PAVE

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Figure 1: Rendered Conditional Images

ABSTRACT

In this work we offer an approachable platform for visualization tasks by employing a neural network for real time rendering and accurate light transport simulation within the framework of Python made compatible for distributed systems and high performance computing (HPC). The provided model is a coalescence of VTK-m, a visualization tookit fit for massively threaded architectures, PyTorch, an increasingly popular language within machine learning due to robust libraries for neural networks, and Adios, an adaptable unified IO framework for data managment at scale. The resulting work accomplishes this combination by utilizing VTK-m to construct a path trace renderer able to fluidly and efficiently communicate to a conditional Generative Advisarial Network (cGAN) by means of Adios during training. The resulting generative model serves as a filter for rendered images and visual simulations capable of approximating indirect illumination and soft shadows at real-time rates while maintaining quality comparable to offline approaches. "in situ deep learning for scientific visualization"

CCS CONCEPTS

• **Theory of computation** → **Parallel computing models**; **Distributed computing models**; **Structured prediction**; **Adversarial learning**; **Data structures and algorithms for data management**; *Probabilistic computation*; *Database query languages (principles)*; • **Applied computing** → **Computer-aided design**.

KEYWORDS

VTKm, neural networks, generative adversarial network, Adios, PyTorch, path tracing

ACM Reference Format:
Samuel Leventhal, Mark Kim, and Dave Pugmire. 2019. PAVE. In *Proceedings of ACM Conference (Conference'17)*. ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 APPLICABLE "AREA OF INTERESTS" TARGETS

(1) In situ data management and infrastructures Current Systems: production quality, research prototypes , Opportunities ,Gaps
Current Systems: integration of VTKm, Adios2 and Python (PyTorch). Prototype being a conditional generative adversarial network (cGAN) designed to use a VTKm based pathtracer applied but not limited to learning global illumination and light behavior in rendering tasks. Opportunities: Introducing a framework allowing researchers easy access to python on HPC systems as well as machine learning aided technique to treat and study experimental data used in scientific simulations as learnable probability distributions with derived conditional dependencies of interest.

(2) System resources, hardware, and emerging architectures. Enabling Hardware, Hardware and architectures that provide opportunities for In situ processing, such as burst buffers, staging computations on I/O nodes, sharing cores within a node for both simulation and in situ processing
Enabling Hardware: By constructing an architecture allowing for Python to interface with VTKm data management controlled by Adios2 the proposed software

allows for a well distributed simulation task among cores.
(3) Methods and algorithms: Analysis: feature detection, statistical methods, temporal methods, geometric and topological methods Visualization: information visualization, scientific visualization, time-varying methods
(4) Case Studies and Data Sources In situ methods/systems applied to data from simulations and/or experiments / observations
(5) Simulation and Workflows: Integration:data modeling, software-engineering, Workflows for supporting complex in situ processing pipelines
(6) Requirements, Usability: Reproducibility, provenance and metadata

2 INTRODUCTION

3 RELATED WORK

Real time true to life quality renerings of light transport remains an active area of research with a number of various approaches. To preserve real-time rates, previous works have stored precomputed radiance transfers for light transport as spherical functions within a fixed scene geometry which are then adjusted for varied light and camera perspective through projections within a basis of spherical harmonics [10]. Similarly, Light Propagation Volumes have been used to iteratively propagate light between consecutive grid positions to emulate single-bounce indirect illumination [5]. More recently, deep neural networks have been employed as a learned look up table for real-time rates with offline quality. With the use of convolutional neural networks Deep Shading is able to translate screen space buffers to into desired screen space effects such as indirect light, depth or motion blur. Similar to the methodology implemented in this work, Deep Illumination uses a conditional advisarial network (cGAN) to train a generative network with screen space buffers allowing for a trained network able to produce accurate global illumination with real-time rates at offline quality through a "one network for one scene" setting [11].

GAN [2]
cGAN [7]
Tomas and Forbes Deep Illumination:
VTKm [8]
Reinforced learning for light transport simulation [1]

4 TECHNIQUE OVERVIEW

Utilization of PAVE consists of three consecutive phases: rendering phase of conditional training images, training phase of the generative neural network, and execution phase of the trained network. Three core components, VTK-m, PyTorch, and Adios2 fufill a unique functional requirement during each stage. In this section we describe the independent design and global role each system plays.

4.1 System Overview

To achieve our goal of a conditional generative neural network capable of rendering geometric dependent object path simulations we begin by rendering informative conditional image buffers along with ground truth scene renderings. For this purpose the VTK-m was chosen due to its scalability and robust capability for HPC visualization tasks. Provided the training set of conditional and ground truth images two neural networks, one convolutional and one generative, play a zero-sum game common to training GANs. To segue data managment of training images the path tracer saves the training set in a distributed setting with the use of Adios2. During training PyTorch is then able to retrieve needed image data through the use of the adaptable IO provided by Adios's Python high-level APIs.

