

Multiplexed Metropolis Light Transport

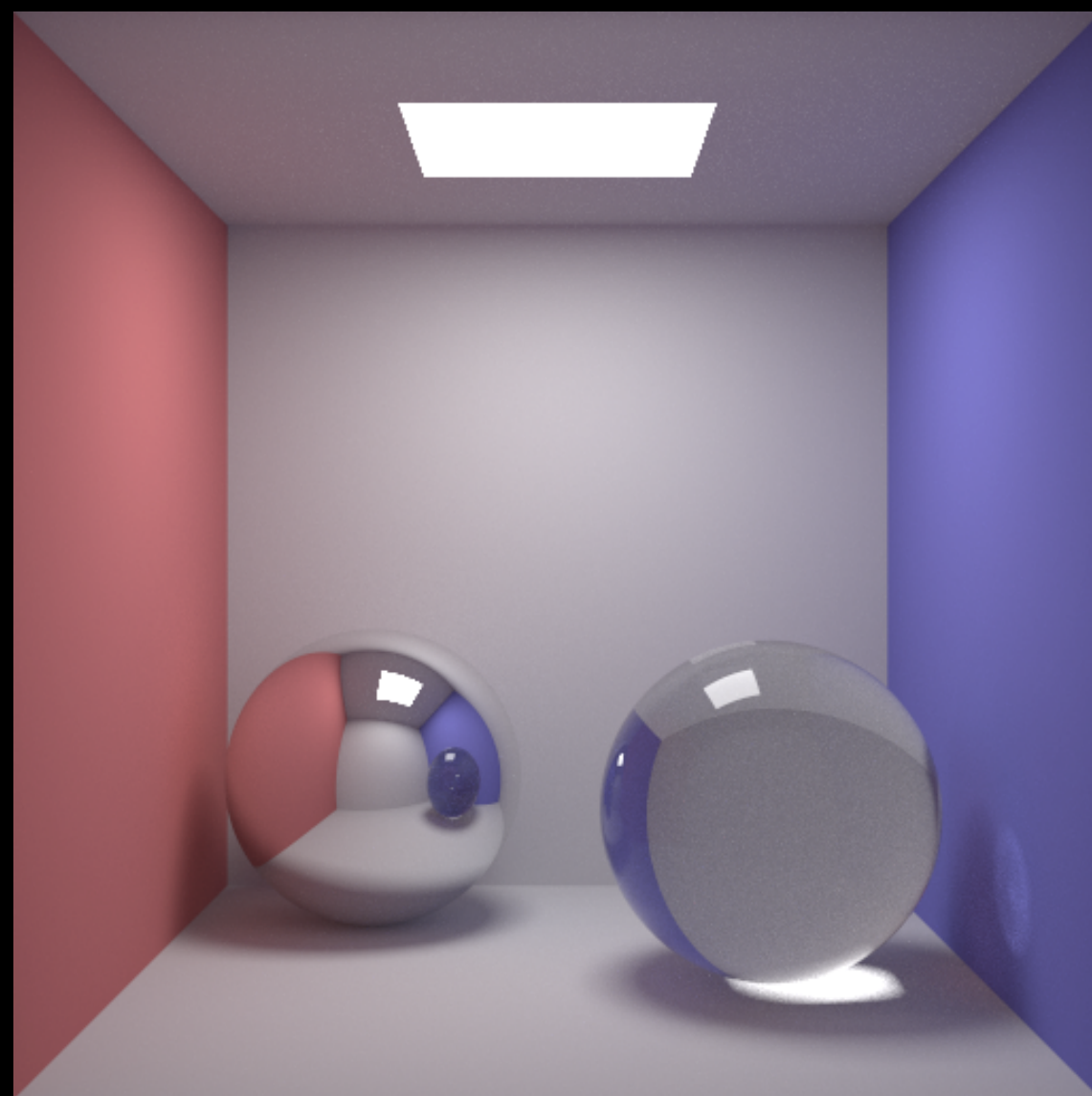
Toshiya Hachisuka^{1,2} Anton S. Kaplanyan³ Carsten Dachsbacher³

