

EUROGRAPHICS 2022

# Machine Learning for Graphics: A Brief Overview

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# Agenda

- Overview of machine learning in graphics (10 mins)
- ML in content generation pipelines (12 mins)
- ML to augment rendering (8 mins)
- Challenges and opportunities (10 mins)

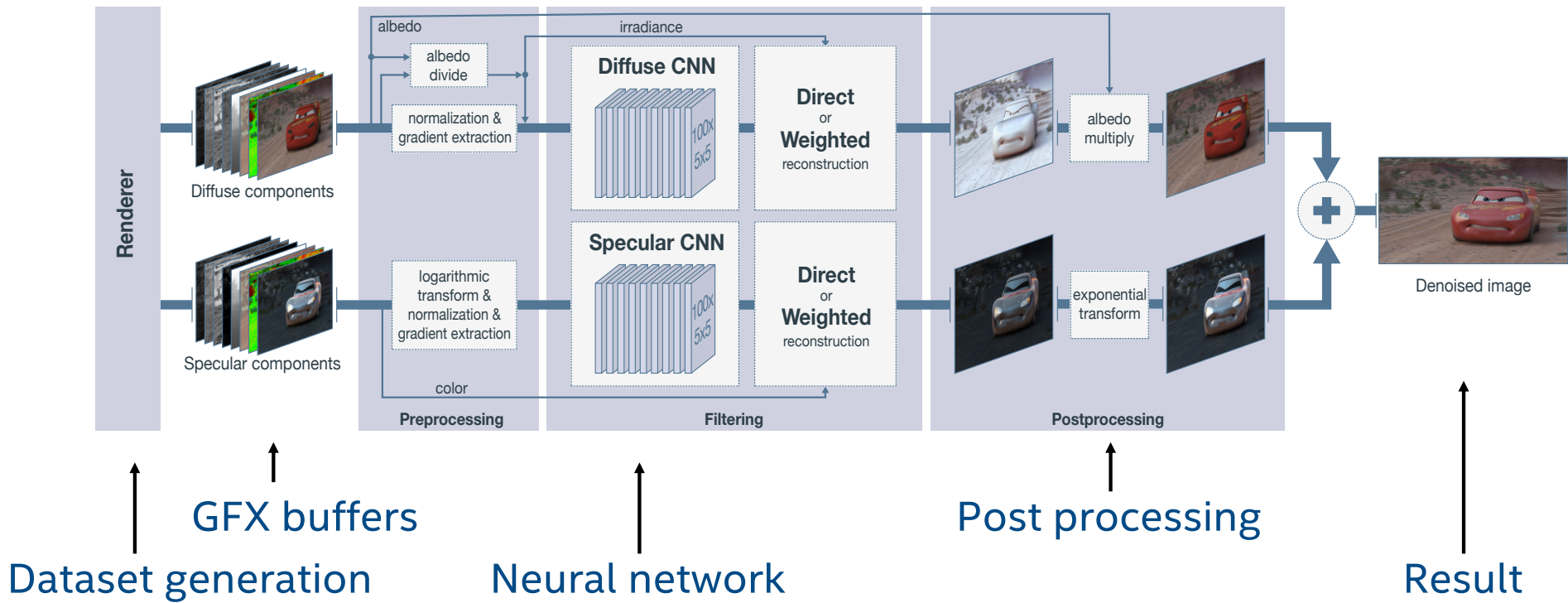
# Increased use of ML in computer graphics

- Asset curation, real-time and offline rendering
  - Across the entire production pipeline – games, VFX, interactive rendering
- Improved quality and/or performance, reduced power
  - Authoring time, final frame rendering, better quality at same power
- Improved tools and learnings
  - Hardware and system support – CPUs, GPUs, TPUs, ASICs

