

Ray Tracing in Entertainment Industry

Tanaboon Tongbuasirilai
Dept. Computer Science
Kasetsart University

Week 9

Sampling techniques and reconstruction

Sampling techniques and reconstruction

What sampling techniques do we have so far ?

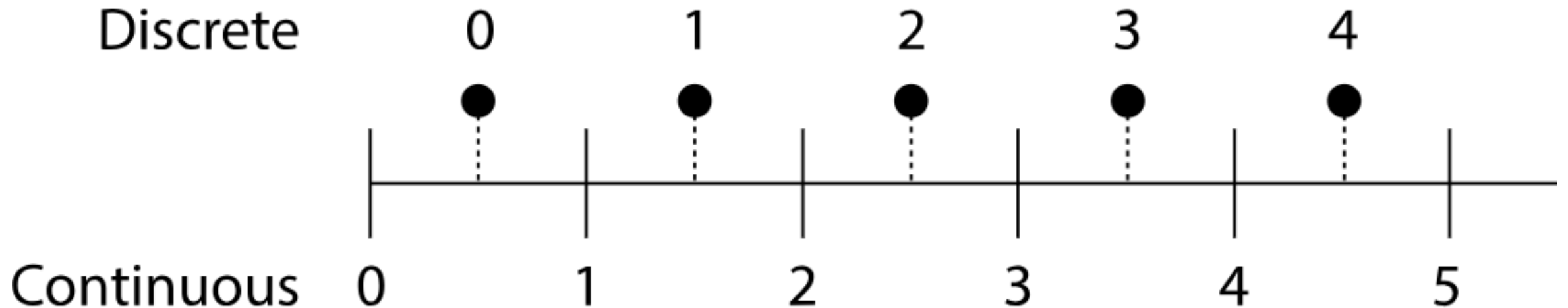
- Random sampling of a 3D vector : `random_vec3()`
- Random unit vector in a unit disk : `random_vec3_in_unit_disk()`
- Random unit vector in a unit sphere : `random_vec3_unit ()`
- Random directions in `scattering()`
- Random locations in a pixel

How random samples impact to the ray tracer ?

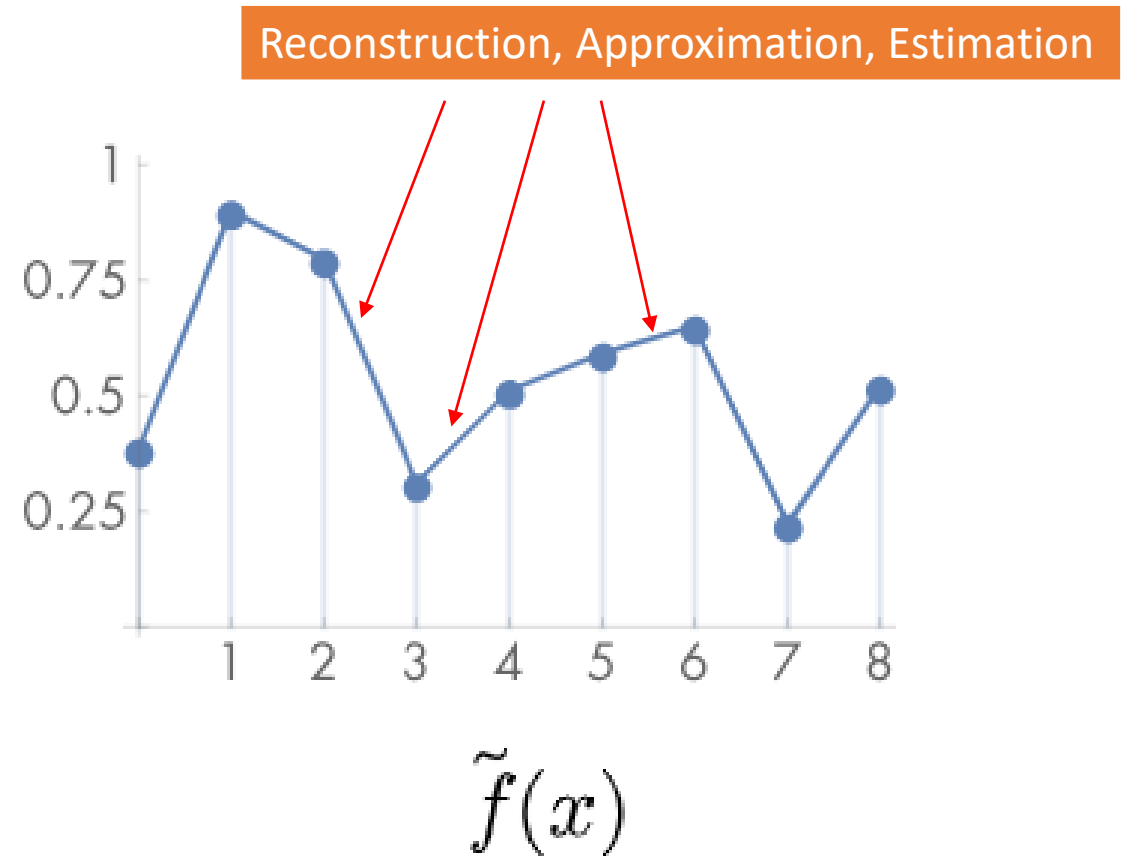
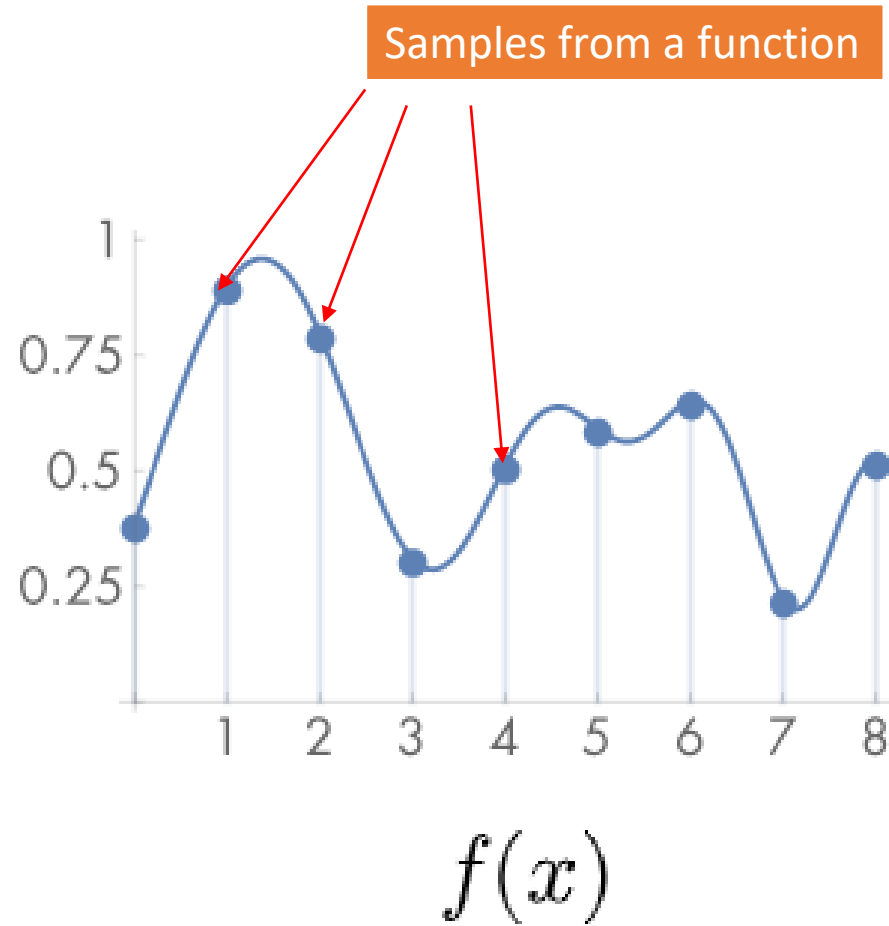
- Camera
- Material
- Light
- Integrator