¹Aarhus University ²University of Tokyo ³Karlsruhe Institute of Technology

SIGGRAPH 2014

Two classes of MC methods

- Ordinary Monte Carlo

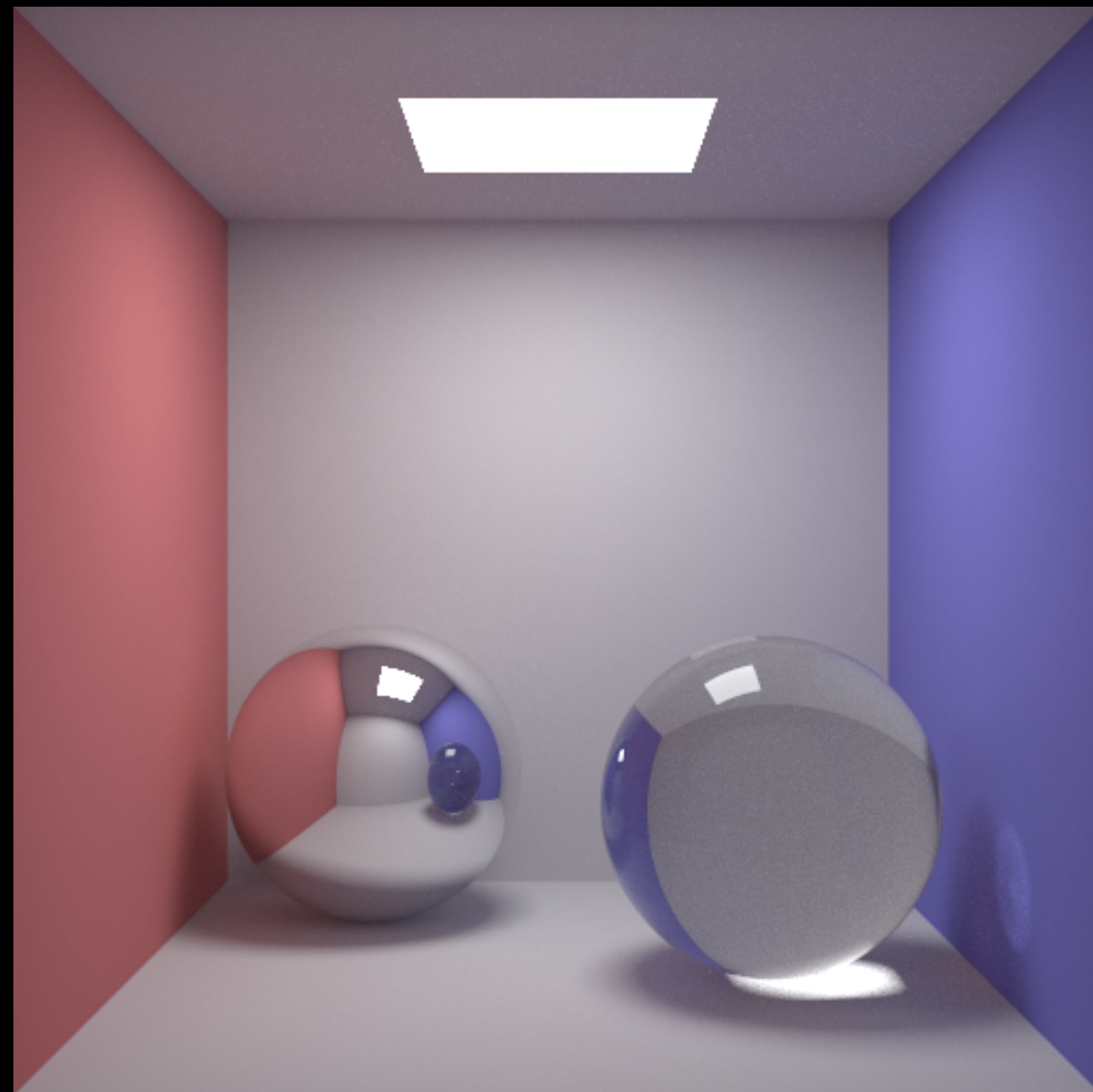


- Markov chain Monte Carlo



Two classes of MC methods

- Ordinary Monte Carlo



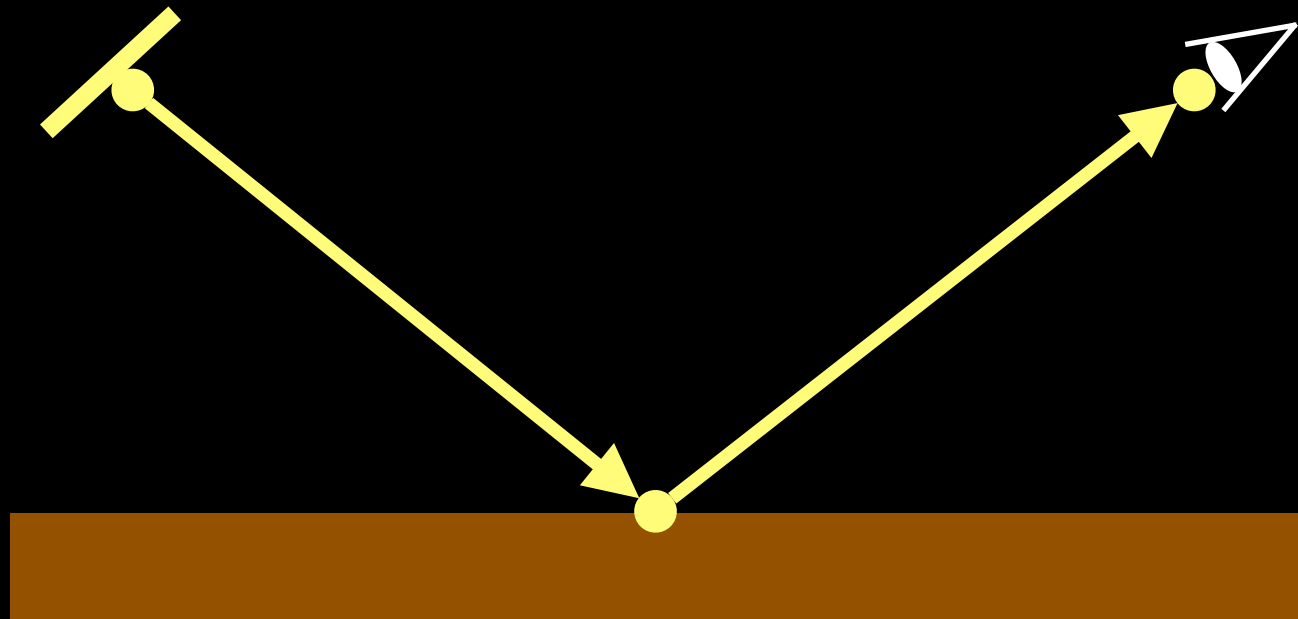
- Markov chain Monte Carlo



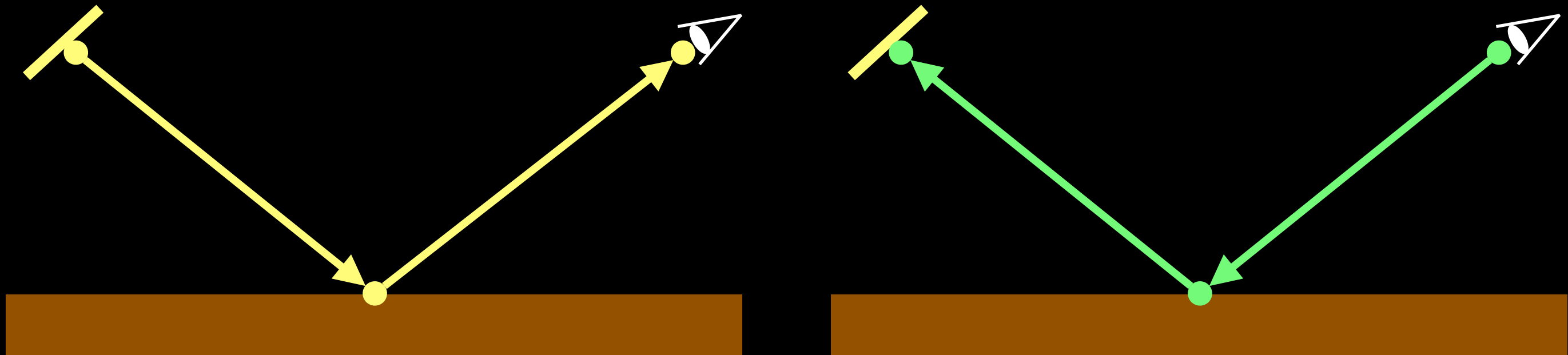
Ordinary Monte Carlo

- Generate independent samples from a known PDF
 - We know how to integrate and invert this PDF
- Multiple importance sampling [Veach and Guibas 95]
 - Utilizes multiple known PDFs