4.2 Path Tracer Design

Conditional image attributes and high quality ground truth rendered images are required for the training stage. For this reason the first stage of PAVE consists of generating a visual scene or simulation with VTK-m. Within the framework of VTK-m the implemented ray tracer renders images through means common to commercial ray tracers such as Monte Carlo sampling for shapes of interest, light scattering, randomly directed light paths, material sampling and direct sampling. The image buffers needed to compute light paths afford an informative conditional dependence on the behavior of lighting based on the geometry and light sources within a scene. These conditional buffers, namely albedo, direct lighting, normals of surfaces and depth with respect to camera are then stored within VTK-m with Adios to maintane scalability of the system. For subsequent phases of PAVE the training data can then be retrieved from file again through Adios differing only in the API needed.

4.3 Neural Network Design

The cGAN used closely follows that introduced by Thomas and Forbes with Deep Illumunation [11]. Both the desriminator and generator network are deep convolutional neural networks implemented in PyTorch using training data retrieved from Adios files formated and stored by the VTK-m path tracer. The training stage relies on four conditional buffers depth, albedo, normals and direct lighting along with an associated ground truth image of high light sample count and ray depth. Given the four conditional buffers the generator attempts to construct the ground truth image from noise. The discriminator is then fed both the generated and ground truth image. The loss used for the gradient backpropagation update of both networks is based on the quality of the descriminators ability to classify the artifical and true image in which the generator is greater penalized when the discriminator accurately differentiates the two images, and similarly, the discriminator has a larger loss when incorrectly identifying real from fabricated images. The generator is then considered to have converged when the descriminator predicts both generated and true images with equal probability. For both descriminator and generator networks the activation functions used between layers is LeakyReLu and Sigmoid for the final layer [6]. Batch normalization is also performed between internal layers to minimize covariant shift of weight updates and improve learning for the deeper networks used [3].

4.3.1 Descriminator Network. For descriminating between artificial and ground truth image renderings a deep convolutional patchGAN network is used motivated by the added advantage of providing a patch-wise probability of an image in question as being real or fake. The benefit of a patch-wise probability allows for higher regional accuracy within an image as well as applicable for image-to-image tasks as introduced by Isola et. al. [4].

As input during training the descriminator network is given the set of conditional space buffers along with either the visualization generated by the cGAN generator network or the ground truth global illumination rendering produced with the VTK-m path tracer. Taking into account the conditional buffers the descriminator attempts to provide the rendered image as artifical, e.g. generated by the advisarial network, or real. Based on the performance of the descriminator the loss is computed using the classic loss for GAN training along with an L1 loss in order to not only produce original content but to also preserve structure and light information [**?**].

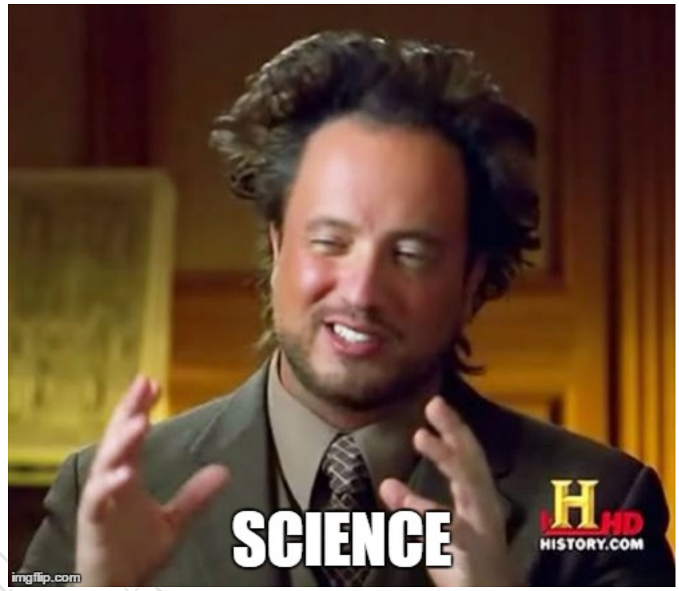
4.3.2 Generator Network. The generative network used is a deep convolutional network consisting of an encoder and decoder with skip connections concatonating equal depth layers of the encoding and decoding stages. Due to the illustrative 'shape' of this design the network is denoted a U-Net as introduced by Ronneberger et. al. for medical segmentation [9]. The motivation for utilizing a U-Net is due to success of the skip connections linking the decoded convolutional process to the encoded deconvolutional in capturing geometric and spatial attributes. The generator retreives as input through Adios global illumination buffers saved to file once rendered with VTK-m.

5 EXPERIMENTS

5.1 Cornell Box

5.2 Streamline Simulation

6 RESULTS



7 CONCLUSIONS

ACKNOWLEDGMENTS

Identification of funding sources and other support, and thanks to individuals and groups that assisted in the research and the preparation of the work should be included in an acknowledgment section, which is placed just before the reference section in your document.

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A APPENDIX