Text-to-3D Generative AI on Mobile Devices: Measurements and Optimizations

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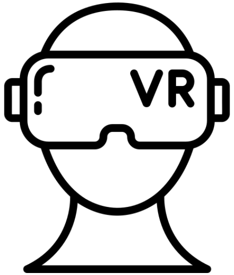
Text-to-3D Generative AI

"A pumpkin" ⟹ **Text-to-3D Generative AI** ⟹ 

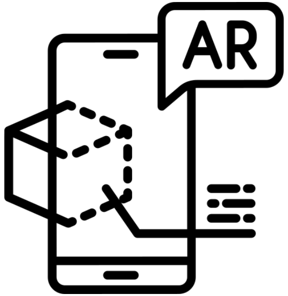
Input: Text Prompt

Output: 3D Model

Application Scenarios:

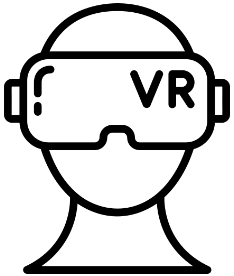


Gaming

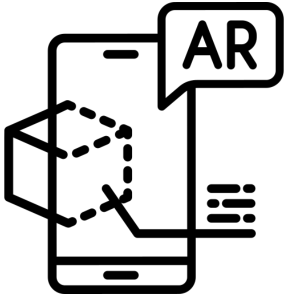


Product Design

Text-to-3D Generative AI



Gaming



Product Design

Mobile Devices

Problems:

Not ready for mobile deployment due to resource constraints (memory, compute, energy, etc.)

E.g., DreamFusion takes 12 hours to generate a 3D object on a NVIDIA V100 GPU

Motivation

We want to deploy Text-to-3D generative AI on mobile devices while ensuring good user experience

