## Part 3: Formal Treatment of MSE, Bias and Variance





Frequency





Variance

## Increasing Samples











Variance

## Increasing Samples













Variance

## Increasing Samples











Variance

## Increasing Samples











## Increasing Samples

Variance

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Variance







Variance





























# Spatial Domain Spatia Domain Spatial Domain Spatial Domain Spatial Domain Spatial









## Samples and function in Fourier Domain Spatial Domain Fourier Domain





















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 $f(x) \mathbf{S}(x)$ 







 $f(x) \mathbf{S}(x)$ 











 $f(x) \mathbf{S}(x)$ 













 $f(x) \mathbf{S}(x)$ 



 $\hat{f}(\omega) \otimes \hat{\mathbf{S}}(\omega)$ 









 $f(x) \mathbf{S}(x)$ 











 $f(x) \mathbf{S}(x)$ 











 $f(x) \mathbf{S}(x)$ 











 $f(x) \mathbf{S}(x)$ 











 $f(x) \mathbf{S}(x)$ 



 $\hat{f}(\omega) \otimes \hat{\mathbf{S}}(\omega)$ 









 $f(x) \mathbf{S}(x)$ 



 $\hat{f}(\omega) \otimes \hat{\mathbf{S}}(\omega)$ 









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# Aliasing in Reconstruction



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# Aliasing in Reconstruction



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#### Aliasing in Reconstruction





























### Aliasing (Reconstruction) vs. Error (Integration)







### Aliasing (Reconstruction) vs. Error (Integration)

Fredo Durand [2011] Belcour et al. [2013]







### Aliasing (Reconstruction) vs. Error (Integration)

Fredo Durand [2011] Belcour et al. [2013]







## Integration in the Fourier Domain



### Integration is the DC term in the Fourier Domain

Spatial Domain:

 $I = \int_D f(x) dx$ 





# Integration is the DC term in the Fourier Domain

Spatial Domain:

Fourier Domain:



 $I = \int_D f(x) dx$ 





# Integration is the DC term in the Fourier Domain

Spatial Domain:

Fourier Domain:



 $I = \int_D f(x) dx$ 

 $\hat{f}(0)$ 



 $\tilde{\mu}_N = \int_D f(x) \mathbf{S}(x) dx$ 





$$\tilde{\mu}_N = \int_D f(x) \mathbf{S}(x) dx$$







$$\tilde{\mu}_N = \int_D f(x) \mathbf{S}(x) dx$$









$$\tilde{\mu}_N = \int_D f(x) \mathbf{S}(x) dx$$



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$$ilde{\mu}_N = \int_D f(x) \mathbf{S}(x) \mathbf{S}(x) \mathbf{S}(x) \mathbf{S}(x) \mathbf{S}(x)$$



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$$\tilde{\mu}_{N} = \int_{D} f(x) \mathbf{S}(x) dx = \int_{\Omega} \hat{f}^{*}(\omega) \hat{\mathbf{S}}(\omega) d\omega$$
$$\mathbf{S}(x) = \frac{1}{N} \sum_{k=1}^{N} \delta(x - x_{k})$$







## Monte Carlo Estimator in Fourier Domain

 $ilde{\mu}_N = \int_D f(x) \mathbf{S}(x)$ 

 $\mathbf{S}(x) = \frac{1}{N}$ 

$$f_{N}(x) dx = \int_{\Omega} \hat{f}^{*}(\omega) \hat{\mathbf{S}}(\omega) d\omega$$

$$\int_{N} \sum_{k=1}^{N} \delta(x - x_{k})$$





## Monte Carlo Estimator in Fourier Domain

 $ilde{\mu}_N = \int_D f(x) \mathbf{S}(x)$ 

 $\mathbf{S}(x) = \frac{1}{N}$ 

$$\mathbf{x})dx = \int_{\Omega} \hat{f}^{*}(\omega)\hat{\mathbf{S}}(\omega)d\omega$$

$$\frac{1}{N}\sum_{k=1}^{N}\delta(x-x_{k})$$





### Monte Carlo Estimator in Fourier Domain

$$\tilde{\mu}_{N} = \int_{D} f(x) \mathbf{S}(x) dx = \boxed{\int_{\Omega} \hat{f}^{*}(\omega) \hat{\mathbf{S}}(\omega) d\omega}$$
$$\mathbf{S}(x) = \frac{1}{N} \sum_{k=1}^{N} \delta(x - x_{k})$$
$$\hat{\mathbf{S}}(\omega) = \frac{1}{N} \sum_{k=1}^{N} e^{-i2\pi\omega x_{k}}$$