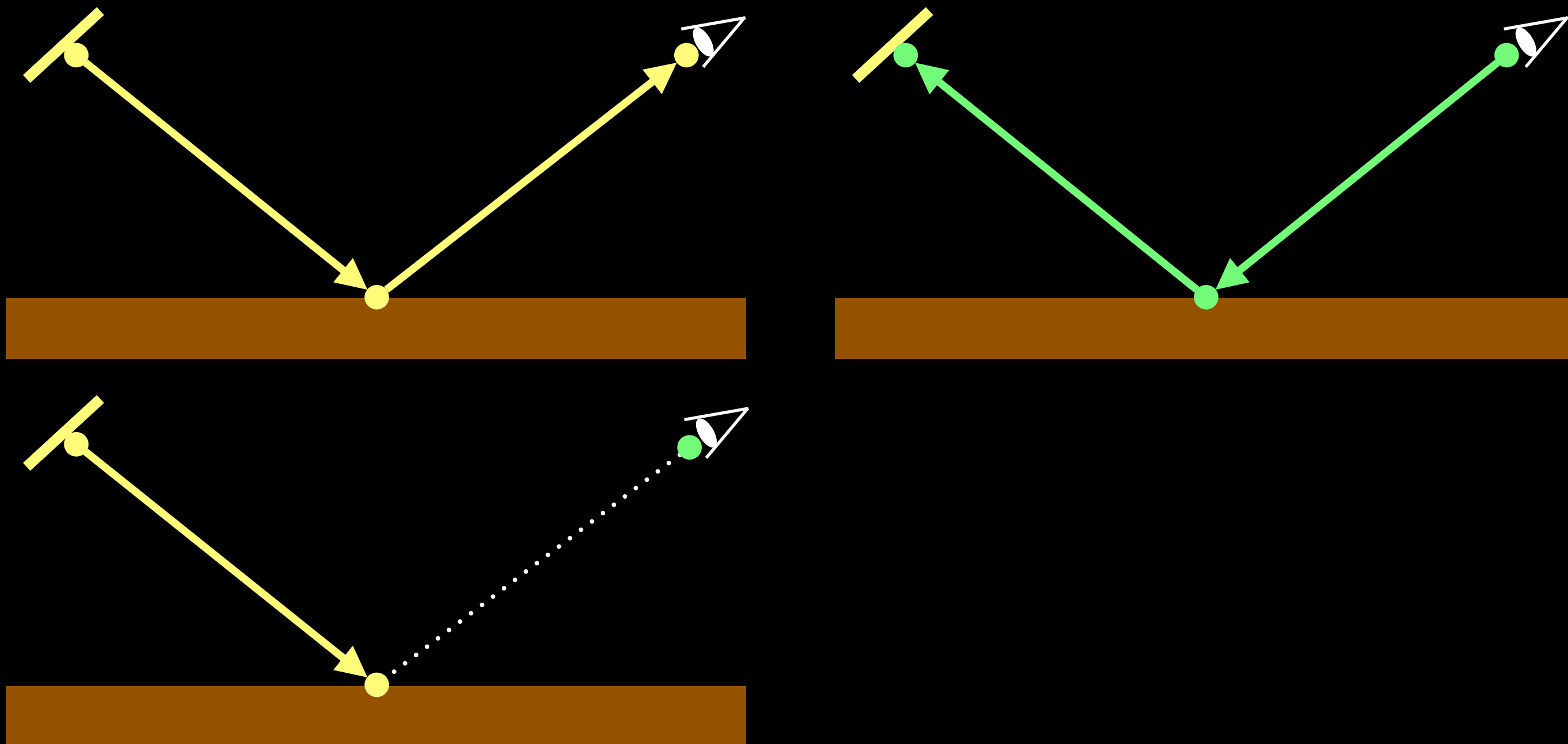
Multiple sampling methods



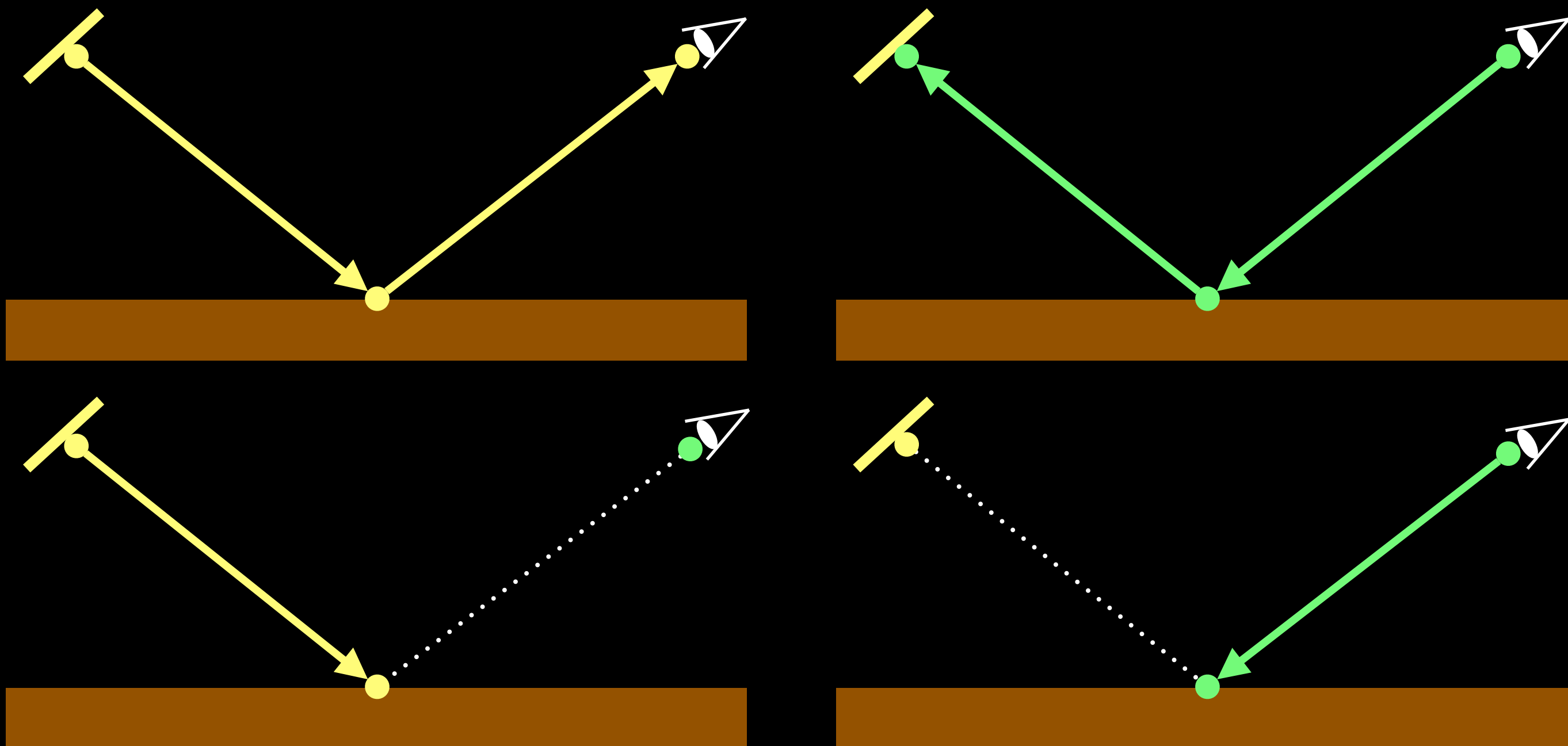
Multiple sampling methods



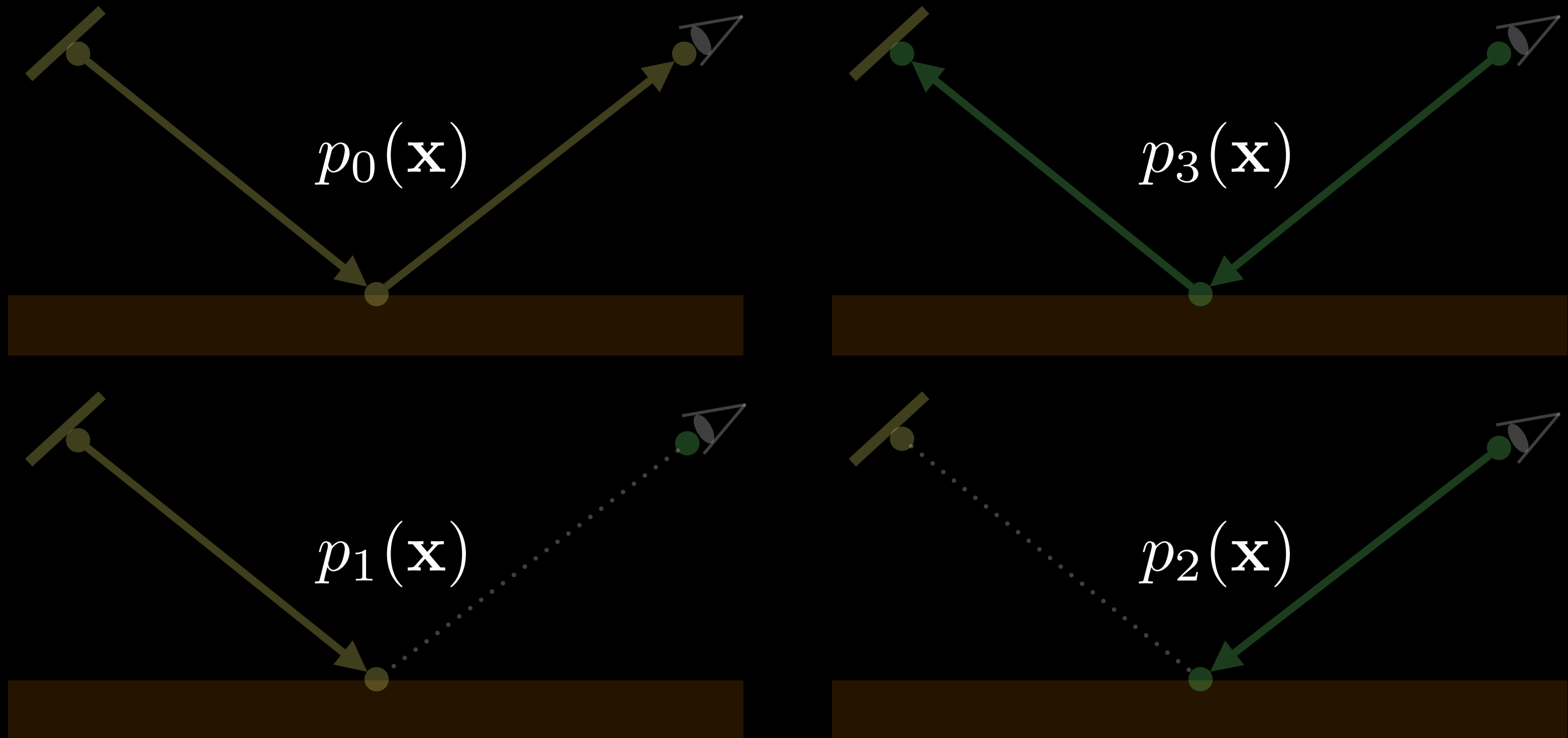
Multiple sampling methods