Why do we need sampling ?

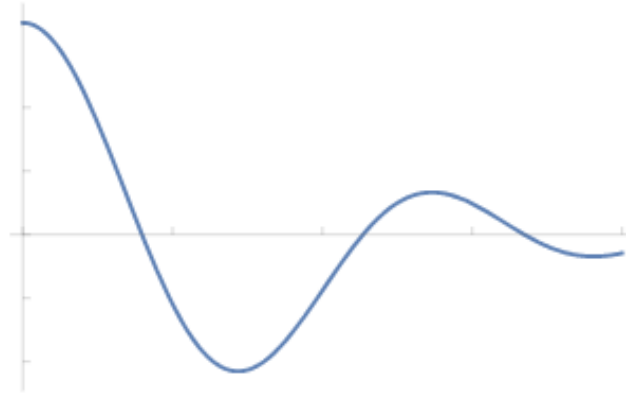
- Discrete vs. Continuous
 - Image with different resolutions
- Functions is defined on Real (continuous) domain.
- We would like to represent continuous functions in an efficient way.



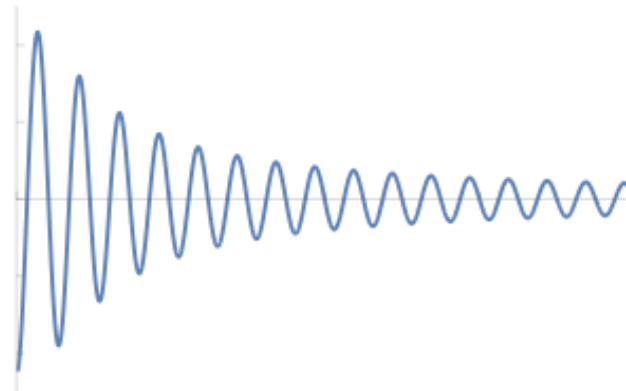
Sampling and reconstruction



High-
frequency vs.
Low-
frequency

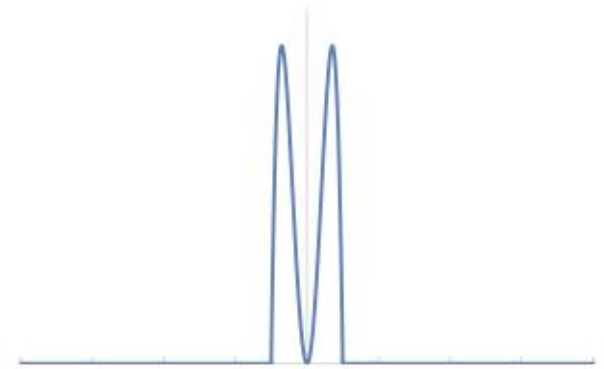


(a)