**Challenges – Datasets, models, generalization, deployment**

# Iterative ML training workflow

Image Credits: S. Bako ©Disney/ Pixar



# ML for content generation



Image credit: T. Aila

## Progressive GAN

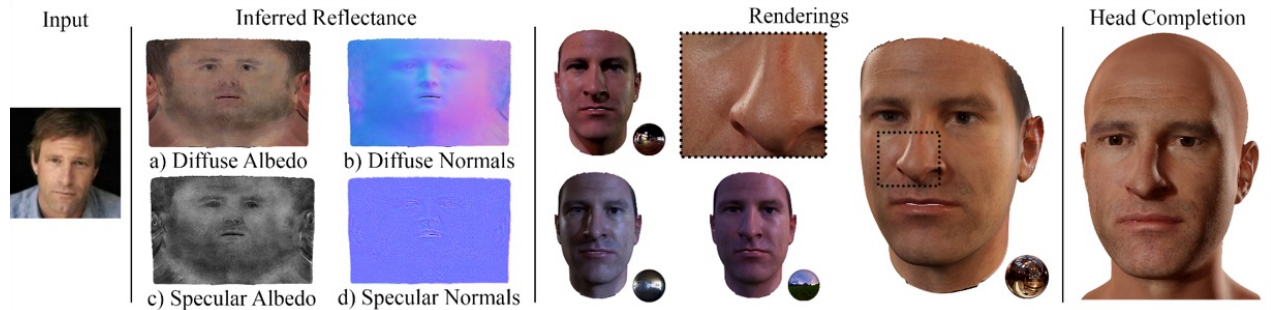


Image credit: A. Lattas

## AvatarMe



Image credit: T Komura

## Animation



Image credit: T.S. Park

## GauGAN

# ML integrated with rendering



Image Denoising

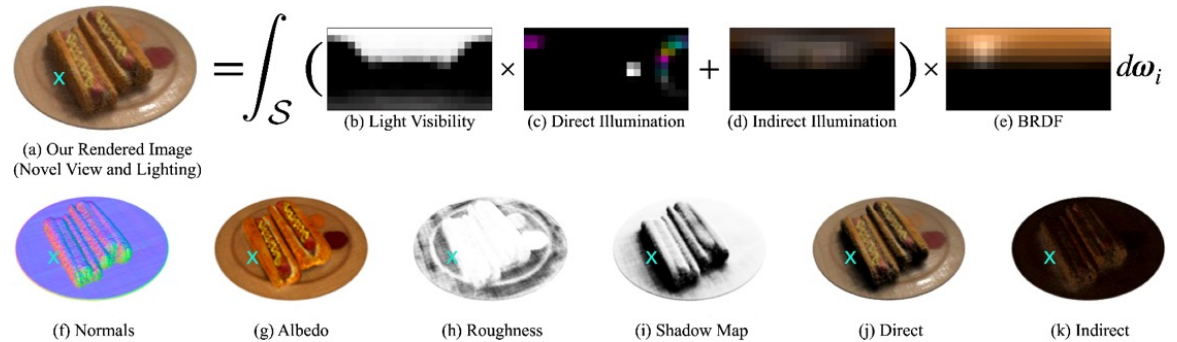


Image credits: P. Srinivasan

Scene relighting



©Nvidia

Neural Scene representation and shading



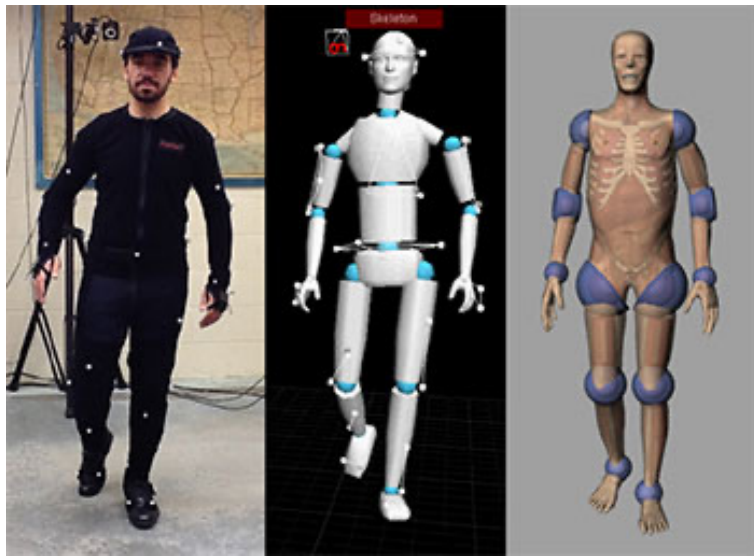
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DL Super Sampling

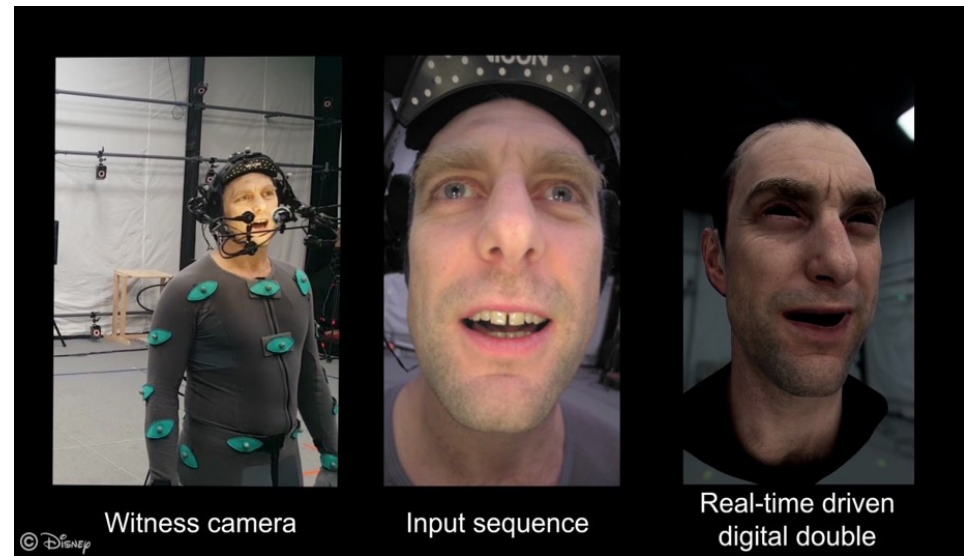
# ML for content generation

Neural Animation, Codec avatars, Photorealistic backgrounds

# Avatar authoring is time consuming



Motion capture



Facial animation capture ©Disney



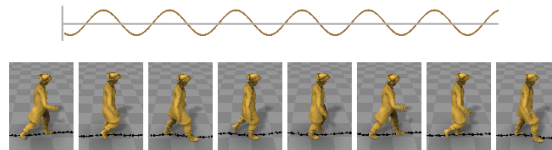
# Phase-functioned neural network (PFNN)