#### How to Formulate Error in Fourier Domain ? $\tilde{\mu}_N = \int_{\Omega} \hat{f}^*(\omega) \hat{\mathbf{S}}(\omega) d\omega$













#### How to Formulate Error in Fourier Domain ? $\tilde{\mu}_N = \int_{\Omega} \hat{f}^*(\omega) \hat{\mathbf{S}}(\omega) d\omega$

















 $I - \tilde{\mu}_N = \int_D f(x) dx - \int_D f(x) \mathbf{S}(x) dx$ 







#### True Integral



 $I - \tilde{\mu}_N = \int_D f(x) dx - \int_D f(x) \mathbf{S}(x) dx$ 







#### True Integral



 $I - \tilde{\mu}_N = \int_D f(x) dx - \int_D f(x) \mathbf{S}(x) dx$ 

Monte Carlo Estimator









 $I - \tilde{\mu}_N = \int_D f(x) dx - \int_D f(x) \mathbf{S}(x) dx$ 







 $I - \tilde{\mu}_N = \int_D f(x) dx - \int_D f(x) \mathbf{S}(x) dx$ 







 $I - \tilde{\mu}_N = \int_D f(x) dx - \int_D f(x) \mathbf{S}(x) dx$ 

 $I - \tilde{\mu}_N = \hat{f}(0) - \int_{\Omega} \hat{f}^*(\omega) \hat{\mathbf{S}}(\omega) d\omega$ 

#### Fredo Durand [2011]





#### Error in Fourier Domain





# $Error = Bias^2 + Variance$



#### • Bias

• Variance



#### • Bias: Expected value of the Error

• Variance





#### - Bias: Expected value of the Error $\langle I - \tilde{\mu}_N angle$

• Variance



#### • Bias: Expected value of the Error $\langle I - ilde{\mu}_N angle$

• Variance: Var(I -

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$$\mu_N)$$

#### Subr and Kautz [2013]







#### Bias in the Monte Carlo Estimator




 $I - \tilde{\mu}_N = \hat{f}(0) - \int_{\Omega} \hat{f}^*(\omega) \hat{\mathbf{S}}(\omega) d\omega$ 





 $I - \tilde{\mu}_N = \hat{f}(0) - \int_{\Omega} \hat{f}^*(\omega) \hat{\mathbf{S}}(\omega) d\omega$ 





### Bias:

 $\langle I - ilde{\mu}_N 
angle$ 

 $I - \tilde{\mu}_N = \hat{f}(0) - \int_{\Omega} \hat{f}^*(\omega) \hat{\mathbf{S}}(\omega) d\omega$ 



### Bias:

 $\langle I - \tilde{\mu}_N \rangle = \hat{f}(0) - \left\langle \int_{\Omega} \hat{f}^*(\omega) \hat{\mathbf{S}}(\omega) d\omega \right\rangle$ 



 $\langle I - \tilde{\mu}_N \rangle = \hat{f}(\mathbf{0}) - \left\langle \int_{\Omega} \hat{f}^*(\omega) \hat{\mathbf{S}}(\omega) d\omega \right\rangle$ 



 $\langle I - \tilde{\mu}_N \rangle = \hat{f}(0) - \left\langle \int_{\Omega} \hat{f}^*(\omega) \hat{\mathbf{S}}(\omega) d\omega \right\rangle$ 



 $\langle I - \tilde{\mu}_N \rangle = \hat{f}(0) - \left\langle \int_{\Omega} \hat{f}^*(\omega) \hat{\mathbf{S}}(\omega) d\omega \right\rangle$  $\langle I - \tilde{\mu}_N \rangle = \hat{f}(0) - \int_{\Omega} \hat{f}^*(\omega) \langle \hat{\mathbf{S}}(\omega) \rangle d\omega$ 



