF MLP corresponds to 36 images at a resolution of 22×22 . Storing the 36 pictures from ShapeNetRender at 256×256 resolution, used to train our NeRF on a single object, requires substantially more memory.

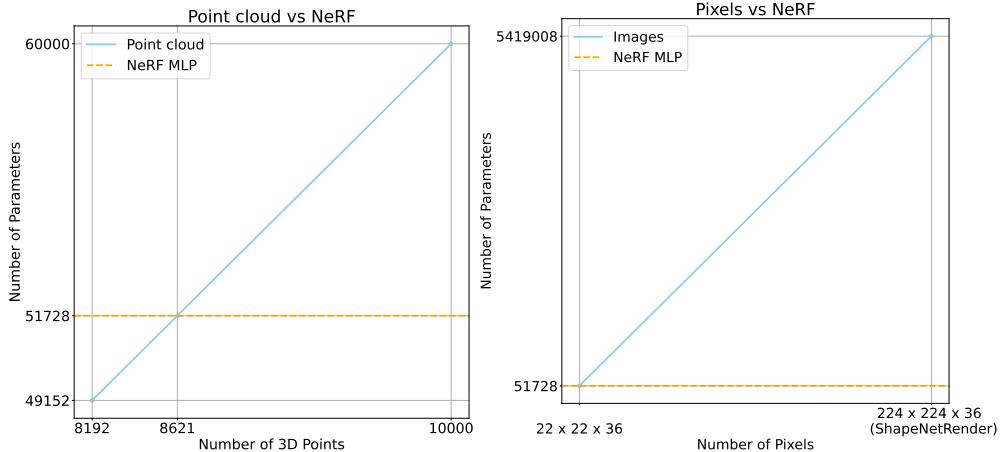


Figure 7: **Memory usage of NeRF compared to images or point clouds.** Left: NeRF vs point clouds. Right: NeRF vs pixels.

B Details on the Meta-Encoder

We employ nf2vec [80] as the meta-encoder of LLaNA. Thus, in the following paragraphs, we describe the details of the nf2vec architecture and training protocol.

B.1 Architecture

The nf2vec encoder consists of 4 linear layers with 512, 512, 512, and 1024 output neurons each. The final embedding extracted for a given MLP is a 1024-dimensional array. Each linear layer is followed by a batch normalization and a ReLU activation function.

B.2 Training

We employ the official code and weights of nf2vec² pre-trained on an augmented version of ShapeNetRender [76]. The encoder was trained in an end-to-end manner together with an implicit

²<https://cvlab-unibo.github.io/nf2vec/>

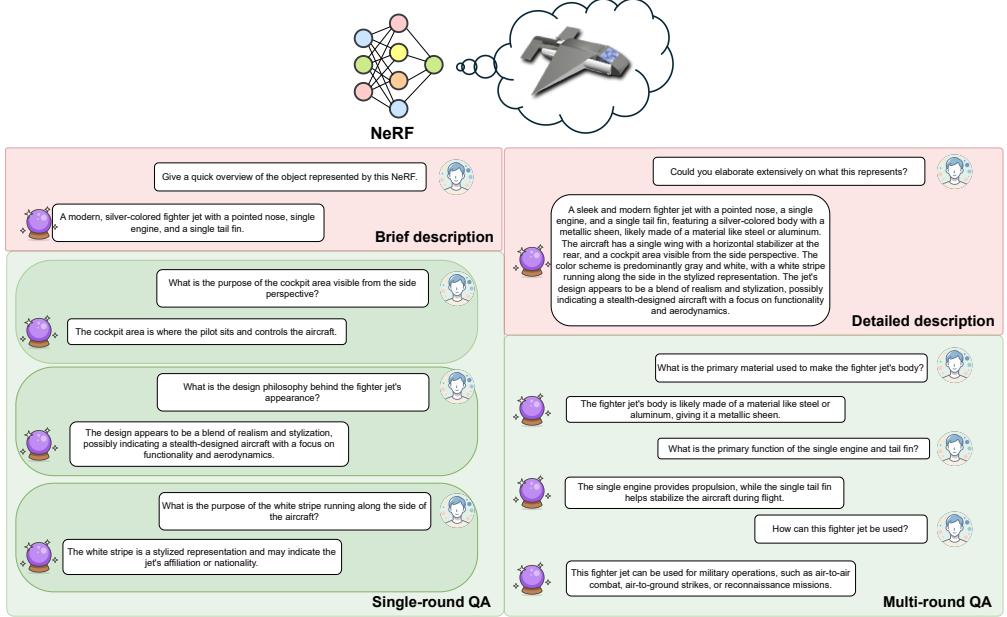


Figure 8: Example of data sample from ShapeNeRF-Text dataset.