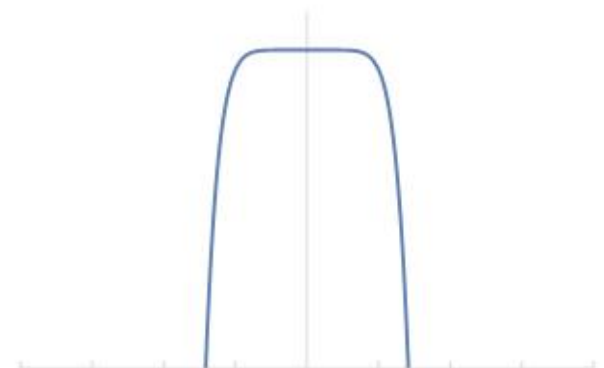


(b)

Spatial domain



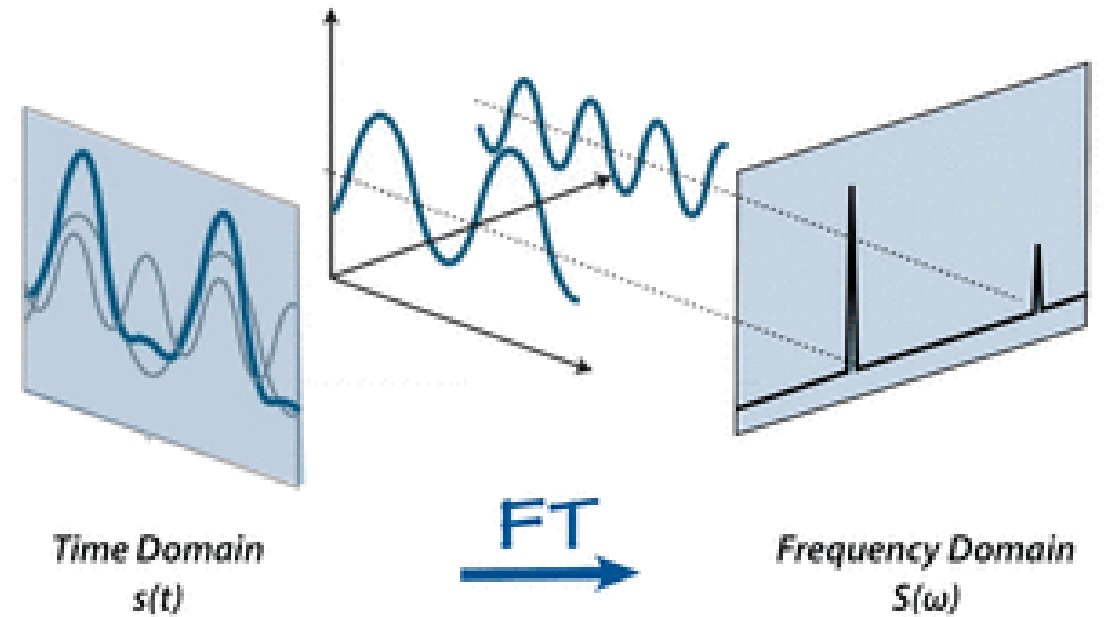
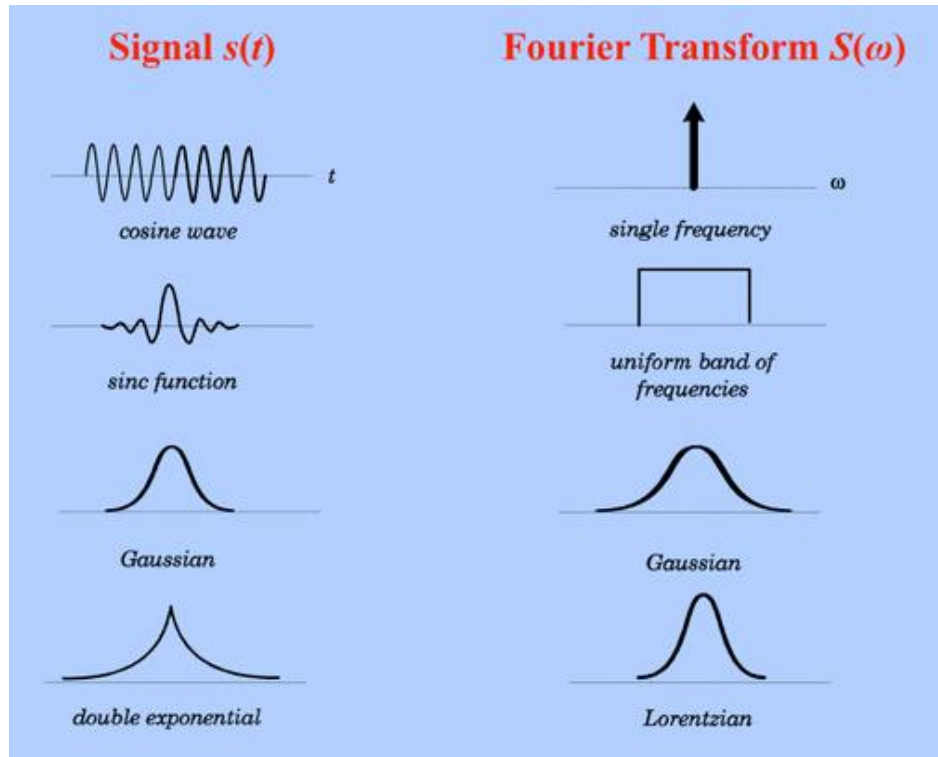
(a)




(b)