➡ **Low Latency**
Low Memory Usage
High 3D Object Synthesis Quality

Motivation

Low Latency
Low Memory Usage
High Synthesis Quality

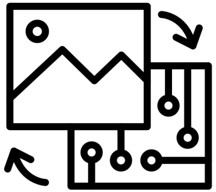
Optimization

Measurements to identify bottlenecks

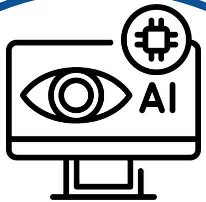
Background

Text - to - 3D

Natural Language Processing



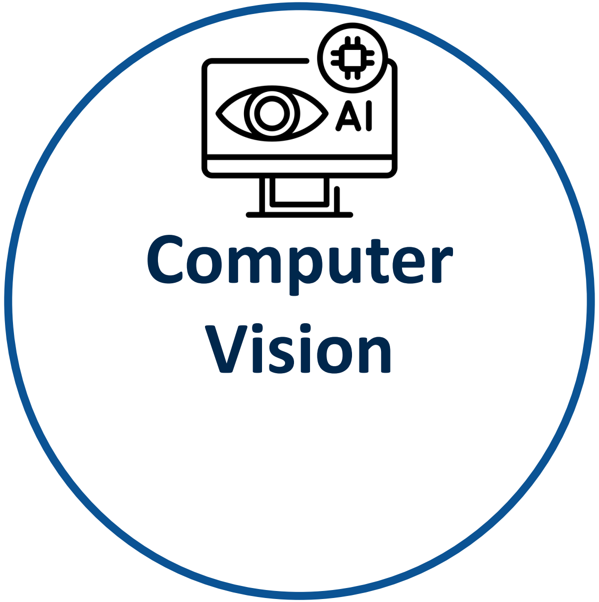
Generative AI



Computer Vision

Background: 3D Representations

3D

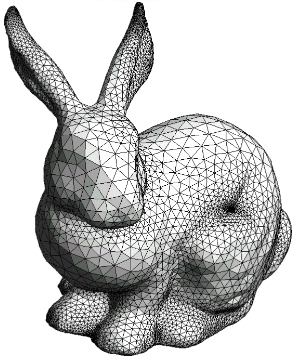


Background: 3D Representations

Explicit Representation

Point Clouds

3D Meshes



Implicit Representation

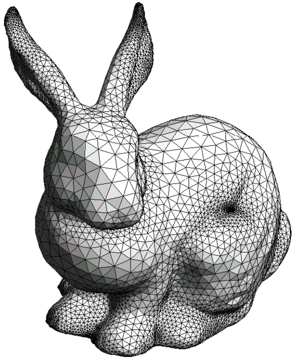
NeRF

SDF

Background: Explicit Representations

Point Clouds

3D Meshes

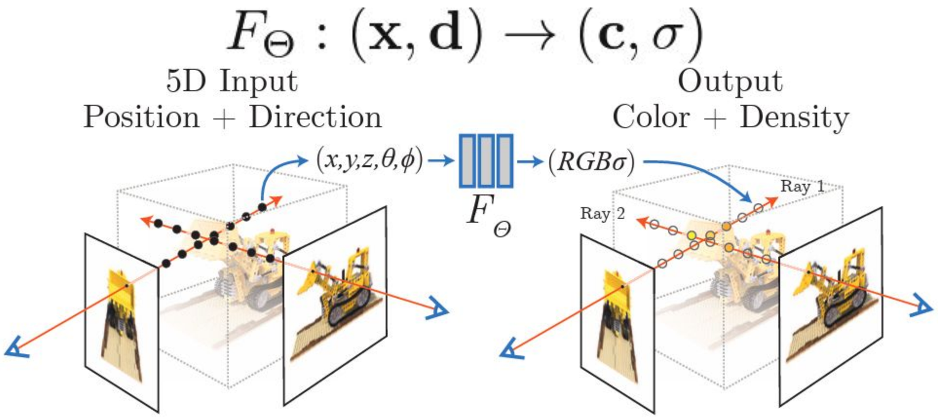


Usually use discrete locations represented by points, edges etc.

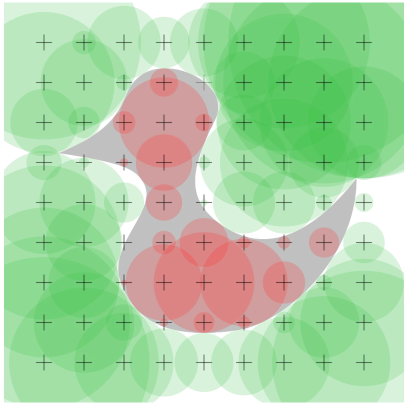
Low Latency
Low Memory Usage
Low Synthesis Quality

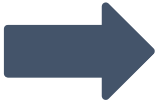
Background: Implicit Representations

NeRF: Neural Radiance Fields



SDF: Signed Distance Field





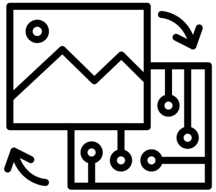
High **Latency** due to Computation
High **Memory Usage** due to Computation
High **Synthesis Quality**

Background: 3D Representations

	Explicit Representations	Implicit Representations
Latency	↓	↑
Memory Usage	↓	↑
Synthesis Quality	↓	↑