Multiple sampling methods



Multiple sampling methods



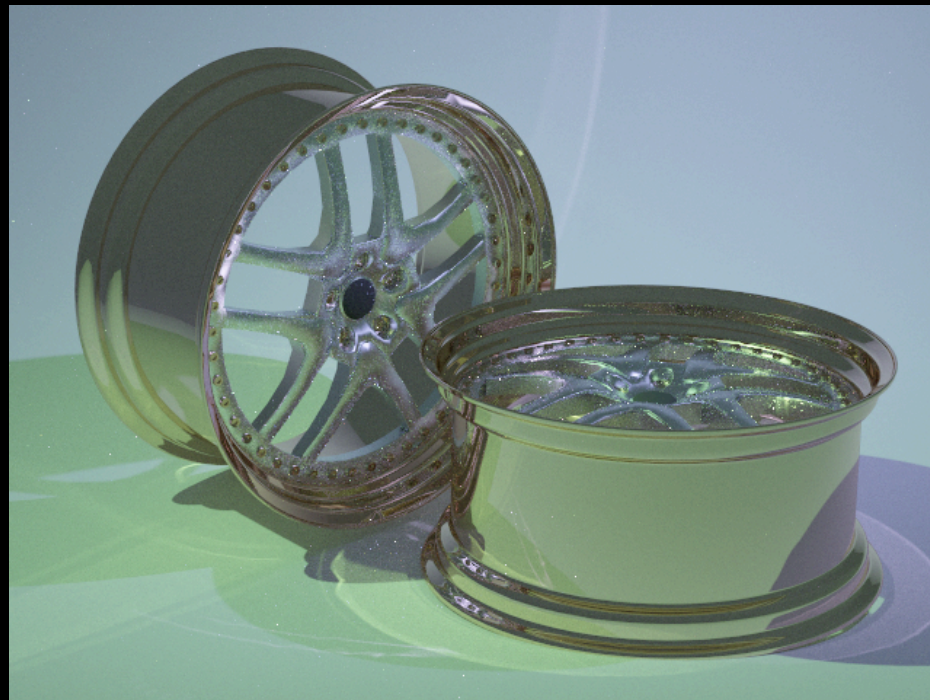
Bidirectional path tracing

- Uses MIS to combine multiple sampling techniques



MIS is a hot topic