## Data Preprocessing

### 1. Motion Capture and Processing



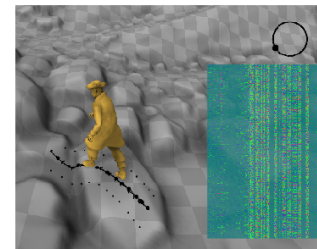
### 2. Phase Extraction



### 3. Terrain Fitting

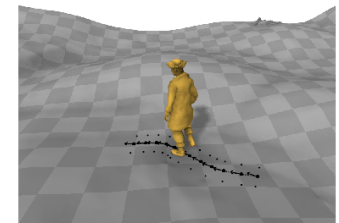


## Training



### 4. PFNN Training by Backpropagation

## Runtime



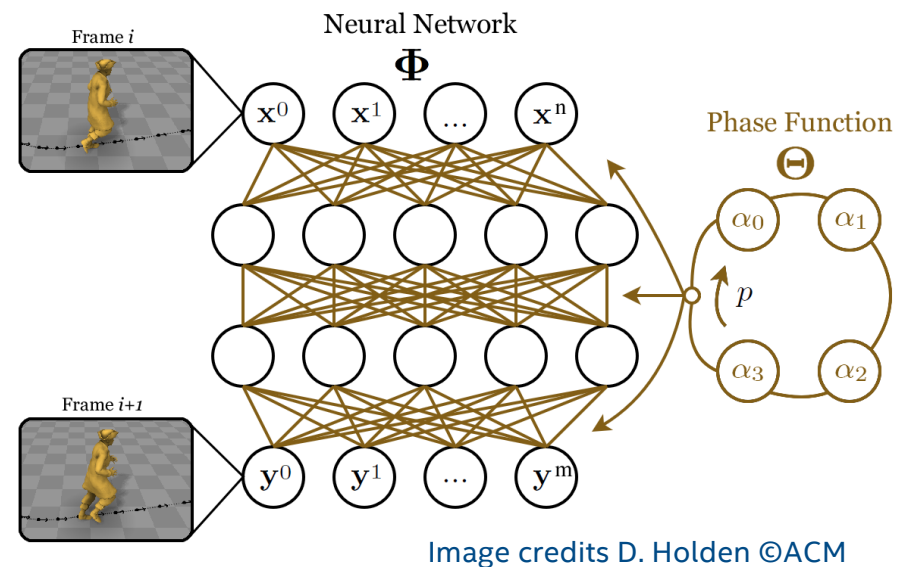
### 5. Realtime Character Control by User

Image credits D. Holden ©ACM

## Using mocap data for character animation in real-time games

# PFNN – Network topology

- Relatively simple network
  - Additional cyclic function
- Prior frame, user input and scene geometry into consideration
- Outputs next step/ motion
- Fast performance (ms)
  - Integrated into games



# Face rendering for virtual reality

- Facial animation is important for VR experiences
  - Improved presence
- Hard to convey with an HMD
  - Augmentation with extra sensors
- Fast transmission to support distributed participants
  - Social interaction in multi-user scenarios