Background

to

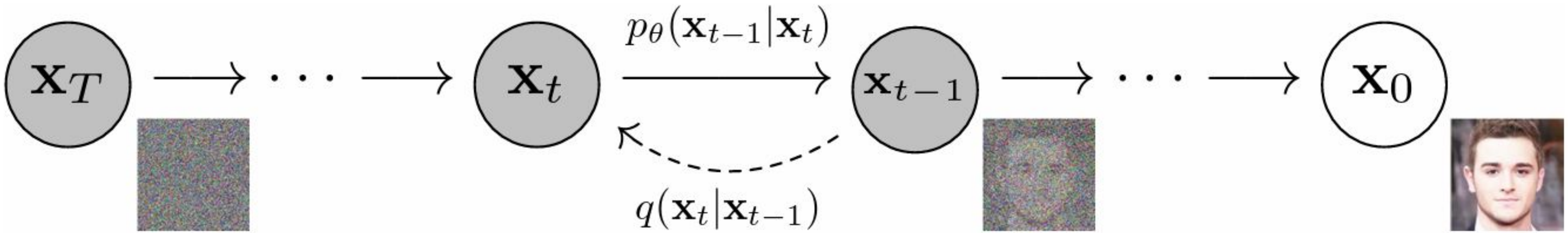


Generative

AI

Background: Diffusion Model

Reverse Diffusion Process

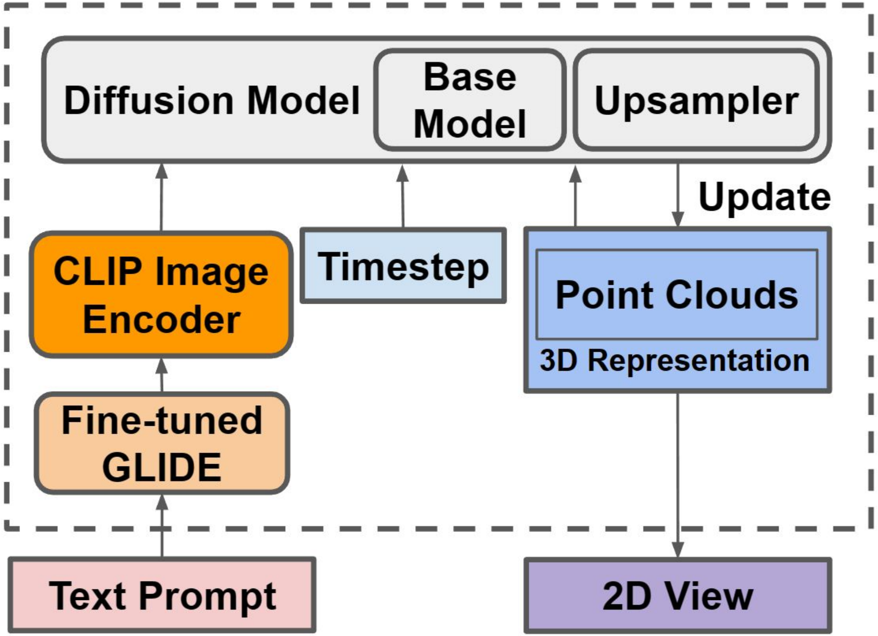


Forward Diffusion Process

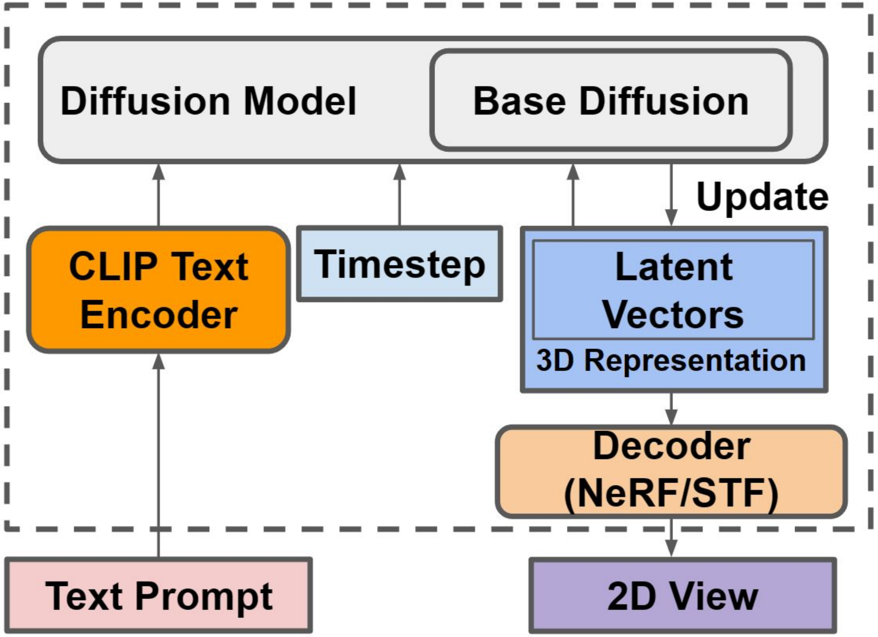
Many steps of an expensive machine learning model (e.g. Unet, ViT) is needed to learn the reverse diffusion process.

Diffusion Model Overview

Point-E (Dec. 2022)



Shap-E (May 2023)



Measurements

What are the bottlenecks to deploy text-to-3D models on mobile devices?