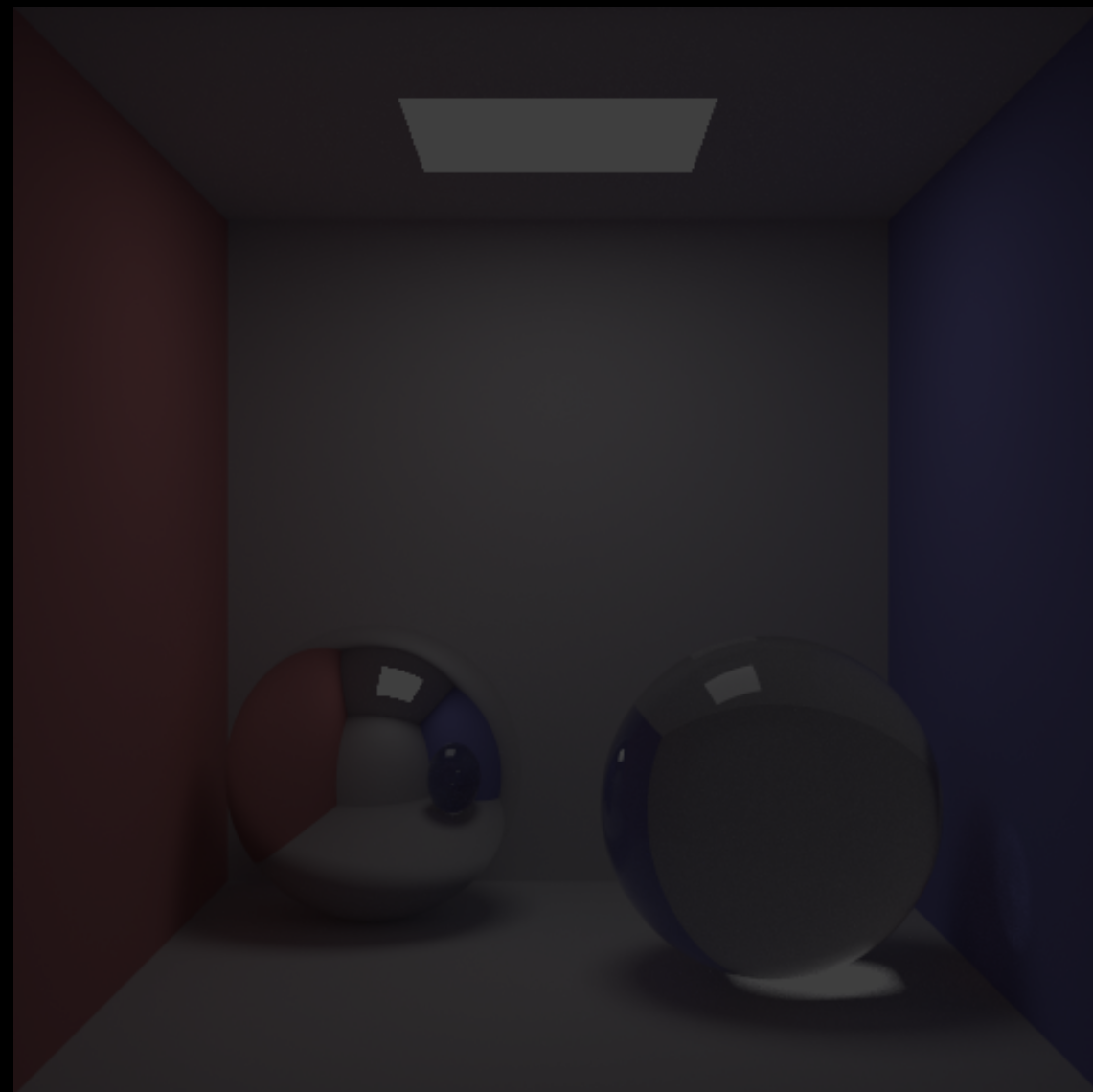
- UPS = VCM [Hachisuka et al. 12, Georgiev et al. 12]
- Bidirectional lightcuts [Walter et al. 12]
- Unified points/beams/paths [Krivanek et al. 14]



[Hachisuka et al. 12]