 $\langle I - \tilde{\mu}_N \rangle = \hat{f}(0) - \int_{\Omega} \hat{f}^*(\omega) \langle \hat{\mathbf{S}}(\omega) \rangle d\omega$ 



 $\langle I - \tilde{\mu}_N \rangle = \hat{f}(0) - \int_{\Omega} \hat{f}^*(\omega) \langle \hat{\mathbf{S}}(\omega) \rangle \, d\omega$ 





### To obtain an unbiased estimator:



 $\langle I - \tilde{\mu}_N \rangle = \hat{f}(0) - \int_{\Omega} \hat{f}^*(\omega) \langle \hat{\mathbf{S}}(\omega) \rangle \, d\omega$ 





### $\langle I - \tilde{\mu}_N \rangle = \hat{f}(0) -$

### To obtain an unbiased estimator:



$$-\int_{\Omega} \hat{f}^*(\omega) \left\langle \hat{\mathbf{S}}(\omega) \right\rangle d\omega$$

### Subr and Kautz [2013]

### $\langle \hat{\mathbf{S}}(\omega) \rangle = 0$ for frequencies other than zero



# How to obtain $\langle \hat{\mathbf{S}}(\omega) \rangle = 0$ ?



# Complex form in Amplitude and Phase

# $\langle \hat{\mathbf{S}}(\omega) \rangle = |\langle \hat{\mathbf{S}}(\omega) \rangle| e^{-\Phi(\langle \hat{\mathbf{S}}(\omega) \rangle)}$





# Complex form in Amplitude and Phase

Amplitude  $\langle \hat{\mathbf{S}}(\omega) \rangle = \left| \langle \hat{\mathbf{S}}(\omega) \rangle \right| e^{-\Phi(\langle \hat{\mathbf{S}}(\omega) \rangle)}$ 





# Complex form in Amplitude and Phase



















### Pauly et al. [2000] Ramamoorthi et al. [2012]











# Multiple realizations







 $\nabla$ 









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# $Error = Bias^2 + Variance$











in terms of variance





### Homogenization allows representation of error only



- Homogenization allows representation of error only in terms of variance
- We can take any sampling pattern and homogenize it to make the Monte Carlo estimator unbiased.







Error:

 $I - \tilde{\mu}_N = \hat{f}(0) - \int_{\Omega} \hat{f}^*(\omega) \hat{\mathbf{S}}(\omega) d\omega$ 



### Error:

 $I - \tilde{\mu}_N = \hat{f}(0) - \int_{\Omega} \hat{f}^*(\omega) \hat{\mathbf{S}}(\omega) d\omega$ 

 $\operatorname{Var}(I - \tilde{\mu}_N)$ 





Error:

 $I - \tilde{\mu}_N = \hat{f}(0) - \int_{\Omega} \hat{f}^*(\omega) \hat{\mathbf{S}}(\omega) d\omega$  $\operatorname{Var}(I - \tilde{\mu}_N) = \operatorname{Var}\left(\hat{f}(0) - \int_{\Omega} \hat{f}^*(\omega) \,\hat{\mathbf{S}}(\omega) \,d\omega\right)$ 



 $\operatorname{Var}(I - \tilde{\mu}_N) = \operatorname{Var}\left(\hat{f}(\mathbf{0}) - \int_{\Omega} \hat{f}^*(\omega) \,\hat{\mathbf{S}}(\omega) \,d\omega\right)$ 



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 $\operatorname{Var}(I - \tilde{\mu}_N) = \operatorname{Var}\left(\hat{f}(0) - \int_{\Omega} \hat{f}^*(\omega) \,\hat{\mathbf{S}}(\omega) \,d\omega\right)$ 

 $\operatorname{Var}(\tilde{\mu}_N) = \operatorname{Var}\left(\int_{\Omega} \hat{f}^*(\omega) \,\hat{\mathbf{S}}(\omega) d\omega\right)$ 