What to measure?

Optimization Goals:

Low Latency

Low Memory Usage

Good Synthesis Quality

Measurement Setup

Hardware:

NVIDIA T4 GPU (weak server GPU)
NVIDIA Jetson AGX Orin (mobile GPU)

Dataset:

COCO
Common Objects in Context

Measurement Setup: Model Configurations

For Point-E and Shap-E:

Parameter count for Diffusion:

- 40M
- 300M
- 1B

Conditioning options:

- Text-only

  Text → 3D

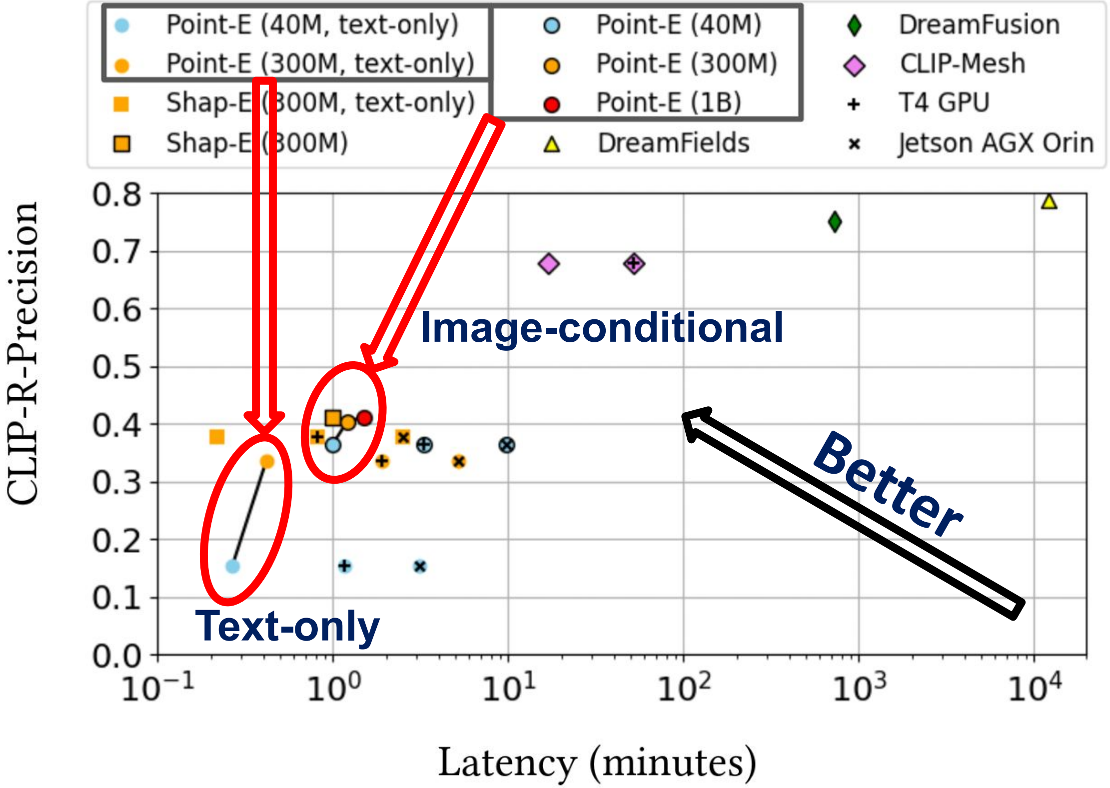
- Image-conditional (Default)