# Facebook – Codec Avatars using deep VAEs

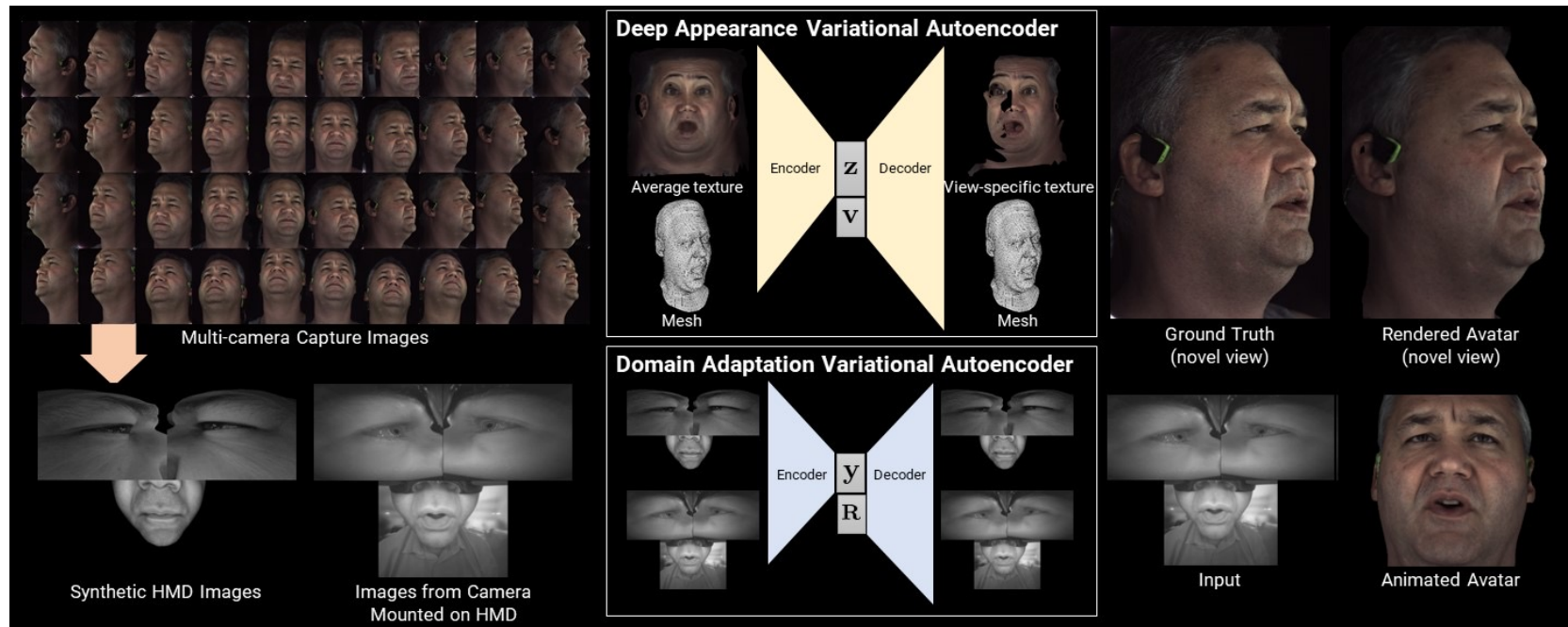


Image credits S. Lombardi ©ACM

## Deep Appearance Models to render avatars

# Cameras in HMD with multi-view capture dataset

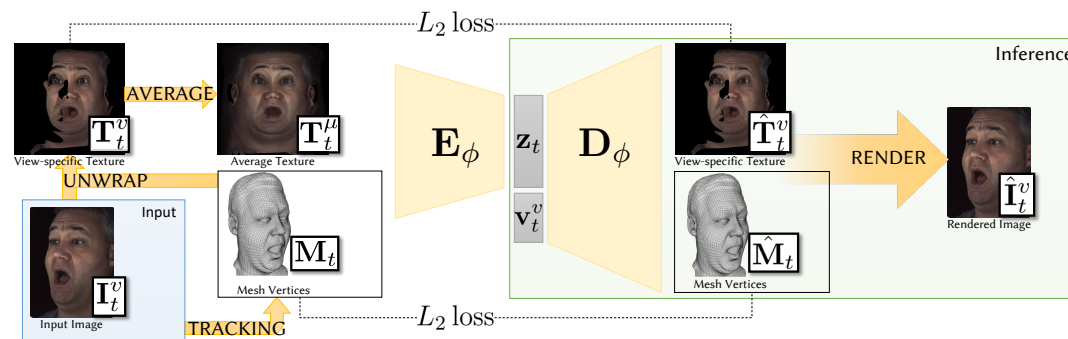
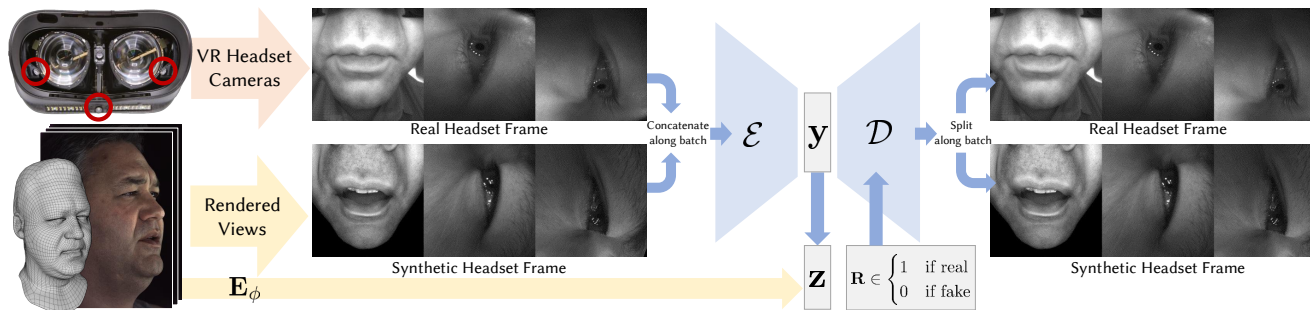


Image credits S. Lombardi ©ACM



# Improved telepresence experience



Image credits S. Lombardi

Recent work with relightable face models (SIGGRAPH 2021)