Frequency domain

Fourier transform





Fourier transform of a 1D function

$$F(\omega) = \int_{-\infty}^{\infty} f(x) e^{-i2\pi\omega x} dx.$$

Fourier transform

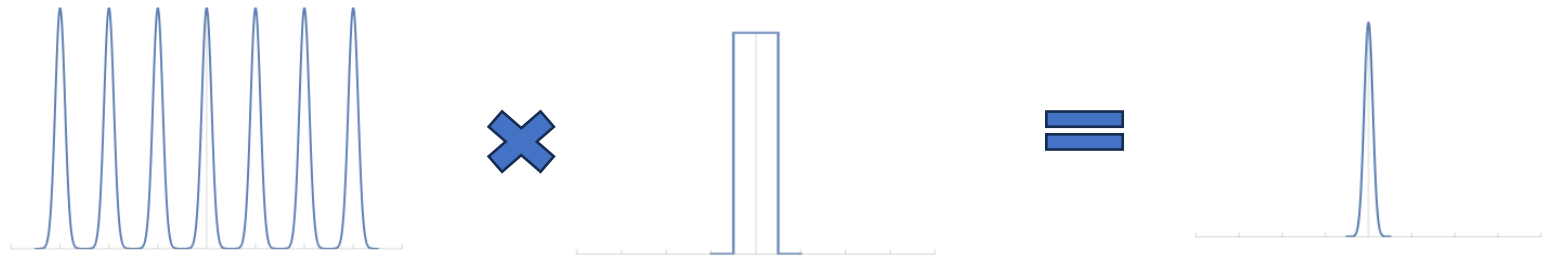
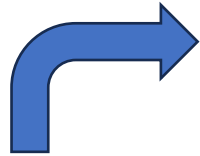
$$f(x) = \int_{-\infty}^{\infty} F(\omega) e^{i2\pi\omega x} d\omega.$$

Inverse Fourier transform

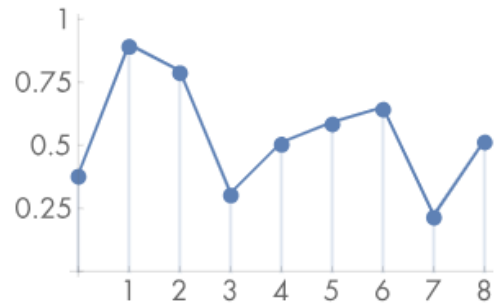
Aliasing

$F(w)$ = Fourier transform of $f(x)$

High-frequency sampling



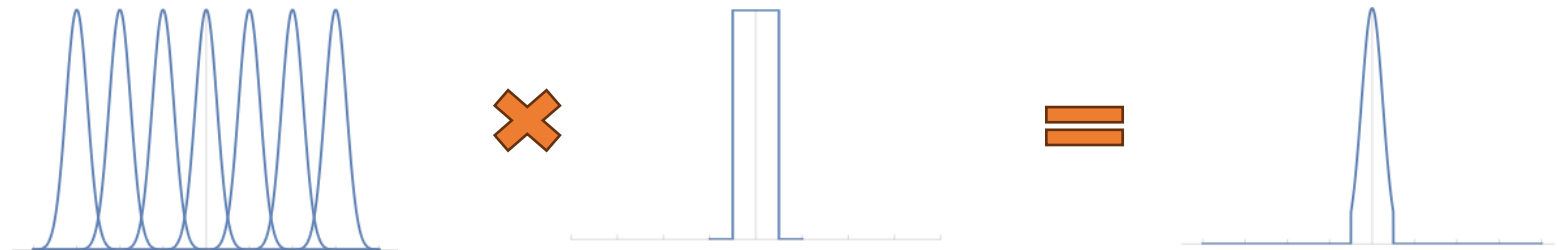
$f(x)$



Convolutions of $F(w)$

A box function

Low-frequency sampling



What it means to image synthesis.

We would like to reconstruct the function representing the 3D scene.

Aliasing occurs naturally for such problem and there are many parameters involving in this issue.

What to write in the image plane.

What we consider in sampling.

- Image resolution
- Time
- Lens
- etc.

Radiance contribution at the location (x,y).

The diagram illustrates the process of image synthesis. A blue box on the left lists sampling parameters: 'What to write in the image plane.' and 'What we consider in sampling.' followed by a list: '- Image resolution', '- Time', '- Lens', and '- etc.'. An orange box on the right states 'Radiance contribution at the location (x,y)'. A blue arrow points from the blue box to the function $f(x, y)$ in the equation $f(x, y) \rightarrow L.$. An orange arrow points from the orange box to the $L.$ part of the equation.

$$f(x, y) \rightarrow L.$$

Antialiasing techniques



Nonuniform sampling

Nonuniform sampling tends to turn the regular aliasing artifacts into noise, which is less distracting to the human visual system.



Adaptive sampling

If we can identify the regions where they need more samples, it will be less expensive than taking more samples in every region.