decoder. The decoder takes in input 3D coordinates after a frequency encoding and the global 1024-dimensional output of the encoder. It consists of 5 linear layers with 1024 neurons each, followed by ReLU activations except for the last layer. It yields a 4-dimensional output $RGB\sigma$, similar to the NeRF given in input to the encoder. The framework supervision comes from the pixel-wise rendering L_1 error computed between the ground truth RGB image and the predicted image, which is obtained through volumetric rendering after encoding and decoding the NeRF.

C Details on ShapeNeRF-Text dataset

The proposed ShapeNeRF-Text dataset consists of 40K paired NeRFs and language annotations for ShapeNet objects [8]. In particular, for every 3D model, multiple annotations have been provided: a brief description, a detailed description, 3 single-round Q&As, and one multi-round Q&A. Figure 8 shows an example of such annotations. These annotations have been obtained by exploiting LLaVA2 and LLaMA3 as described in section 4 of the main paper.

Instruction prompts for LLaVA and LLaMA to generate the dataset For constructing ShapeNeRF-Text, first, descriptive captions for multiple views of each object have been obtained using the following input request to LLaVA:

- “*USER:<image>\nYou will be provided the image of an object, seen from the <view_point>. Describe the object in detail. Include as much information as possible, but do not infer anything that is not in the image. Avoid describing the background. Generate an answer with a maximum length of 30 words.\nASSISTANT:*”

The placeholder `<view_point>` was replaced with “back”, “side”, or “front” according to the viewpoint of the image provided as input. To expedite computation and leverage the high symmetry of ShapeNet objects, 7 views have been employed for this process.

After obtaining the captions for each view, LLaMA was queried to aggregate these single-view captions into comprehensive descriptions and Q&A rounds. The input provided to LLaMA was:

- *You will be shown 7 different descriptions of an object, obtained from different points of view. Please provide two descriptions, which aggregates all these ones. The first description must*

be concise, the second one will be more descriptive. Both these descriptions must refer to the same subject. Avoid repetitions. Important: The output descriptions must be followed by the string "Final concise description:" and "Final more detailed description:". Notice: There are errors in some descriptions, due to occlusion and improper angle. You need to combine all the descriptions and eliminate possible wrong details (please fix the errors directly, do not tell me). Input descriptions: [list of the single-view captions generated by LLaVA]

The detailed description was then used to generate multiple Q&A rounds, through the following request:

- *Given this description of an object, generate 6 short Q&A dialogues regarding diverse aspects of the object described, ensuring logical relevance between the questions and answers. Include always a question about how this object can be used. Question begins with 'Q'. Answer begins with 'A'. IMPORTANT: Do not mention size, background. Do not mention "how many". Do not add text after the last answer."*

From the 6 generated Q&A pairs, 3 were randomly sampled to build the sequence of multi-round Q&A, while the remaining pairs were used as single-round Q&A.

Instruction Prompts Tab. 6 and Tab. 7 provide the list of questions used to build the ground-truth data of ShapeNeRF–Text, as explained in Sec. 4.1.

Table 6: List of questions to prompt the model to produce brief descriptions. An instruction from the list is randomly selected and coupled with a ShapeNeRF–Text brief caption to form a ground-truth data sample.