Two classes of MC methods

- Ordinary Monte Carlo



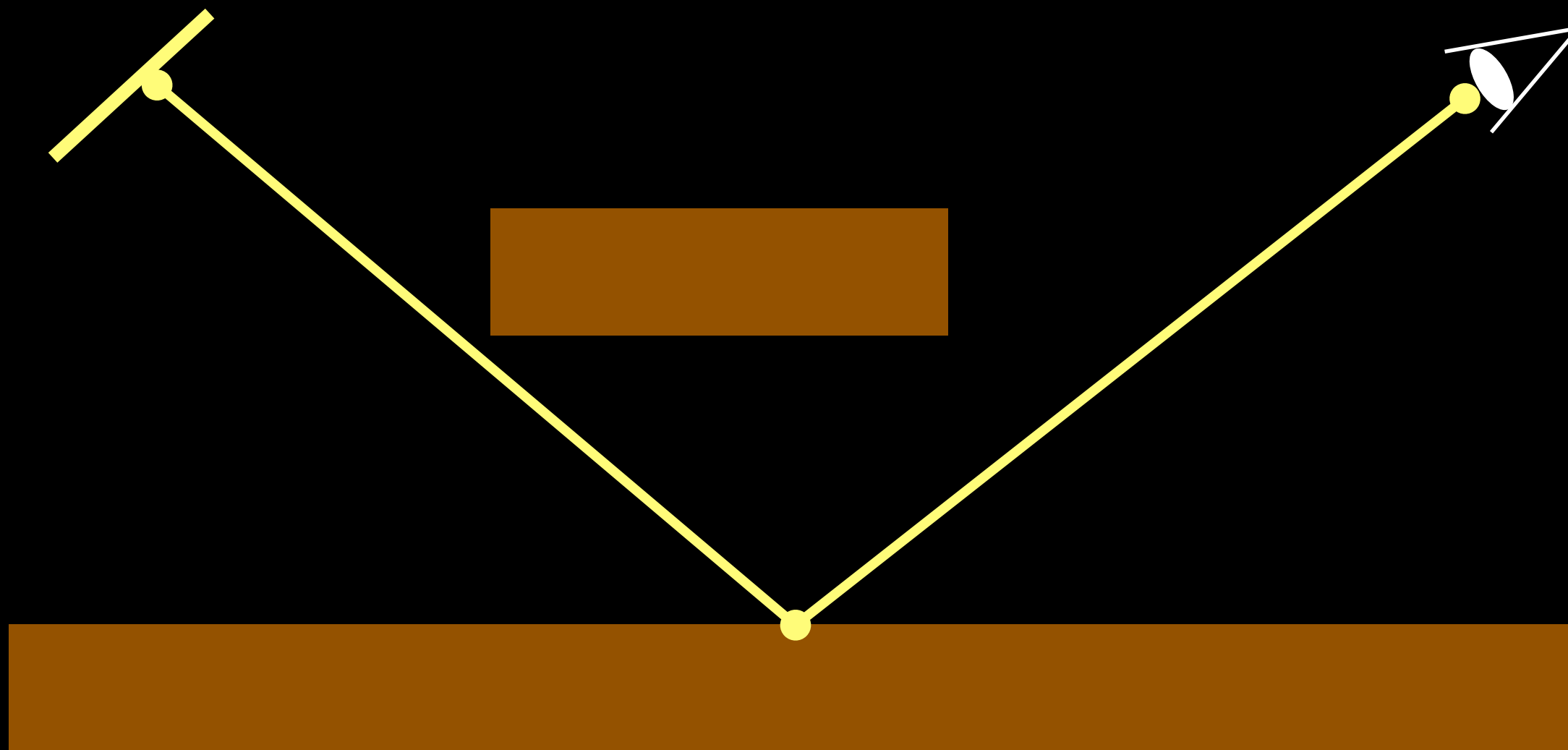
- Markov chain Monte Carlo



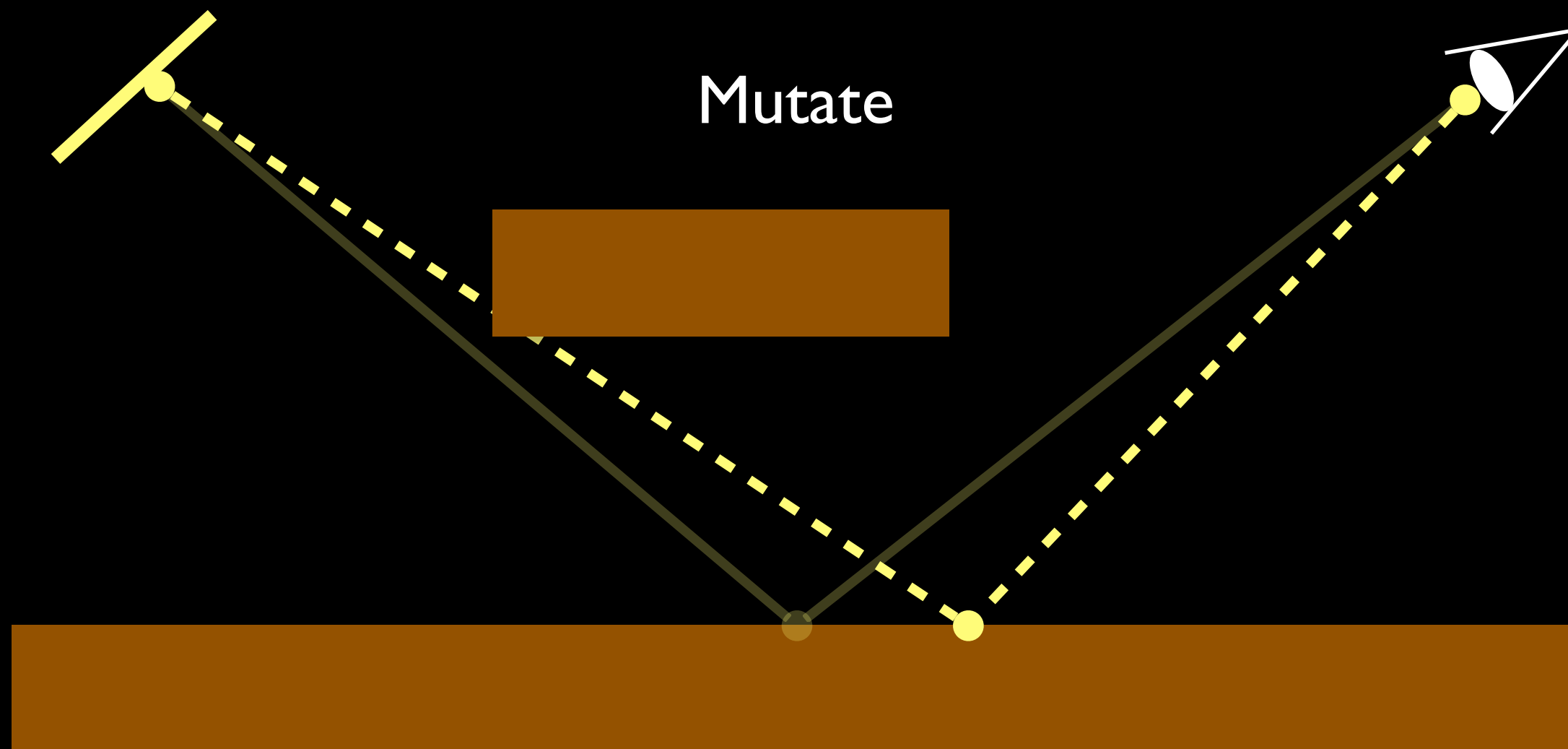
Markov chain Monte Carlo

- Generate correlated samples from **any** distribution
 - Can sample paths based on contributions (visibility etc.)
- Metropolis light transport [Veach and Guibas 97]