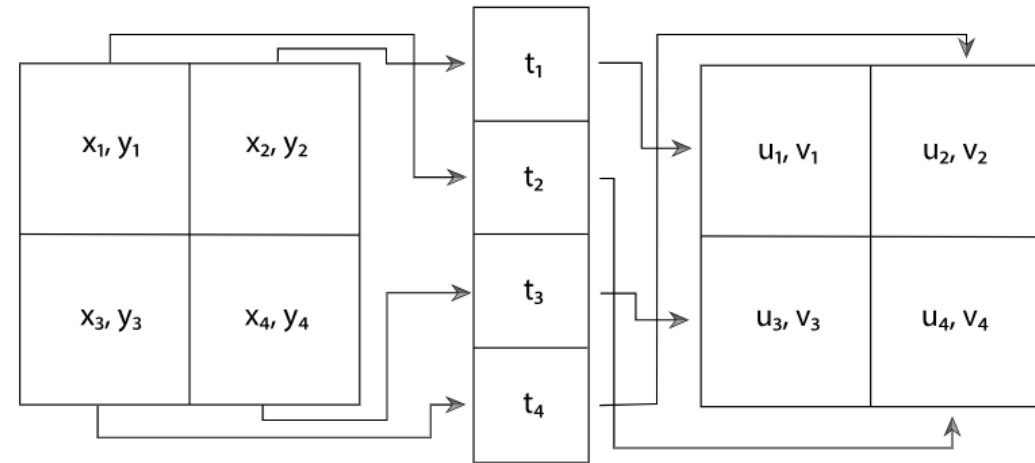
Prefiltering

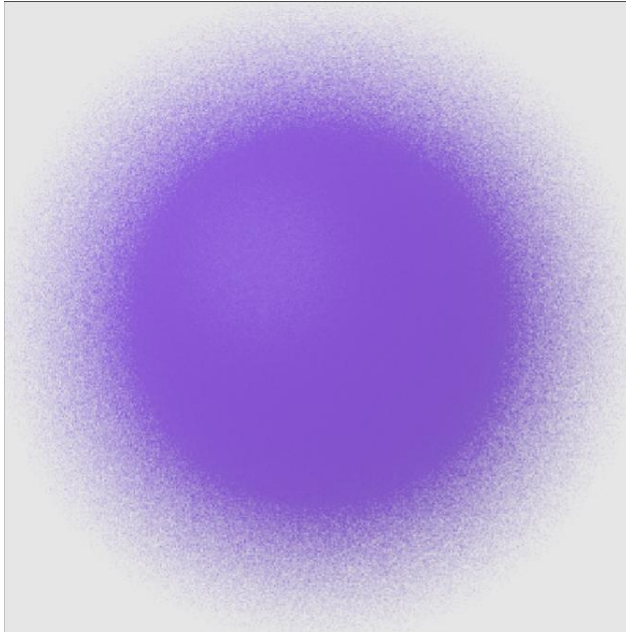
Filtering can be used to mitigate aliasing by lower frequencies so that the current sampling rate cannot capture the aliasing.

Sampling over image
plane

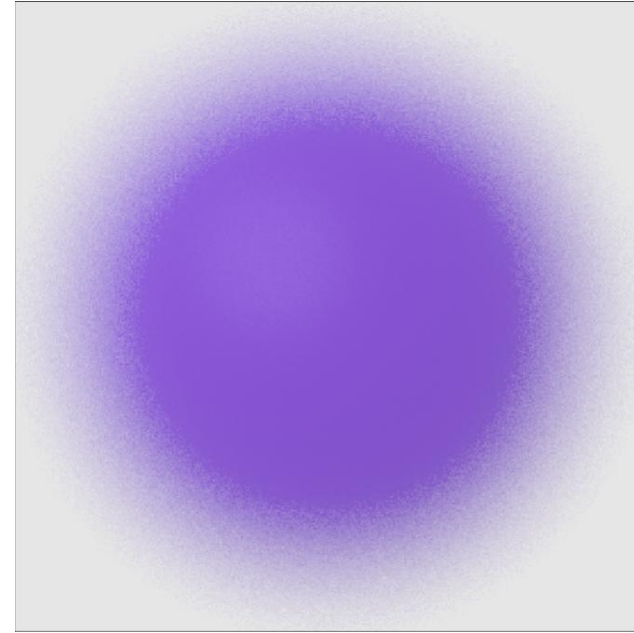
Stratified sampling

- Subdividing region into smaller sub regions.
- Each sub regions is called strata.
- The more sub regions there is, the higher the sampling rate is.
- Each sample variable is drawn independently to each other in high-dimensional space.
 - This turns the aliasing problem into a noisy pattern.
 - The drawn samples can cover the sample space without excessive computation.