- Summarize the 3D object briefly.
- What kind of object is depicted by this NeRF?
- Provide a short explanation of this object.
- What does this NeRF represent?
- Can you give a brief overview of this object?
- Characterize the object this NeRF is illustrating.
- Share a brief interpretation of this NeRF.
- Provide an outline of this 3D shape's characteristics.
- What object is this NeRF rendering?
- Deliver a quick description of the object represented here.
- How would you describe the 3D form shown in this NeRF?
- What is the nature of the object this NeRF is representing?
- Present a compact account of this 3D object's key features.
- What can you infer about the object from this NeRF?
- Offer a clear and concise description of this object.
- How would you summarize this 3D data?
- Give a brief explanation of the object that this NeRF represents.
- What kind of structure does this NeRF depict?
- Could you delineate the object indicated by this NeRF?
- Express in brief, what this NeRF is representing.
- Give a quick overview of the object represented by this NeRF.
- Convey a summary of the 3D structure represented in this NeRF.
- What kind of object is illustrated by this NeRF?
- Describe the object that this NeRF forms.
- How would you interpret this NeRF?
- Can you briefly outline the shape represented by this NeRF?
- Give a concise interpretation of the 3D data presented here.
- Explain the object this NeRF depicts succinctly.
- Offer a summary of the 3D object illustrated by this NeRF.

Table 7: List of questions to prompt the model to produce detailed descriptions. An instruction from the list is randomly selected and paired with a ShapeNeRF–Text detailed caption to form a ground-truth data sample.

- Can you tell me more about this?
- What does this represent?
- Can you describe this in more detail?
- I’m interested in this. Can you explain?
- Could you provide more information about this?
- What exactly am I looking at here?
- What is this?
- Could you describe the detailed structure of this?
- This looks interesting. Can you expand on it?
- Can you explain more about this form?
- What can you tell me about the shape of this object?
- Could you delve deeper into this?
- I want to know more about this. Can you help?
- Can you walk me through the details of this object?
- Can you provide a comprehensive account of this object?
- Offer a detailed interpretation of this NeRF.
- Please elucidate on the characteristics of this form.
- Could you provide an in-depth description of this structure?
- What does this NeRF represent in its entirety?
- Elaborate on the details of this NeRF, please.
- Kindly furnish me with more information about this object.
- Please expand on the intricate structure of this form.
- Provide a meticulous explanation of what this NeRF represents.
- Provide a detailed explanation of what this NeRF represents.
- I request a detailed breakdown of this structure.
- Give a thorough rundown of this NeRF.
- Can you offer a complete analysis of this object?
- I would like a comprehensive explanation of this form.
- Please detail the specific features of this NeRF.
- Could you elaborate extensively on what this represents?

D Ground truth images and point clouds

This section presents the results of an experiment in which the baseline 2D and 3D MLLM models have been provided with ground-truth input images and point clouds extracted from the original 3D meshes in the dataset rather than from the NeRFs. This scenario estimates an upper bound for the performance of such approaches when used as NeRF assistants, by simulating perfect extraction of images or point clouds from the NeRFs. In other words, it simulates the ideal scenario in which the encoding of information inside a NeRF is lossless, a non-realistic situation in which the baselines can achieve their best performance. Tab. 8, Tab. 9, and Tab. 10 show the results of this experiments on the tasks of brief description, detailed description, and single-round Q&A, respectively. For brevity, the best-performing 2D model, i.e., LLaVA [44] (on front views) and the best-performing 3D model, i.e., PointLLM [77], have been tested in this scenario. The results demonstrate that, even in this idealized and most favorable scenario for the baselines, LLaNA outperforms them.

Model	Modality	Sentence-BERT	SimCSE	BLEU-1	ROUGE-L	METEOR
LLaVA-vicuna-13b	Image (Front View)	68.61	67.99	17.48	23.08	27.03
PointLLM-7b	Point cloud	51.99	51.70	17.19	18.63	15.03
LLaNA-7b	NeRF	68.63	70.54	20.64	28.33	31.76

Table 8: **NeRF captioning - brief descriptions on ShapeNeRF–Text dataset.** Baseline results obtained on data extracted from ShapeNet mesh data. Best results in **bold**. Runner-up underlined.

Model	Modality	Sentence-BERT	SimCSE	BLEU-1	ROUGE-L	METEOR
LLaVA-vicuna-13b	Image (Front View)	68.32	67.35	27.46	26.62	24.40
PointLLM-7b	Point cloud	61.87	61.77	10.65	19.90	10.93
LLaNA-7b	NeRF	77.43	79.81	41.32	36.18	32.39

Table 9: **NeRF captioning - detailed descriptions on ShapeNeRF-Text dataset.** Baseline results obtained on data extracted from ShapeNet mesh data. Best results in **bold**. Runner-up underlined.