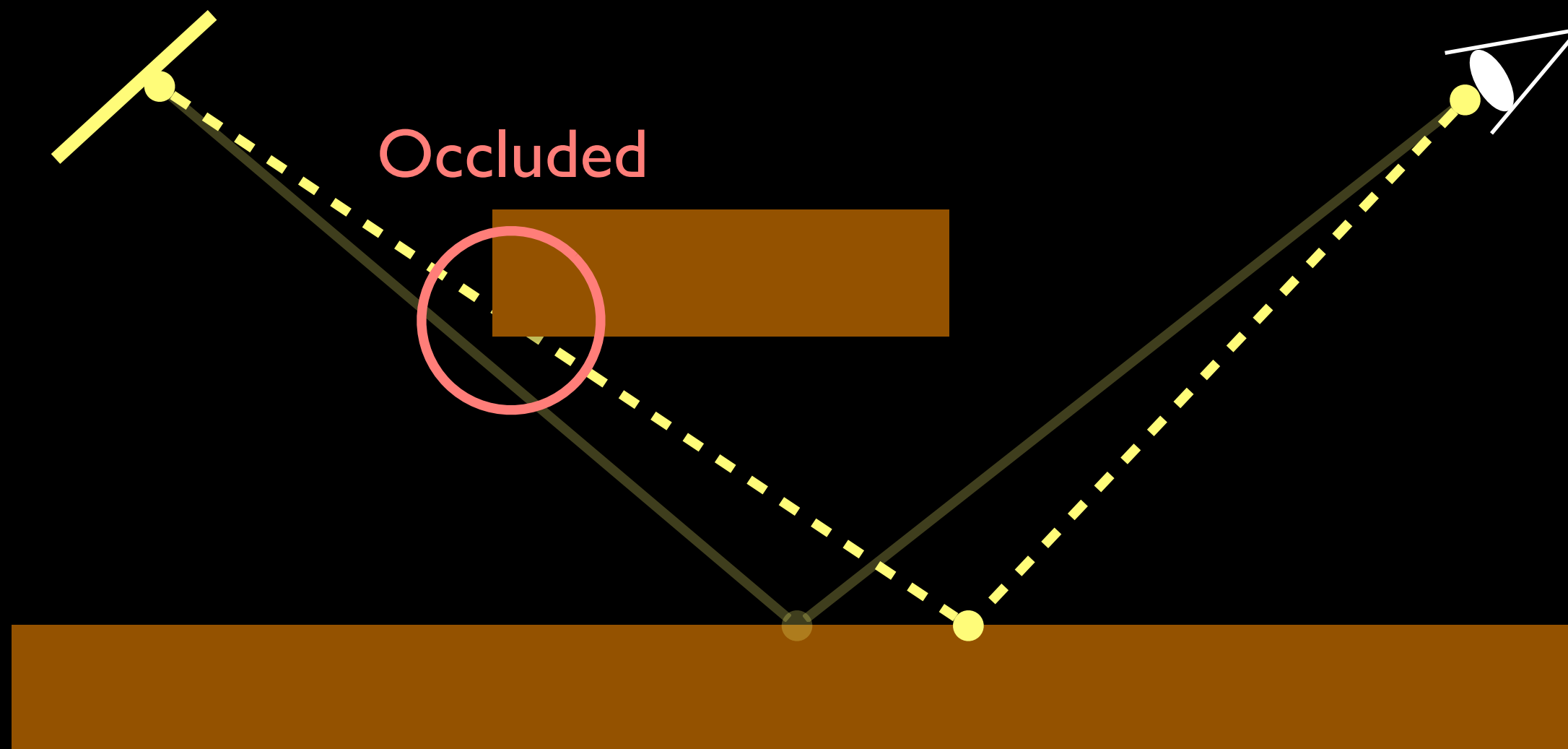
Markov chain Monte Carlo



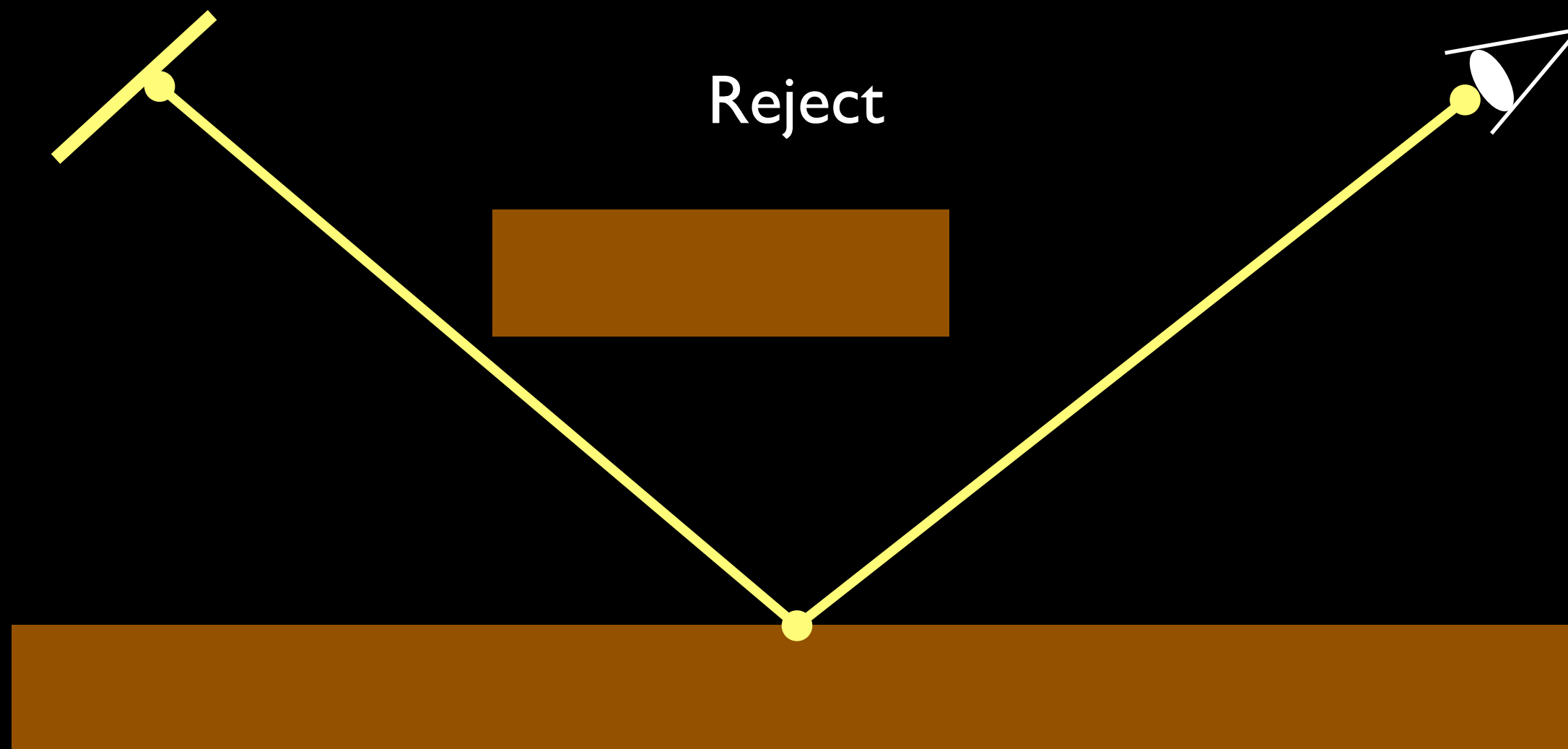
Markov chain Monte Carlo



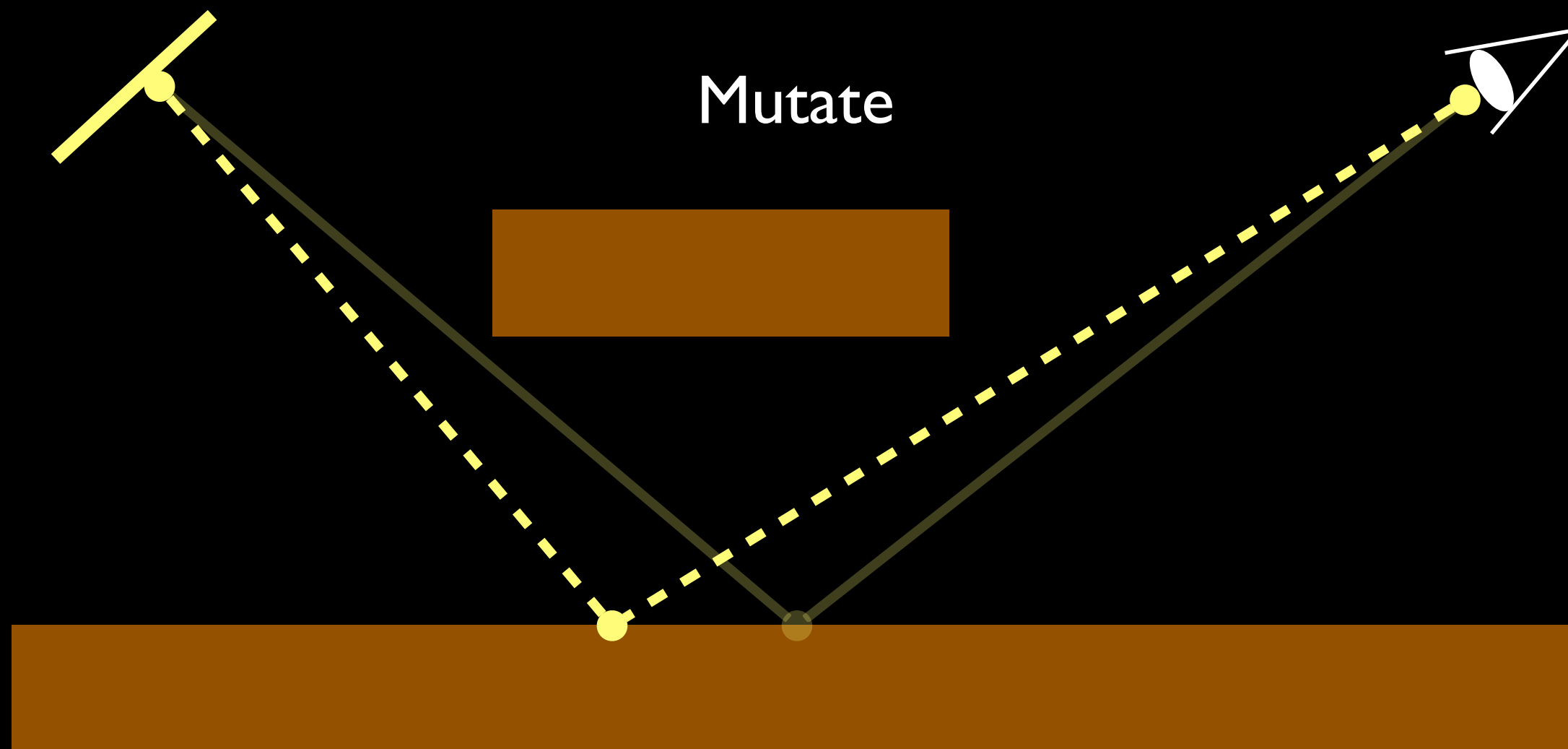
Markov chain Monte Carlo



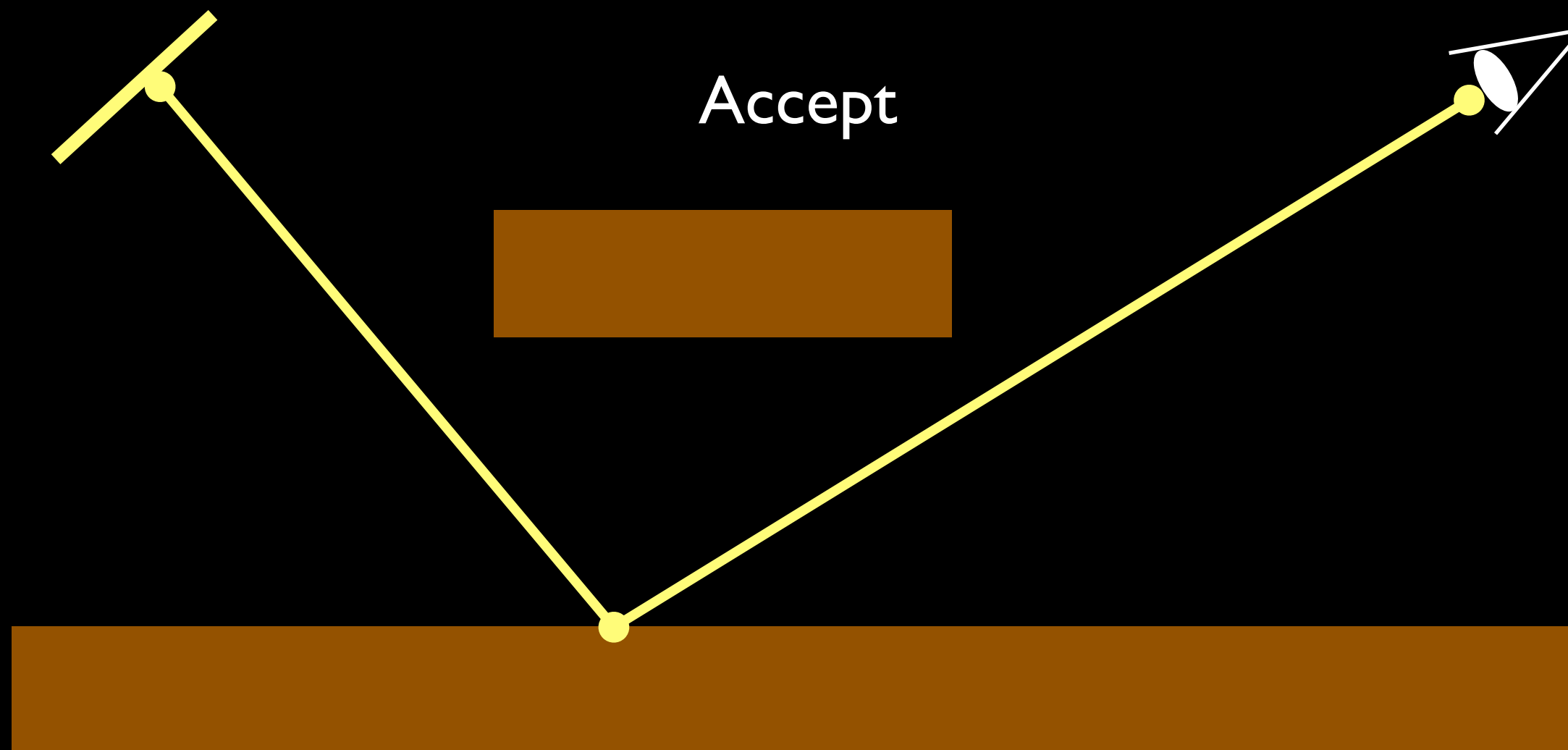
Markov chain Monte Carlo



Markov chain Monte Carlo



Markov chain Monte Carlo



Metropolis light transport



MCMC is also a hot topic

- Manifold exploration [Jakob and Marschner 12]