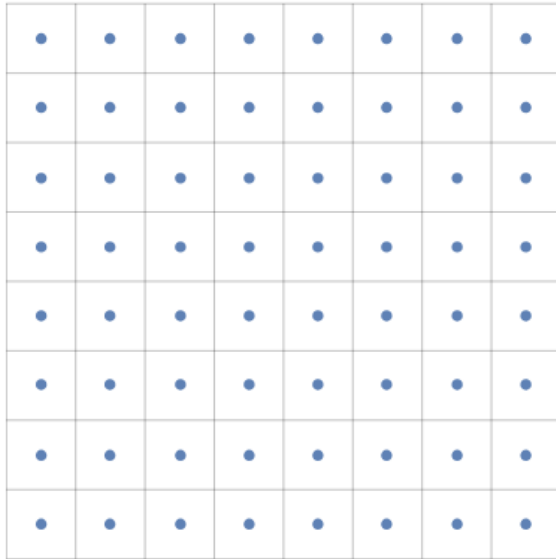


Random



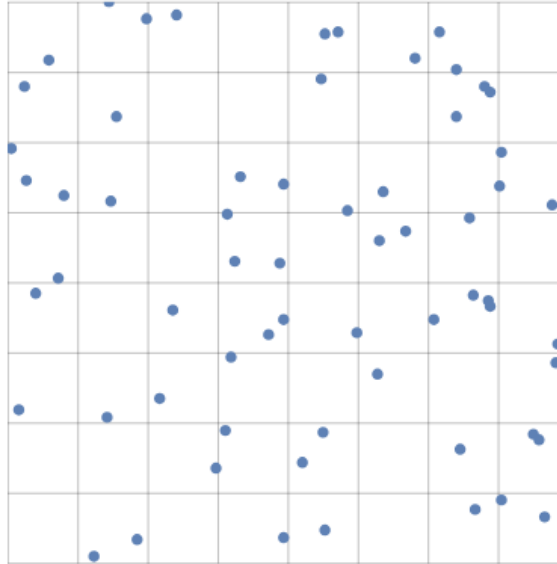
Stratified

Comparison



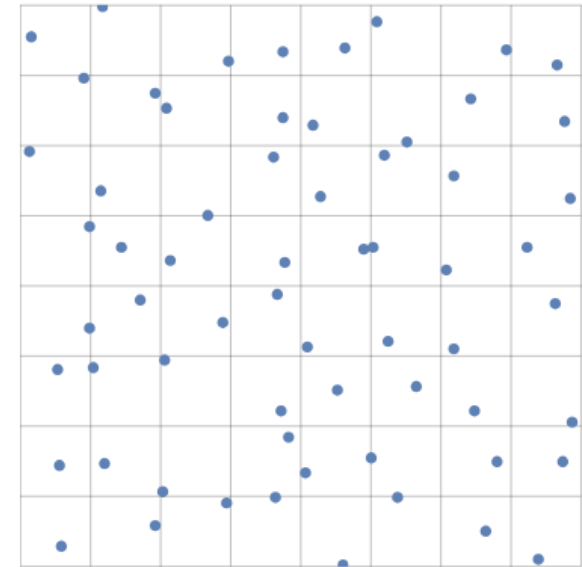
Uniform stratified pattern

subdividing regions but still
uniform sampling



Uniform random pattern

uniform random the whole
region



A stratified jittered pattern

subdividing regions and
jittering each subregion

Comparison

Jittered vs. Unjittered



Coding Renderer

```
def render(self):
    # gather lights to the light list
    self.scene.find_lights()

    for j in range(self.camera.img_height):
        for i in range(self.camera.img_width):

            pixel_color = rtu.Color(0,0,0)
            # shoot multiple rays at random locations inside the pixel
            for spp in range(self.camera.samples_per_pixel):
                generated_ray = self.camera.get_ray(i, j)
                pixel_color = pixel_color + self.integrator.compute_scattering(generated_ray, self.scene, self.camera.max_depth)

            self.camera.write_to_film(i, j, pixel_color)
```

```
def render_jittered(self):
    # gather lights to the light list
    self.scene.find_lights()
    sqrt_spp = int(math.sqrt(self.camera.samples_per_pixel))

    for j in range(self.camera.img_height):
        for i in range(self.camera.img_width):

            pixel_color = rtu.Color(0,0,0)
            # shoot multiple rays at random locations inside the pixel
            for s_j in range(sqrt_spp):
                for s_i in range(sqrt_spp):

                    generated_ray = self.camera.get_jittered_ray(i, j, s_i, s_j)
                    pixel_color = pixel_color + self.integrator.compute_scattering(generated_ray, self.scene, self.camera.max_depth)

            self.camera.write_to_film(i, j, pixel_color)
```


Coding Camera

```
def get_jittered_ray(self, i, j, s_i, s_j):  
    pixel_center = self.pixel00_location + (self.pixel_du*i) + (self.pixel_dv*j)  
    pixel_sample = pixel_center + self.pixel_sample_square(s_i, s_j)  
  
    ray_origin = self.center  
    ray_direction = pixel_sample - ray_origin  
  
    return rtr.Ray(ray_origin, ray_direction)
```

```
def pixel_sample_square(self, s_i, s_j):  
    px = -0.5 + self.one_over_sqrt_spp * (s_i + rtu.random_double())  
    py = -0.5 + self.one_over_sqrt_spp * (s_j + rtu.random_double())  
    return (self.pixel_du * px) + (self.pixel_dv * py)
```



Sampling over
directions

Sampling a direction on hemisphere

```
@staticmethod
def random_vec3_on_hemisphere(vNormal):
    in_unit_sphere = Vec3.random_vec3_unit()
    if Vec3.dot_product(in_unit_sphere, vNormal) > 0.0:
        return in_unit_sphere
    else:
        return -in_unit_sphere
```

It might take a long time to get the correct result.

A Las Vegas algorithm is a randomized algorithm that always gives correct results.

A Monte Carlo algorithm is a randomized algorithm whose output may be incorrect, but it will improve when the samples are increased.



Scattered directions

```
def scattering(self, rRayIn, hHinfo):
    reflected_direction = -hHinfo.getNormal()
    # check if the reflected direction is below the surface normal
    while rtu.Vec3.dot_product(reflected_direction, hHinfo.getNormal()) <= 1e-8:

        # compute scattered ray
        reflected_direction = hHinfo.getNormal() + rtu.Vec3.random_vec3_unit()
        if reflected_direction.near_zero():
            reflected_direction = hHinfo.getNormal()

    reflected_ray = rtr.Ray(hHinfo.getP(), reflected_direction)
    phong_color = self.BRDF(rRayIn, reflected_ray, hHinfo)

    return rtu.Scatterinfo(reflected_ray, phong_color)
```

This may drop our sampling performance.