  Text → 2D → 3D

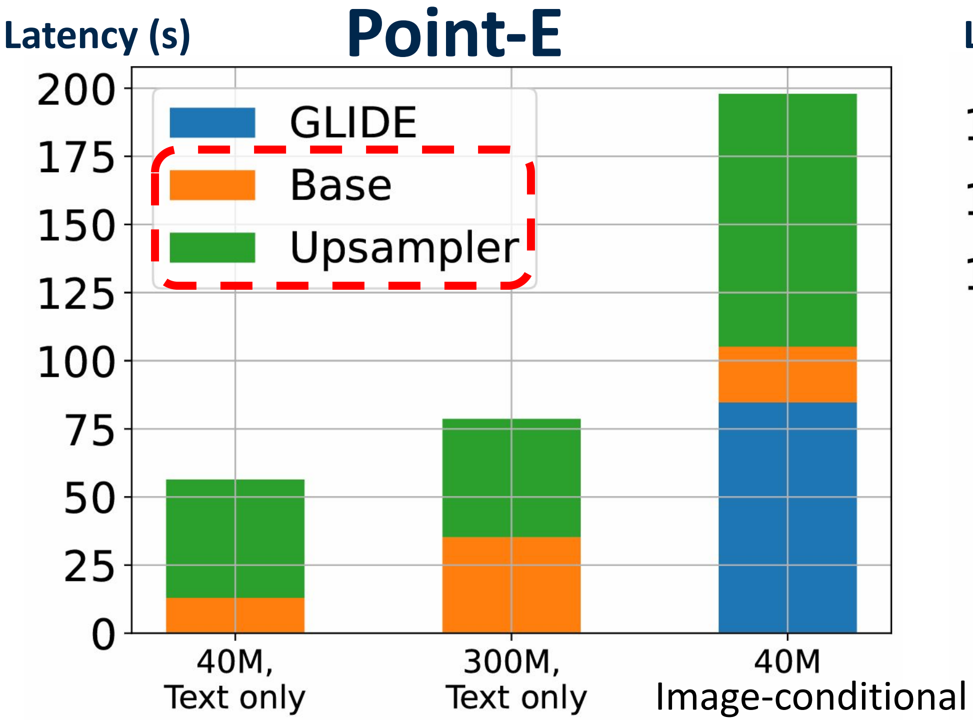
Latency-Quality Tradeoff

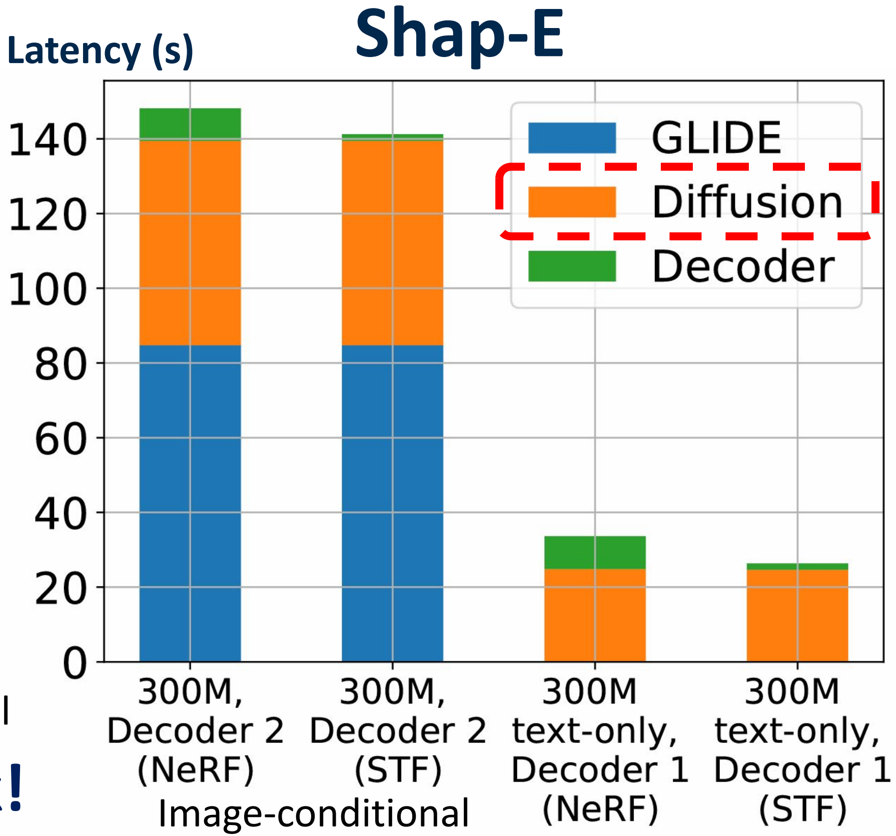
Synthesis quality:
Image-conditional > Text-only