# Fast content generation from semantic maps

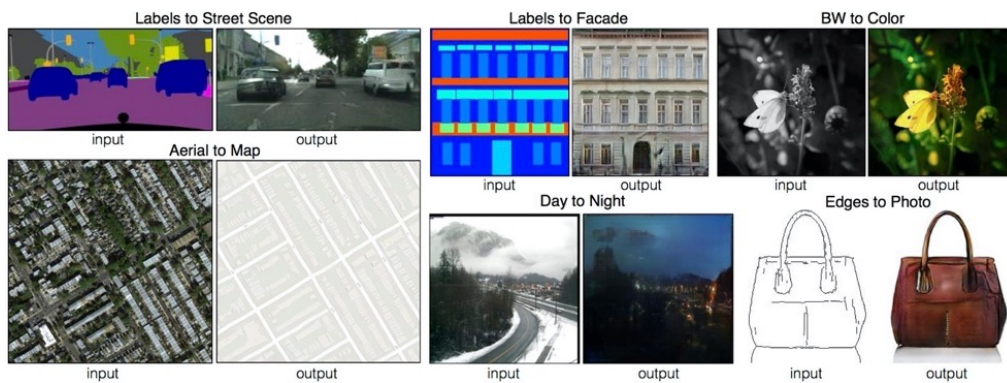


Image credits P. Isola ©IEEE

Image to Image translation



Image credits Q. Chen© ICCV

Synthesizing images

# NeRF – Novel view synthesis

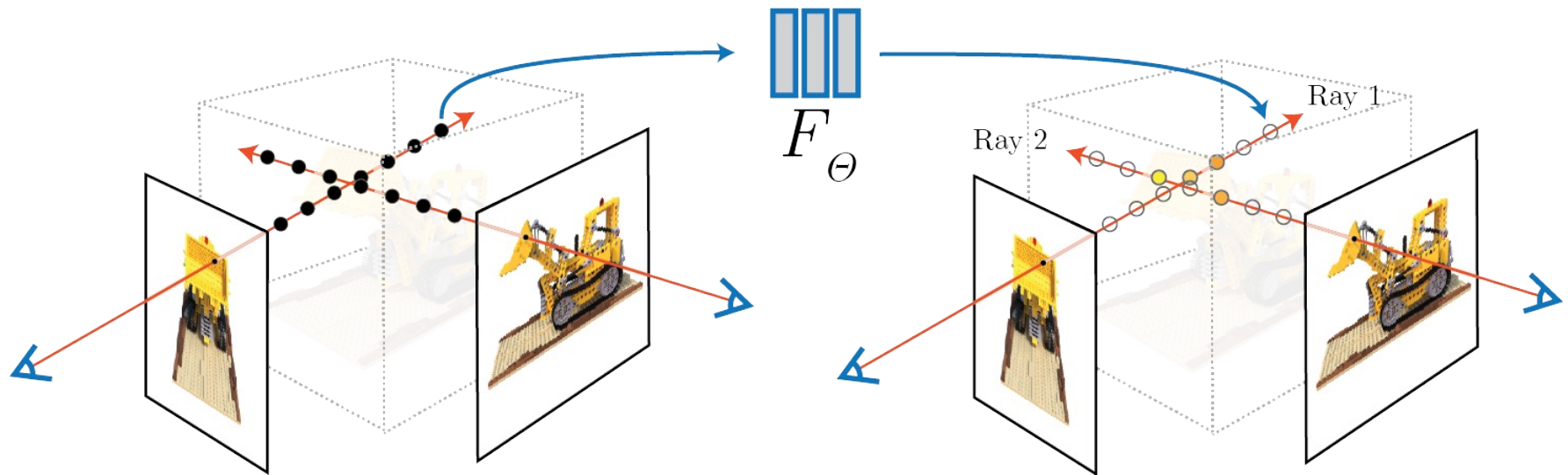


Image credits B. Mildenhall

Easing real-world content capture



# Instant NGP - ~real-time training



# ML for Rendering

Post processing, super sampling, denoising

# Deep learning for post-processing effects

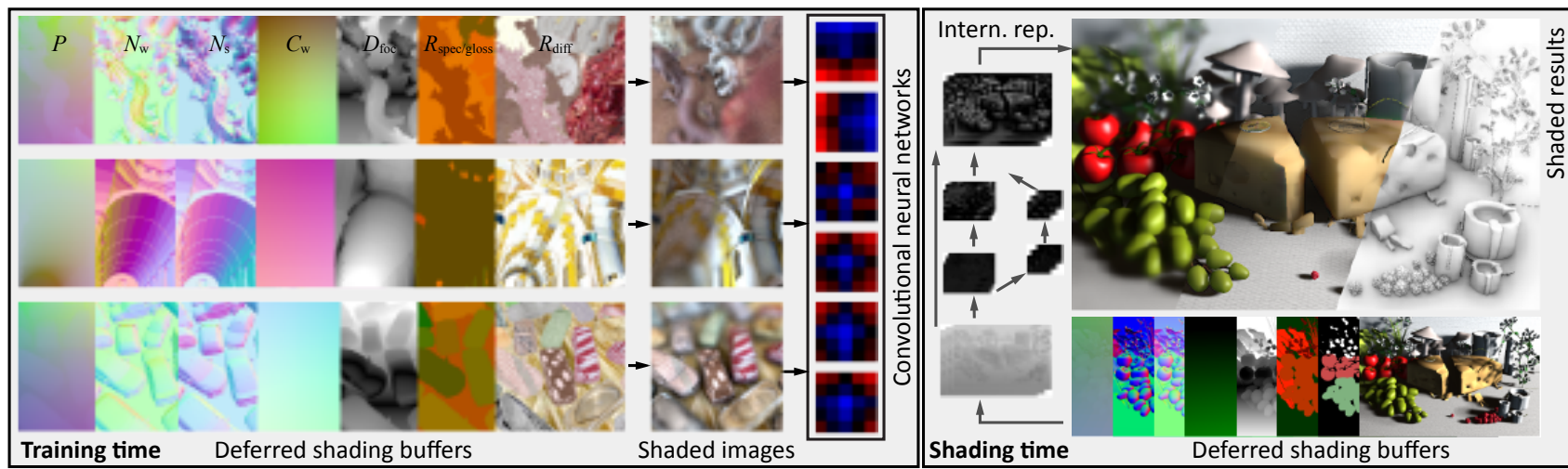


Image credit: O. Nalbach ©Eurographics

## Deep Shading- Synthesizing screen space effects using CNNs

# Deep Shading network architecture

- U-shaped CNN
- Input buffers depend on post processing effect desired
  - Usually Normals, albedo, motion vectors
- Combined effects using same network
- Fast inference performance

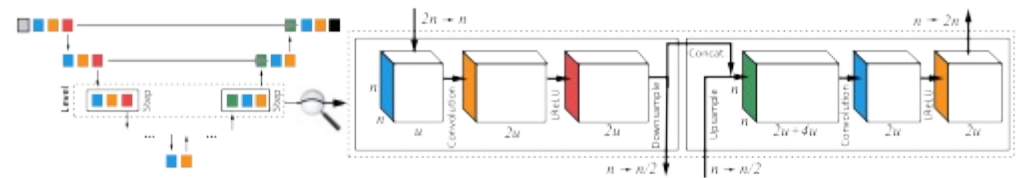
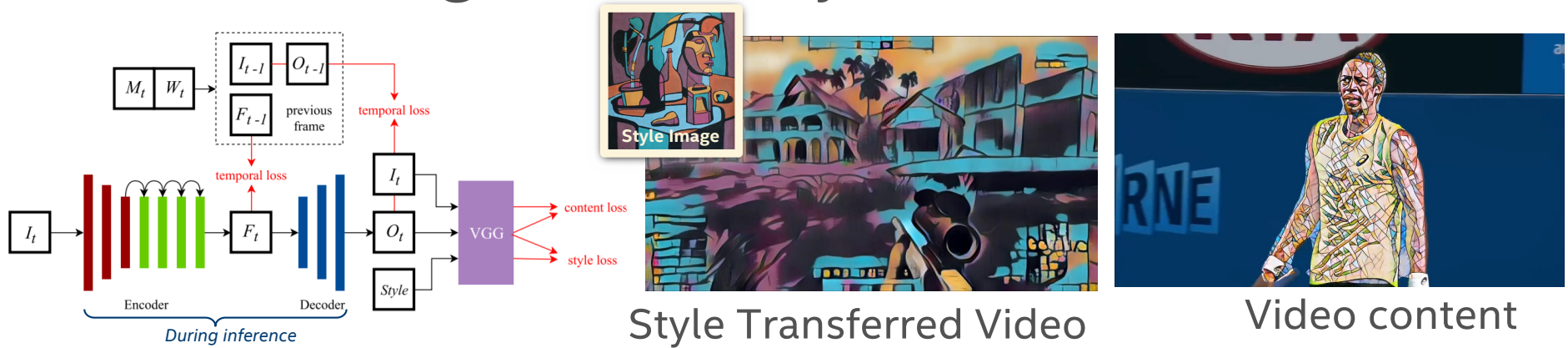