Sampling a direction in a unit sphere – Generating random directions relative to the Z axis

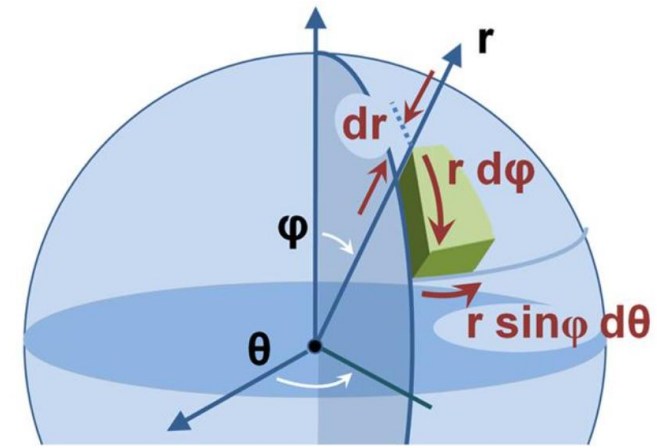
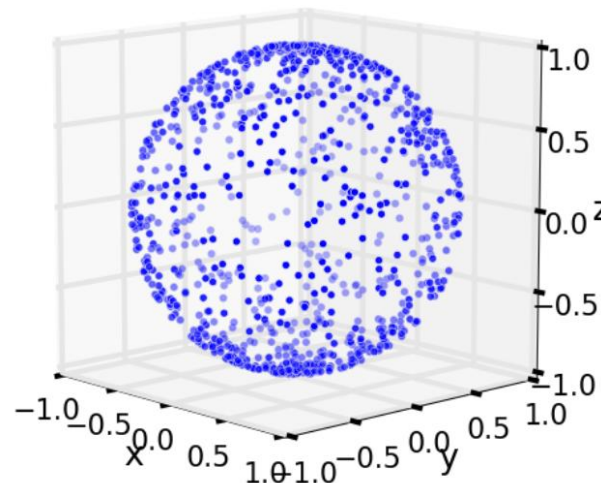
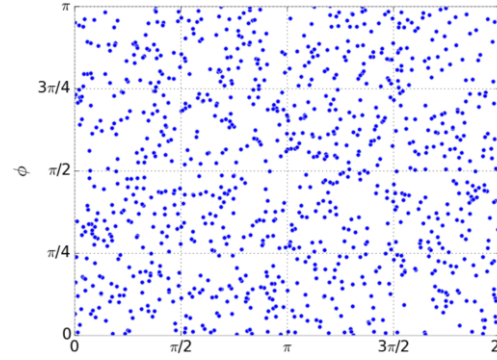
$$\theta \in (0, 90)$$
$$\varphi \in (0, 180)$$

A direction from spherical coordinate to cartesian coordinates

$$x = \cos(\varphi) \cdot \sin(\theta)$$

$$y = \sin(\varphi) \cdot \sin(\theta)$$

$$z = \cos(\theta)$$



The issue is the differential surface.



A more effective sampling approach

Cosine Sampling

Uniform sampling on ...

Sphere

$$x = \cos(2\pi r_1) \cdot 2\sqrt{r_2(1 - r_2)}$$

$$y = \sin(2\pi r_1) \cdot 2\sqrt{r_2(1 - r_2)}$$

$$z = 1 - 2r_2$$

$$r_1 \in [0,1]$$

$$r_2 \in [0,1]$$

hemisphere

$$z = \cos(\theta) = \sqrt{1 - r_2}$$

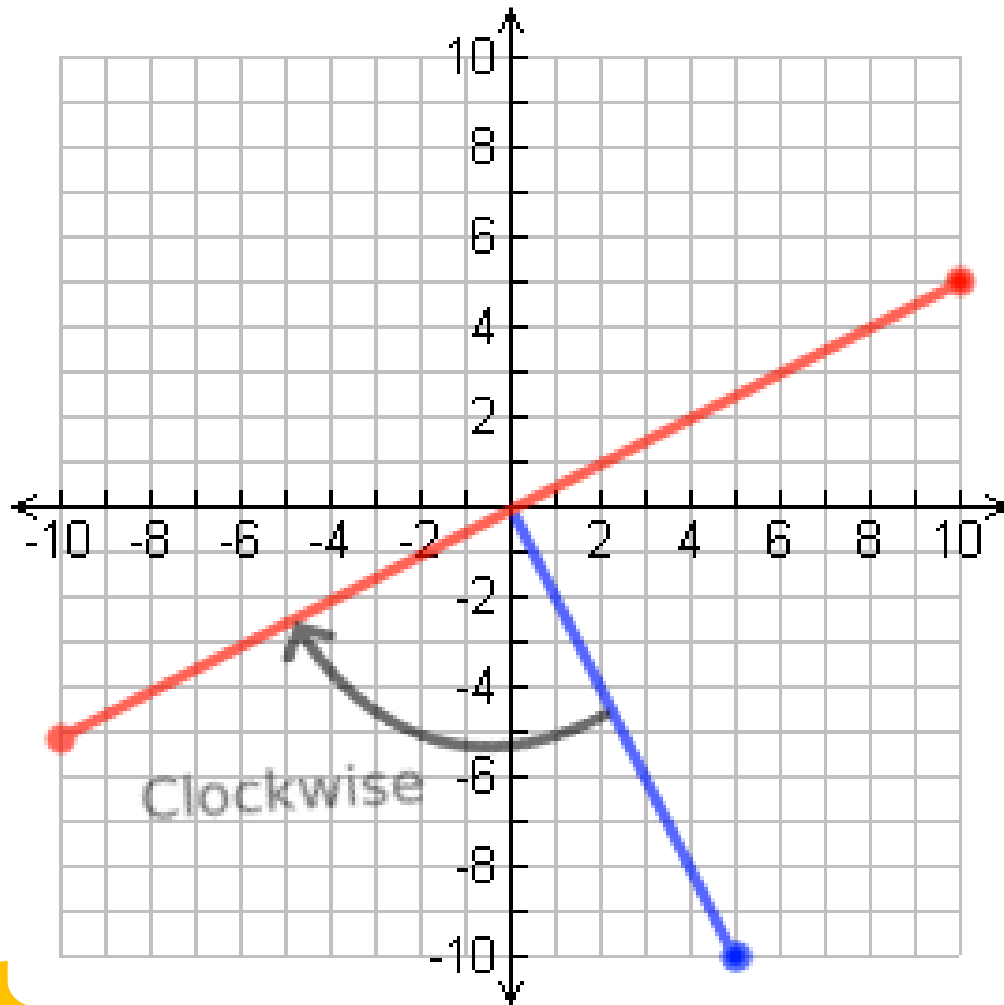
$$x = \cos(\phi) \sin(\theta) = \cos(2\pi r_1) \sqrt{1 - z^2} = \cos(2\pi r_1) \sqrt{r_2}$$