Model	Modality	Sentence-BERT	SimCSE	BLEU-1	ROUGE-L	METEOR
LLaVA-vicuna-13b	Image (Front View)	78.40	75.68	22.65	33.04	35.70
PointLLM-7b	Point cloud	74.98	74.90	36.93	44.60	39.87
LLaNA-7b	NeRF	81.03	81.56	46.16	53.17	50.15

Table 10: **NeRF Q&A - single-round Q&A on ShapeNeRF-Text dataset.** Baseline results obtained on data extracted from ShapeNet mesh data. Best results in **bold**. Runner-up underlined.

E Additional qualitative examples

This section provides additional qualitative comparisons between the proposed method, i.e. LLaNA which directly processes NeRF, and the baselines that take as input images [44, 39] or 3D representations [77, 58]. In particular, Figs. 9 to 11 show additional brief descriptions, detailed descriptions, and single-round Q&A provided as output by the different methods. Many examples, such as the white speaker in the third row of Fig. 10, are not described properly by MLLMs operating on point clouds. Indeed, due to the input point cloud containing only 8192 points, these methods cannot perceive the object details, such as the curved surface of the speaker, therefore they predict that the object is a “cubic white object” or an “ice cube”. In other examples, such as the white screen sample in the last row of Fig. 11, the LLM operating on images cannot give the right answer to the question on the button location as it is not visible from the given viewpoint. Contrarily, by operating directly on the holistic representation provided by NeRFs, LLaNA provides the right answer in these situations.

F Information about datasets, models, and source code licenses

This section provides details about the datasets, models, and source code licenses used in the paper, ensuring proper credit to the creators or original owners, and adherence to license terms.

Datasets: the datasets employed in our work and the relative licenses are listed below:

- **ShapeNet**: licensed under GNU Affero General Public License v3.0.
- **GPT2Shape HST**: licensed under Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License.

Models: the models used in all our experiments and their relative licenses are detailed in the following:

- **nf2vec**: licensed under MIT License.
- **PointLLM**: licensed under Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License.
- **GPT4Point**: licensed under Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License.
- **LLAMA-2**: licensed under META LLAMA 2 COMMUNITY LICENSE AGREEMENT³.
- **LLAMA-3**: licensed under META LLAMA 3 COMMUNITY LICENSE AGREEMENT⁴.
- **LLAVA**: licensed under Apache License 2.0.

Proper care has been taken to ensure that all licenses and terms of use are explicitly mentioned and respected throughout this paper.