Image credit: O. Nalbach ©Eurographics

# Real-time Segmented Style Transfer

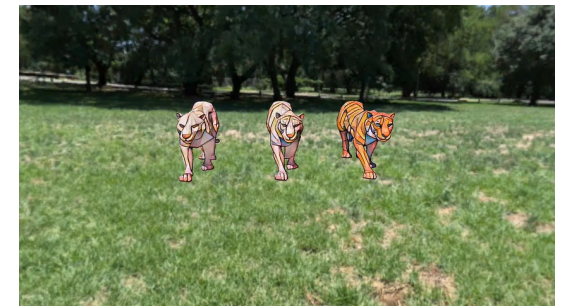


Style Transferred Video

Video content

Goal: Real-time, temporal consistent, high resolution, per object

- A Feedforward Network design using VGG for perpetual loss
- Use exact pixel segmentation for synthesized content



3D rendered content

# Challenges in rendering high resolution games

- Interactive gaming at high resolutions/ high fps
  - 4K gaming @60fps
- Bottlenecks in texture sizes, model detail
  - Many millions of polygons, multi GB textures
- Hybrid rendering
  - Global illumination, ray traced reflections, post processing effects

Traditional rendering methods may not suffice

# Deep learning super sampling (DLSS)

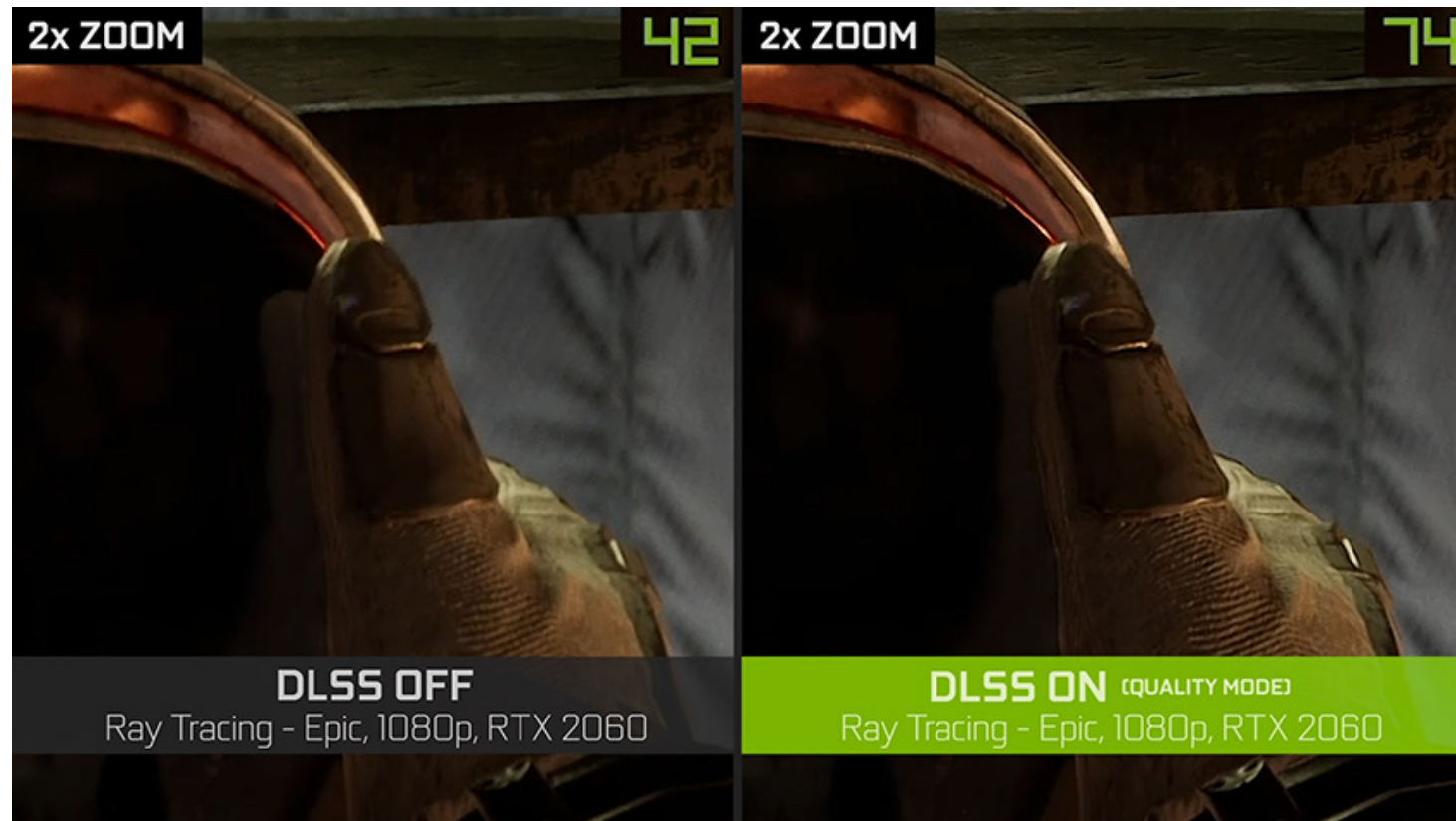


Image credit ©Nvidia

# DLSS 2.0 – Auto encoder with motion vectors

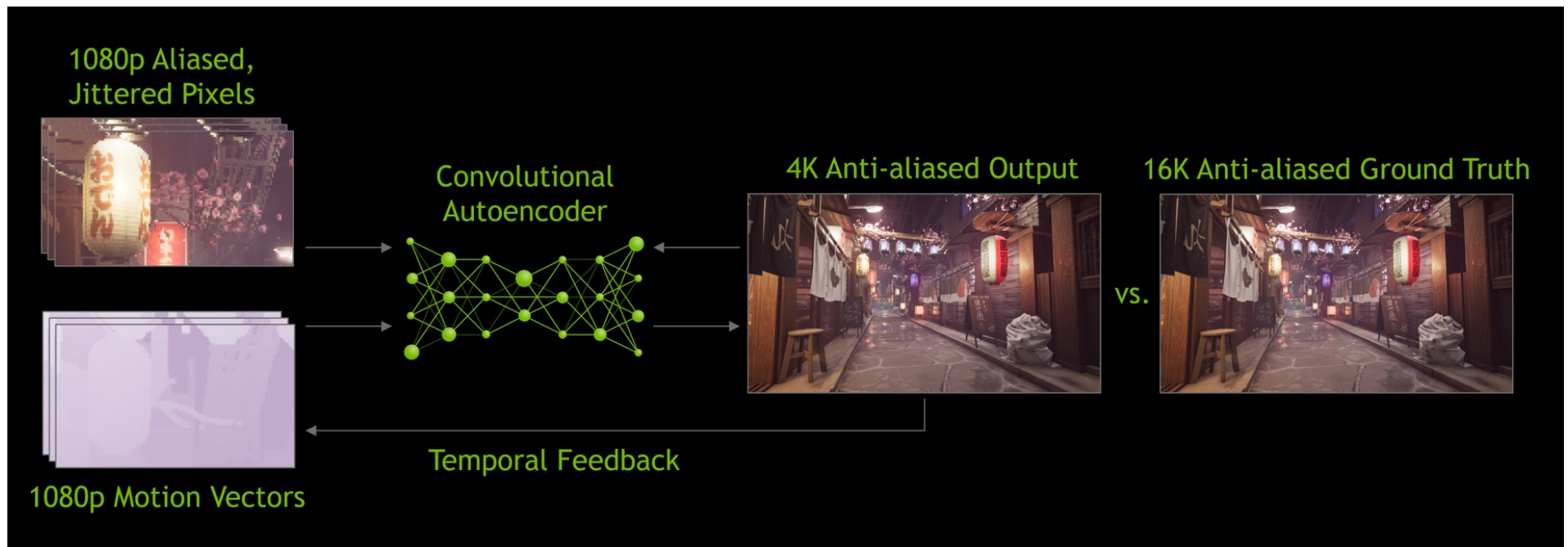


Image credit ©Nvidia



# Improved performance in games

- Render low resolution image
  - Image upscale using DL
- Async compute using Tensorcores
  - Significant performance improvement v/s rendering at higher resolution
- Wide adoption
  - Unity/ Unreal



Image credit ©Nvidia

# Intel® Open Image Denoise

- Denoising library for ray traced images
  - Final frames and baked lightmaps
- High-quality ML-based denoising filters
- Suitable for interactive and offline rendering
- Simple C/C++ API
- Easy integration into rendering applications
- Open Source under Apache\* 2.0 license
  - [www.openimagedenoise.org](http://www.openimagedenoise.org)

Scene courtesy of Frank Meinel,  
downloaded from Morgan McGuire's  
Computer Graphics Archive.



Ground truth:  
32K spp



The Junk Shop by [Alex Treviño](#). Original Concept by [Anaïs Maamar](#).

Ground truth:  
32K spp

Low sample count:  
16 spp



The Junk Shop by [Alex Treviño](#). Original Concept by [Anaïs Maamar](#).

Ground truth:  
32K spp

Low sample count:  
16 spp (denoised)



The Junk Shop by [Alex Treviño](#). Original Concept by [Anaïs Maamar](#).