$$y = \sin(\phi) \sin(\theta) = \sin(2\pi r_1) \sqrt{1 - z^2} = \sin(2\pi r_1) \sqrt{r_2}$$

$$r_1 \in [0,1]$$

$$r_2 \in [0,1]$$

Before we continue further on sampling, Let me introduce you a useful tool for handling a change of coordinate system.



Orthonormal bases

- Two important properties for this.
 - Orthogonality
 - The vectors are all pairwise perpendicular, meaning their dot product is zero.
 - Normality
 - Each vector has a magnitude (length) of 1.

Why ?



Scene, objects, rays, cameras must be aligned in the same coordinate system.



Cartesian coordinate system (x, y, z) is an example of a subset of orthonormal basis.



Sometimes it is difficult to do operations on the original coordinate system, like Cartesian coordinate system.



Generating an orthonormal basis is a way to handle arbitrary points on the original coordinate system.

Relative coordinates

Location is $\mathbf{O} + 3\mathbf{x} - 2\mathbf{y} + 7\mathbf{z}$

Point of origin

Relative point to the origin

Location is $\mathbf{O}' + u\mathbf{u} + v\mathbf{v} + w\mathbf{w}$



A point with coefficients (u, v, w) on U, V, W coordinate system relative to the origin \mathbf{O}' .

Generating an orthonormal basis given that we have a normal vector

Pick an arbitrary axis, \mathbf{a} , not parallel to the normal, \mathbf{n} .

Find a vector \mathbf{s} perpendicular to \mathbf{a} and \mathbf{n} .

Find a vector \mathbf{t} perpendicular to \mathbf{s} and \mathbf{n} .

A vector $(\mathbf{x}, \mathbf{y}, \mathbf{z})$ relative to the \mathbf{z} axis is :

$$x\mathbf{s} + y\mathbf{t} + z\mathbf{n}$$

The ONB class

```
class ONB():
    def __init__(self) -> None:
        self.axis[0] = Vec3()
        self.axis[1] = Vec3()
        self.axis[2] = Vec3()

    def u(self):
        return self.axis[0]

    def v(self):
        return self.axis[1]

    def w(self):
        return self.axis[2]

    def local(self, val):
        if isinstance(val, Vec3):
            return self.u()*val.x() + self.v()*val.y() + self.w()*val.z()
        else:
            return self.u()*val[0] + self.v()*val[1] + self.w()*val[2]

    def build_from_w(self, vNormal):
        unit_w = Vec3.unit_vector(vNormal)
        vec_a = Vec3(1, 0, 0)
        if math.fabs(unit_w.x()) > 0.9:
            vec_a = Vec3(0, 1, 0)
        vec_v = Vec3.unit_vector(Vec3.cross_product(unit_w, vec_a))
        vec_u = Vec3.cross_product(unit_w, vec_v)

        self.axis[0] = vec_u
        self.axis[1] = vec_v
        self.axis[2] = unit_w
```


Replace the scattering

```
class Lambertian(Material):
    def __init__(self, cAlbedo) -> None:
        super().__init__()
        self.color_albedo = rtu.Color(cAlbedo.r(), cAlbedo.g(), cAlbedo.b())

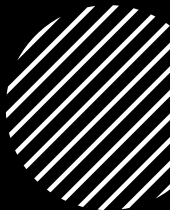

    def scattering(self, rRayIn, hHinfo):
        uvw = rtu.ONB()
        uvw.build_from_w(hHinfo.getNormal())

        scattered_direction = uvw.local(rtu.Vec3.random_cosine_hemisphere_on_z())
        scattered_ray = rtr.Ray(hHinfo.getP(), scattered_direction)
        attenuation_color = self.BRDF(rRayIn, scattered_ray, hHinfo)
        return rtu.Scatterinfo(scattered_ray, attenuation_color)

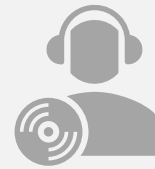
    def BRDF(self, rView, rLight, hHinfo):
        attenuation_color = rtu.Color(self.color_albedo.r(), self.color_albedo.g(), self.color_albedo.b())
        return attenuation_color
```



Final words for Image reconstruction



In ideal reconstruction, the uniform sampling is required.



For image sampling, nonuniform sampling is widely used as a trade-off between noise and aliasing.



The reconstruction techniques have been shifted towards minimizing errors.

Codes and class assignment !

- Github : RT-python-week09
 - <https://github.com/KUGA-01418283-Raytracing/RT-python-week09>