³<https://ai.meta.com/llama/license/>

⁴<https://ai.meta.com/llama/license/>

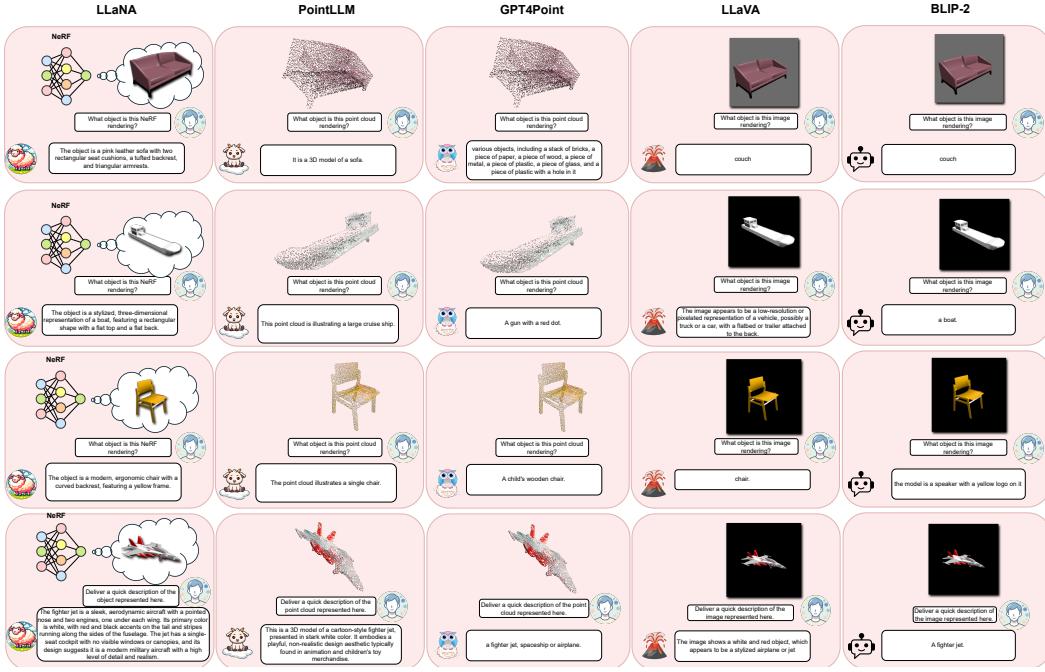


Figure 9: Additional qualitative examples for the brief description task.

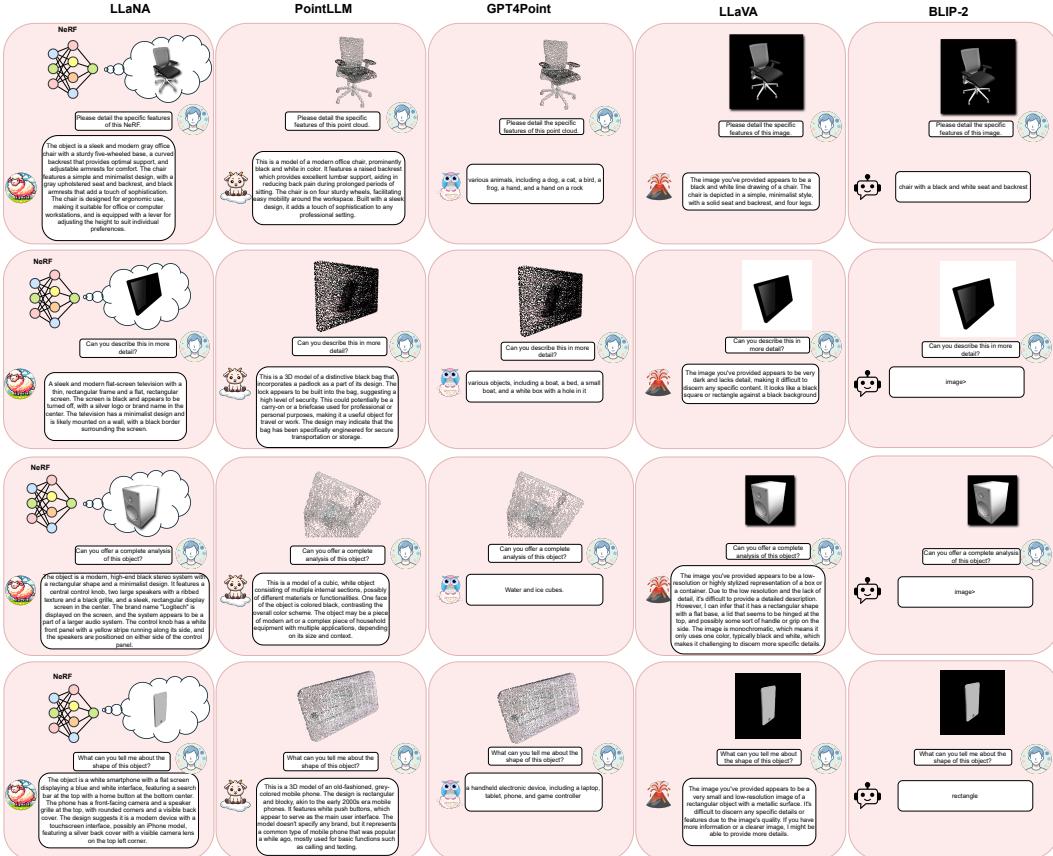


Figure 10: Additional qualitative examples for the detailed description task.



Figure 11: Additional qualitative examples for the single-round Q&A task.