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 $\operatorname{Var}(\tilde{\mu}_N) = \operatorname{Var}\left(\int_{\Omega} \hat{f}^*(\omega) \,\hat{\mathbf{S}}(\omega) d\omega\right)$ 



where,

 $P_f(\omega) = |\hat{f}^*(\omega)|^2$  Power Spectrum

 $\operatorname{Var}(\tilde{\mu}_N) = \operatorname{Var}\left(\int_{\Omega} \hat{f}^*(\omega) \,\hat{\mathbf{S}}(\omega) d\omega\right)$ 

 $\operatorname{Var}(\tilde{\mu}_N) = \int_{\Omega} P_f(\omega) \operatorname{Var}\left(\hat{\mathbf{S}}(\omega)\right) d\omega$ 



 $\operatorname{Var}(\tilde{\mu}_N) = \int_{\Omega} P_f(\omega) \operatorname{Var}\left(\hat{\mathbf{S}}(\omega)\right) d\omega$ 





$$\operatorname{Var}(\tilde{\mu}_N) = \int_{\Omega}$$

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 $P_f(\omega) \operatorname{Var}\left(\hat{\mathbf{S}}(\omega)\right) d\omega$ 

Subr and Kautz [2013]

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$$\operatorname{Var}(\tilde{\mu}_N) = \int_{\Omega} P_f(\omega) \operatorname{Var}\left(\hat{\mathbf{S}}(\omega)\right) d\omega$$

#### This is a general form, both for homogenised as well as non-homogenised sampling patterns

Subr and Kautz [2013]







$$\operatorname{Var}(\tilde{\mu}_N) = \int_{\Omega}$$

 $P_f(\omega) \operatorname{Var}\left(\hat{\mathbf{S}}(\omega)\right) d\omega$ 



$$\operatorname{Var}(\tilde{\mu}_N) = \int_{\Omega} P_f(\omega) \operatorname{Var}\left(\hat{\mathbf{S}}(\omega)\right) d\omega$$





$$\operatorname{Var}(\tilde{\mu}_N) = \int_{\Omega} P_f(\omega) \operatorname{Var}\left(\hat{\mathbf{S}}(\omega)\right) d\omega$$





$$\operatorname{Var}(\tilde{\mu}_N) = \int_{\Omega} P_f(\omega) \operatorname{Var}\left(\hat{\mathbf{S}}(\omega)\right) d\omega$$

For purely random samples:





$$\operatorname{Var}(\tilde{\mu}_N) = \int_{\Omega} P_f(\omega) \operatorname{Var}\left(\hat{\mathbf{S}}(\omega)\right) d\omega$$

For purely random samples:

$$\operatorname{Var}(\tilde{\mu}_N) = \int_{\Omega} P_f(\omega) \left\langle P_S(\omega) \right\rangle d\omega$$

#### where,

 $P_S(\omega) = |\hat{\mathbf{S}}(\omega)|^2$ 

#### Fredo Durand [2011]



$$\operatorname{Var}(\tilde{\mu}_N) = \int_{\Omega} P_f(\omega) \operatorname{Var}\left(\hat{\mathbf{S}}(\omega)\right) d\omega$$

For purely random samples:  $\langle \hat{\mathbf{S}}(\omega) \rangle =$ 

$$\operatorname{Var}(\tilde{\mu}_N) = \int_{S}$$

#### where,

 $P_S(\omega) = |\hat{\mathbf{S}}(\omega)|^2$ 

 $P_f(\omega) \langle P_S(\omega) \rangle d\omega$  $\Omega$ 

#### Fredo Durand [2011]



Homogenizing any sampling pattern makes  $\langle \hat{\mathbf{S}}(\omega) \rangle = 0$ 







Homogenizing any sampling pattern makes  $\langle \hat{\mathbf{S}}(\omega) \rangle = 0$ 

$$\operatorname{Var}(\tilde{\mu}_N) = \int_{\Sigma}$$

where,

 $P_S(\omega) = |\hat{\mathbf{S}}(\omega)|^2$ 

 $P_f(\omega) \langle P_S(\omega) \rangle d\omega$  $\Omega$ 

Pilleboue et al. [2015]