Latency:
Text-only < Image-conditional



Latency Breakdown

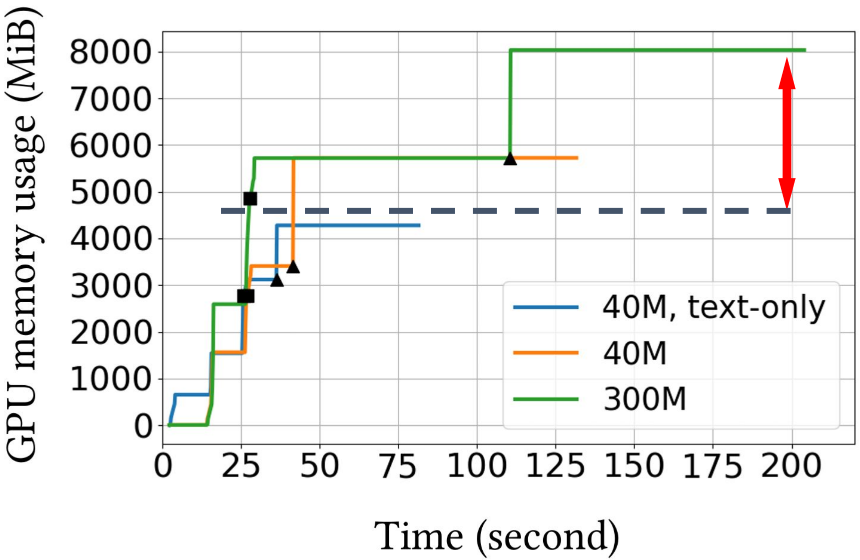




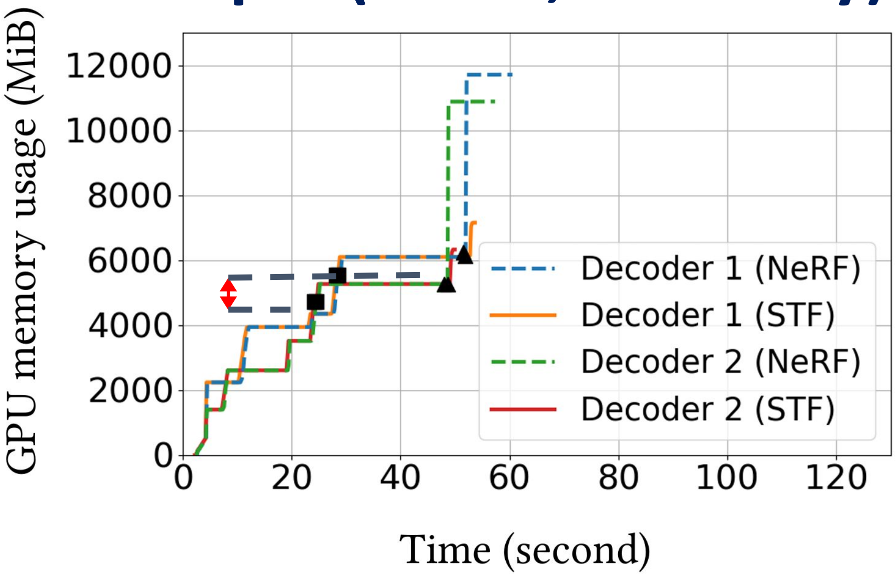
Diffusion is a latency bottleneck!

GPU Memory Measurement

Point-E



Shap-E (300M, Text-only)



■ Start base diffusion ▲ Start upsampling ■ Start diffusion ▲ Start decoding (renderin

Implicit representation can save memory usage during generation.

Model Optimization

What to optimize?

Diffusion process!

Model Optimization

How to optimize?