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**OPEN IMAGE  
DENOISE**

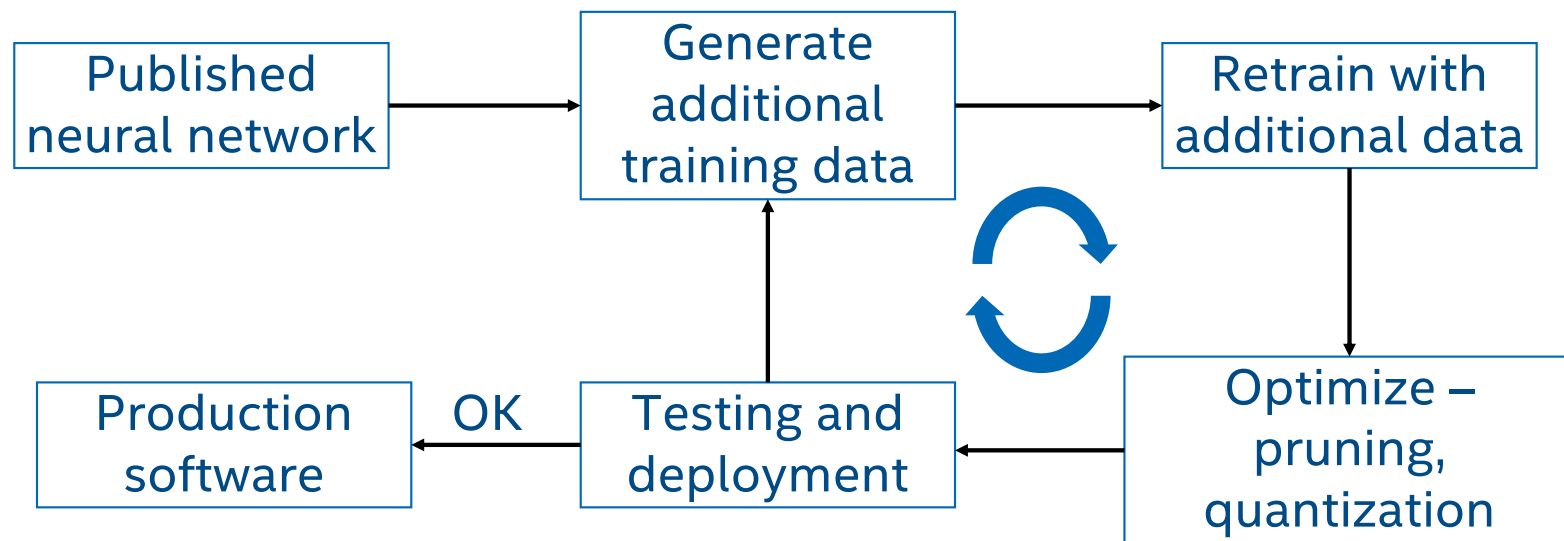
# More recent papers show promise

- Photogrammetry and novel view synthesis
- Vfx usages
  - Relighting, appearance capture
- Ray tracing and path tracing
  - Importance sampling, adaptive sampling with denoising
- Improving photorealism in games

# Challenges

Datasets, neural networks, deployment

# Testing and deploying a published ML model

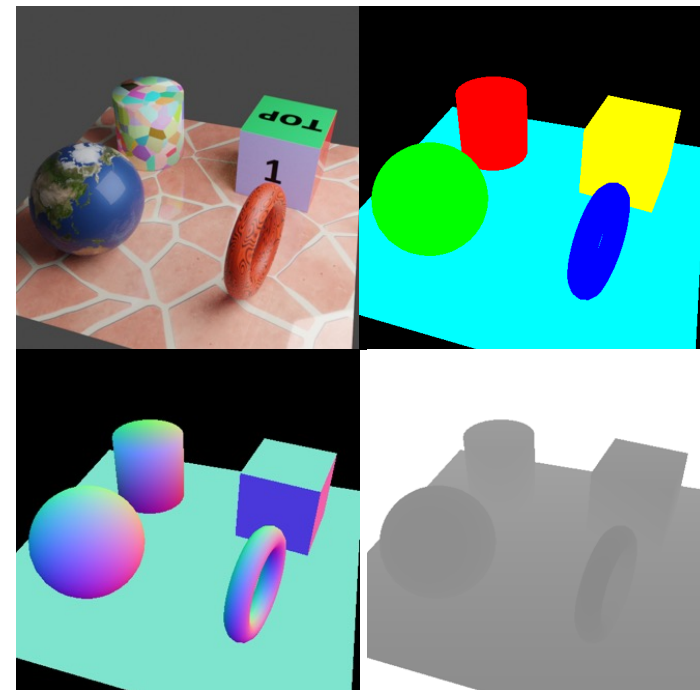


Iterative process and requires a lot of additional steps



# Dataset curation and augmentation

- Common buffers used – normal, albedo, color, position, depth, specular, motion vectors
- Most data can be directly obtained from renderers
- Input resolution
- Rendering time for dataset



# Some considerations for dataset generation

- Size of dataset to be collected – small v/s large
  - Training time v/s quality
- Licensing of datasets – open v/s closed
- Generalizability across different scenes
  - Rendering time implications
- Compressed v/s uncompressed data
  - Memory costs and training time
- Data format – color space, dynamic range

# Neural network architecture and optimizations

- Takes some effort to deploy published work
  - Understand performance targets and deployment system
- Common network optimizations
  - Pruning, quantization, sparsity
- Use tools such as TensorRT, OpenVINO for auto optimization
  - Most take an ONNX file as input
- Considerations for extending from images to videos
  - Minimize flicker, include temporal loss terms

# Deployment considerations

- Training generally uses Pytorch/ Tensorflow
  - Impractical for deployment in real-time usages
- Hardware compatibility and driver support
  - Fallback software path may not be as performant as hardware supported path
- Standards and APIs evolving to support ML
  - DirectML with DirectX, ONNX as model interchange format
- Third party and ecosystem support
  - E.g: Unity Barracuda for inference deployments

# Exciting time to be in graphics

- Increased use of ML in graphics
- Potential to improve quality, reduce rendering times and democratize content generation costs
- Improved hardware and systems support,

But..

- Challenges – datasets, networks, deployments

**We have just scratched the surface**

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