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 $\operatorname{Var}(\tilde{\mu}_N) = \int_{\Omega} P_f(\omega) \left\langle P_S(\omega) \right\rangle d\omega$ 





$$\operatorname{Var}(\tilde{\mu}_N) = \int_{S}$$

 $\mathbf{P}$  $P_f(\omega) \langle P_S(\omega) \rangle d\omega$  $\Omega$ 



### Variance in terms of n-dimensional Power Spectra

$$\operatorname{Var}(\tilde{\mu}_N) = \int_{S}$$



1  $P_f(\omega) \langle P_S(\omega) \rangle d\omega$  $\sum$ 

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### Variance in terms of n-dimensional Power Spectra

$$\operatorname{Var}(\tilde{\mu}_N) = \int_{\Omega}$$



1  $P_f(\omega) \langle P_S(\omega) \rangle d\omega$  $\sum$ 

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$$\operatorname{Var}(\tilde{\mu}_N) = \int_{\Omega}$$

 $\mathbf{P}$  $P_f(\omega) \langle P_S(\omega) \rangle d\omega$  $\Omega$ 



$$\operatorname{Var}(\tilde{\mu}_N) = \int_{S}$$

In polar coordinates:

 $\mathbf{P}$  $P_f(\omega) \left\langle P_S(\omega) \right\rangle d\omega$  $\Omega$ 



$$\operatorname{Var}(\tilde{\mu}_N) = \int_{S}$$

In polar coordinates:

$$Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^{d-1}) \int_0^0$$

 $\int_{\Omega} P_f(\omega) \left\langle P_S(\omega) \right\rangle d\omega$  $\Omega$ 

 $\int_{S^{d-1}} P_f(\rho \mathbf{n}) \left\langle P_S(\rho \mathbf{n}) \right\rangle d\mathbf{n} \, d\rho$ 



$$\operatorname{Var}(\tilde{\mu}_N) = \int_{S}$$

In polar coordinates:

$$Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^{d-1}) \int_0^0$$

 $\int_{\Omega} P_f(\omega) \left\langle P_S(\omega) \right\rangle d\omega$  $\Omega$ 

 $\int_{S^{d-1}} P_f(\rho \mathbf{n}) \left\langle P_S(\rho \mathbf{n}) \right\rangle d\mathbf{n} \, d\rho$ 



 $Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^{d-1}) \int_0^\infty \int_{\mathbb{S}^{d-1}} P_f(\rho \mathbf{n}) \langle P_{\mathbf{S}}(\rho \mathbf{n}) \rangle \, d\mathbf{n} \, d\rho$ 



#### 

 $Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^{d-1}) \int_0^\infty \int_{\mathcal{S}^{d-1}} P_f(\rho \mathbf{n}) \langle P_{\mathbf{S}}(\rho \mathbf{n}) \rangle \, d\mathbf{n} \, d\rho$ 





#### 

 $Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^{d-1}) \int_0^\infty \int_{\mathcal{S}^{d-1}} P_f(\rho \mathbf{n}) \langle P_{\mathbf{S}}(\rho \mathbf{n}) \rangle \, d\mathbf{n} \, d\rho$ 





#### For isotropic power spectra:

 $Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^{d-1}) \int_0^\infty \int_{\mathcal{S}^{d-1}}^\infty P_f(\rho \mathbf{n}) \langle P_{\mathbf{S}}(\rho \mathbf{n}) \rangle \, d\mathbf{n} \, d\rho$ 





#### For isotropic power spectra:

 $Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^{d-1}) \int_0^\infty \int_{\mathcal{S}^{d-1}} P_f(\rho \mathbf{n}) \langle P_{\mathbf{S}}(\rho \mathbf{n}) \rangle \, d\mathbf{n} \, d\rho$ 





#### For isotropic power spectra:

 $Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^{d-1}) \int_0^\infty \int_{\mathbf{S}^{d-1}} P_f(\rho \mathbf{n}) \langle P_{\mathbf{S}}(\rho \mathbf{n}) \rangle \, d\mathbf{n} \, d\rho$ 





 $Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^{d-1}) \int_0^\infty \int_{\mathbf{S}^{d-1}} \frac{P_f(\rho \mathbf{n}) \langle P_{\mathbf{S}}(\rho \mathbf{n}) \rangle \, d\mathbf{n} \, d\rho}{|\mathbf{S}^{d-1}|}$ 