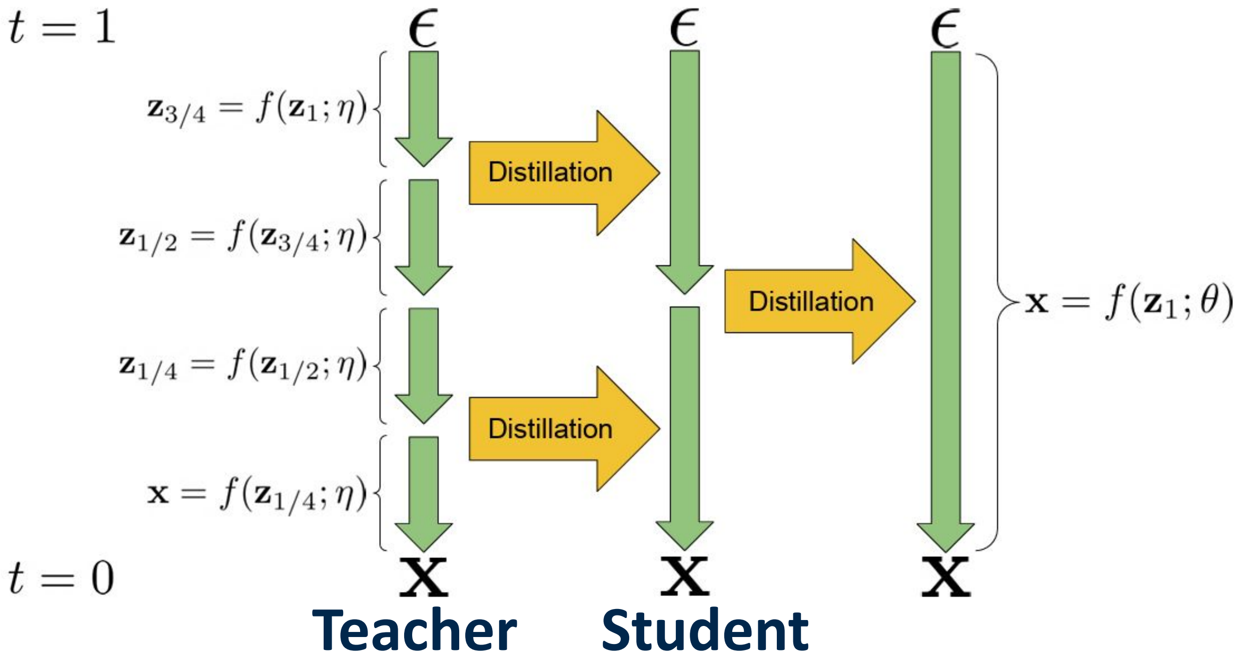
- Distillation
- Quantization

Can be generalized for other diffusion based models

- Neural Architecture Search, Pruning, etc.

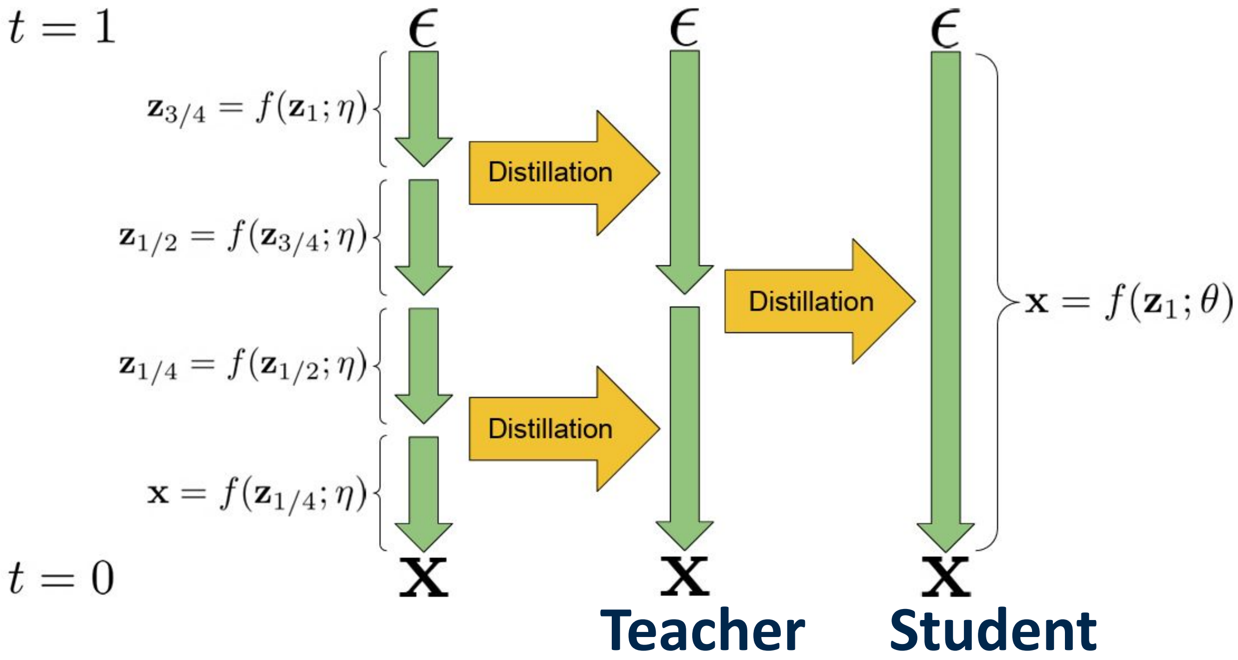
Model Optimization: Distillation

Speed up the model by reducing steps



Model Optimization: Distillation

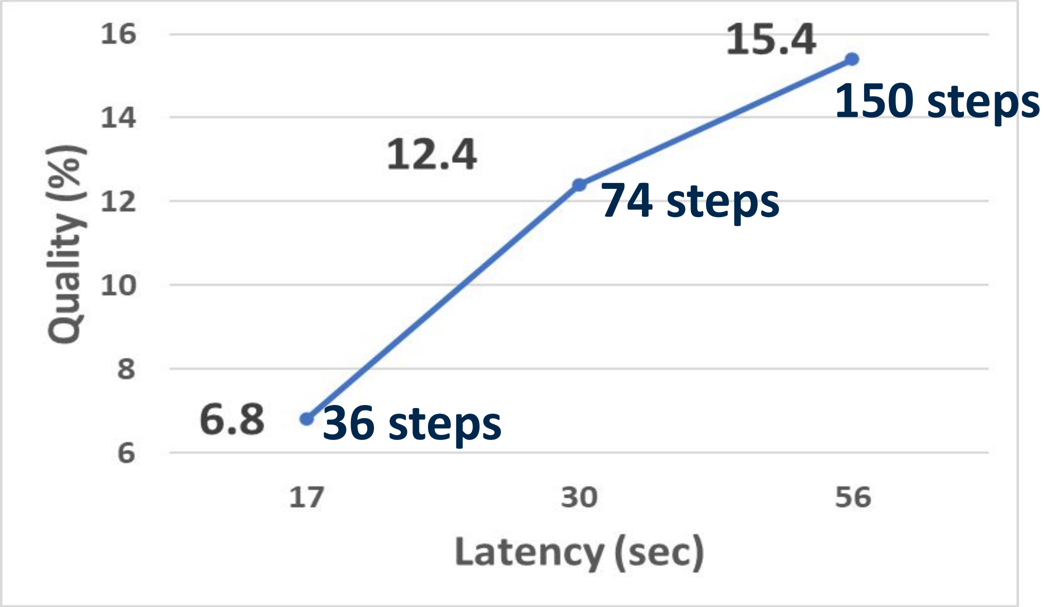
Speed up the model by reducing steps



Model Optimization: Distillation

Speed up the model by reducing steps

Point-E results:



Synthesis quality severely degrades at lower latency.

Model Optimization: Quantization

Speed up the model and **reduce memory usage** by using **lower precision parameters:** 32 bit → 8 bit

Quantization

Point-E results:

Library	Layers	Quality ↑	Speed
Original	n/a	15.4%	×1
TensorRT	Linear	10.2%	×1.3
TensorRT	All	1.7%	×1.8
PyTorch (FBGEMM)	Linear	11%	×1.3

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Quantization

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May need custom per-layer quantization

Summary

Thank you! Questions?

Custom optimization (e.g. distillation, quantization) of text-to-3D models needed for mobile deployment.

Shap-E outperforms Point-E on mobile devices, possibly due to its efficient implicit representation.

Synthesis quality:

Text → 2D → 3D > Text → 3D