#### For isotropic power spectra:



 $Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^{d-1}) \int_0^\infty \tilde{P}_f(\rho) \langle \tilde{P}_{\mathbf{S}}(\rho) \rangle d\rho$ 





$$Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^{d-1}) \int_0^{\infty}$$

#### For isotropic power spectra:

$$Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^d)$$

 $\int_{\Omega}^{\infty} \int_{\mathfrak{S}^{d-1}} P_f(\rho \mathbf{n}) \left\langle P_{\mathbf{S}}(\rho \mathbf{n}) \right\rangle d\mathbf{n} \, d\rho$ 

 $^{d-1})\int_{0}^{\infty}\tilde{P}_{f}(\rho)\langle\tilde{P}_{\mathbf{S}}(\rho)\rangle\,d\rho$ 





$$Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^{d-1}) \int_0^{\infty}$$

#### For isotropic power spectra:

$$Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^{d})$$

 $\int_{0}^{\infty} \int_{\mathbf{S}^{d-1}}^{\infty} \frac{P_f(\rho \mathbf{n}) \langle P_{\mathbf{S}}(\rho \mathbf{n}) \rangle \, d\mathbf{n} \, d\rho}{P_{\mathbf{S}}(\rho \mathbf{n})}$ 

 $^{d-1})\int_{0}^{\infty}\tilde{P}_{f}(\rho)\langle\tilde{P}_{S}(\rho)\rangle\,d\rho$ 



### Variance in terms of 1-dimensional Power Spectra

$$Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^{d})$$





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 $^{l-1})\int_{0}^{\infty}\tilde{P}_{f}(\rho)\langle\tilde{P}_{\mathbf{S}}(\rho)\rangle\,d\rho$ 

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### Variance in terms of 1-dimensional Power Spectra

$$Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^{d})$$





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 $^{l-1})\int_{0}^{\infty}\tilde{P}_{f}(\rho)\left\langle \tilde{P}_{\mathbf{S}}(\rho)\right\rangle d
ho$ 

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### Variance: Integral over Product of Power Spectra

$$Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^{d})$$

 $^{l-1})\int_{0}^{\infty}\tilde{P}_{f}(\rho)\langle\tilde{P}_{\mathbf{S}}(\rho)\rangle\,d
ho$ 





### Variance: Integral over Product of Power Spectra

$$Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^{d})$$

Integrand Radial Power Spectrum



 $(l-1) \int_{0}^{0} \tilde{P}_{f}(\rho) \langle \tilde{P}_{\mathbf{S}}(\rho) \rangle d\rho$ 

#### Sampling Radial Power Spectrum

#### For given number of Samples

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$$Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^{d})$$

Integrand Radial Power Spectrum



 $(l-1) \int_{0}^{0} \tilde{P}_{f}(\rho) \langle \tilde{P}_{\mathbf{S}}(\rho) \rangle d\rho$ 

#### Sampling Radial Power Spectrum

#### For given number of Samples



$$Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^{d})$$

Integrand Radial Power Spectrum



 $^{l-1})\int_{0}^{\infty}\tilde{P}_{f}(\rho)\langle\tilde{P}_{\mathbf{S}}(\rho)\rangle\,d\rho$ 



For given number of Samples



$$Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^{d})$$

Integrand Radial Power Spectrum



 $^{l-1})\int_{0}^{\infty}\tilde{P}_{f}(\rho)\langle\tilde{P}_{\mathbf{S}}(\rho)\rangle\,d\rho$ 



For given number of Samples



$$Var[\tilde{\mu}_N] = \mathcal{M}(\mathcal{S}^{d-1})$$

Integrand Radial Power Spectrum



 $^{l-1})\int_{0}^{\infty}\tilde{P}_{f}(\rho)\langle\tilde{P}_{\mathbf{S}}(\rho)\rangle\,d\rho$ 



For given number of Samples







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Samplers	Worst Case	Best Case
Random		
Jitter		
Poisson Disk		
CCVT		









Samplers	Worst Case	Best Case
Random	$\mathcal{O}(N^{-1})$	
Jitter		
Poisson Disk		
CCVT		









Samplers	Worst Case	Best Case
Random	$\mathcal{O}(N^{-1})$	$\mathcal{O}(N^{-1})$
Jitter		
Poisson Disk		
CCVT		









Samplers	Worst Case	Best Case
Random	$\mathcal{O}(N^{-1})$	$\mathcal{O}(N^{-1})$
Jitter	$\mathcal{O}(N^{-1.5})$	
Poisson Disk		
CCVT		









Samplers	Worst Case	Best Case
Random	$\mathcal{O}(N^{-1})$	$\mathcal{O}(N^{-1})$
Jitter	$\mathcal{O}(N^{-1.5})$	$\mathcal{O}(N^{-2})$
Poisson Disk		
CCVT		









Samplers	Worst Case	Best Case
Random	$\mathcal{O}(N^{-1})$	$\mathcal{O}(N^{-1})$
Jitter	$\mathcal{O}(N^{-1.5})$	$\mathcal{O}(N^{-2})$
Poisson Disk	$\mathcal{O}(N^{-1})$	
CCVT		









Samplers	Worst Case	Best Case
Random	$\mathcal{O}(N^{-1})$	$\mathcal{O}(N^{-1})$
Jitter	$\mathcal{O}(N^{-1.5})$	$\mathcal{O}(N^{-2})$
Poisson Disk	$\mathcal{O}(N^{-1})$	$\mathcal{O}(N^{-1})$
CCVT		









Samplers	Worst Case	Best Case
Random	$\mathcal{O}(N^{-1})$	$\mathcal{O}(N^{-1})$
Jitter	$\mathcal{O}(N^{-1.5})$	$\mathcal{O}(N^{-2})$
Poisson Disk	$\mathcal{O}(N^{-1})$	$\mathcal{O}(N^{-1})$
CCVT	$\mathcal{O}(N^{-1.5})$	









Samplers	Worst Case	Best Case
Random	$\mathcal{O}(N^{-1})$	$\mathcal{O}(N^{-1})$
Jitter	$\mathcal{O}(N^{-1.5})$	$\mathcal{O}(N^{-2})$
Poisson Disk	$\mathcal{O}(N^{-1})$	$\mathcal{O}(N^{-1})$
CCVT	$\mathcal{O}(N^{-1.5})$	$\mathcal{O}(N^{-3})$











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Vorst Case	Best Case
$\mathcal{O}(N^{-1})$	$\mathcal{O}(N^{-1})$
$\mathcal{O}(N^{-1.5})$	$\mathcal{O}(N^{-2})$
$\mathcal{O}(N^{-1})$	$\mathcal{O}(N^{-1})$
$\mathcal{O}(N^{-1.5})$	$\mathcal{O}(N^{-3})$







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# Disk Doisson

## Jitter

Power

Power

### Low Frequency Region



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# Disk Poisson

## Jitter

Power

Power

### Low Frequency Region





### Low Frequency Region



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### Variance for Low Sample Count



▼ € ⊑



### Variance for Low Sample Count



▼ € ⊑





## Experimental Verification





#### Increasing Samples

### Convergence rate







#### Increasing Samples

Variance

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### Convergence rate









#### Increasing Samples

Variance

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- [Schlömer et al. 2011]
- [DeGoes et al. 2012]
- [Heck et al. 2013]









- [Schlömer et al. 2011]
- [DeGoes et al. 2012]
- [Heck et al. 2013]





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### Gaussian as Best Case







#### ▼/ € !-

### Gaussian as Best Case





## Ambient Occlusion Examples



### Random vs Jittered 96 Secondary Rays



#### MSE: 4.74 x 10e-3

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MSE: 8.56 x 10e-4





#### MSE: 4.24 x 10e-4

## CCVT vs. Poisson Disk

#### 96 Secondary Rays



#### MSE: 6.95 x 10e-4



## Convergence rates



#### ▼ € ∟





## Convergence rates



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#### Jittered vs Poisson Disk





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## What are the benefits of this analysis?





# What are the benefits of this analysis ?

 For offline rendering, an would converge faster.



• For offline rendering, analysis tells which samplers



## What are the benefits of this analysis?

- would converge faster.
- number of samples

• For offline rendering, analysis tells which samplers

• For real time rendering, blue noise samples are more effective in reducing variance for a given