- Gradient-domain MLT [Lehtinen et al. 13]
- Half-vector MLT [Kaplanyan et al. 14]



[Jakob and Marschner 12]

	Multiple techniques	Arbitrary distribution
Ordinary MC	Yes (via MIS)	No

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Ordinary MC	Yes (via MIS)	No
MCMC	No	Yes

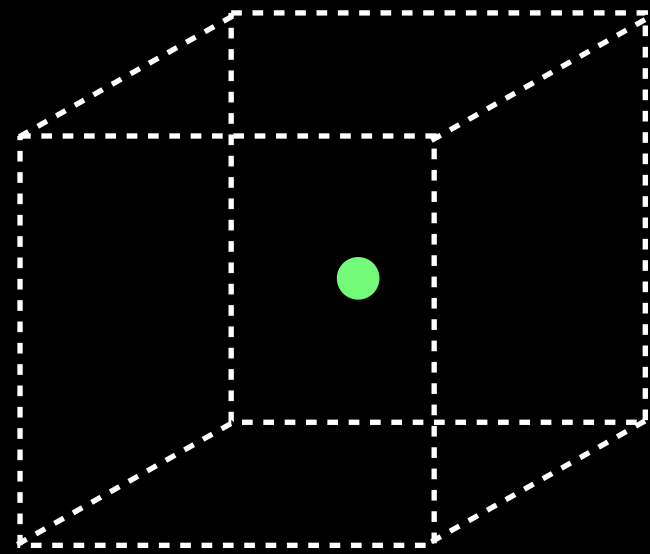
Question

	Multiple techniques	Arbitrary distribution
Ordinary MC	Yes (via MIS)	No
MCMC	No	Yes
?	Yes	Yes


Multiplexed MLT

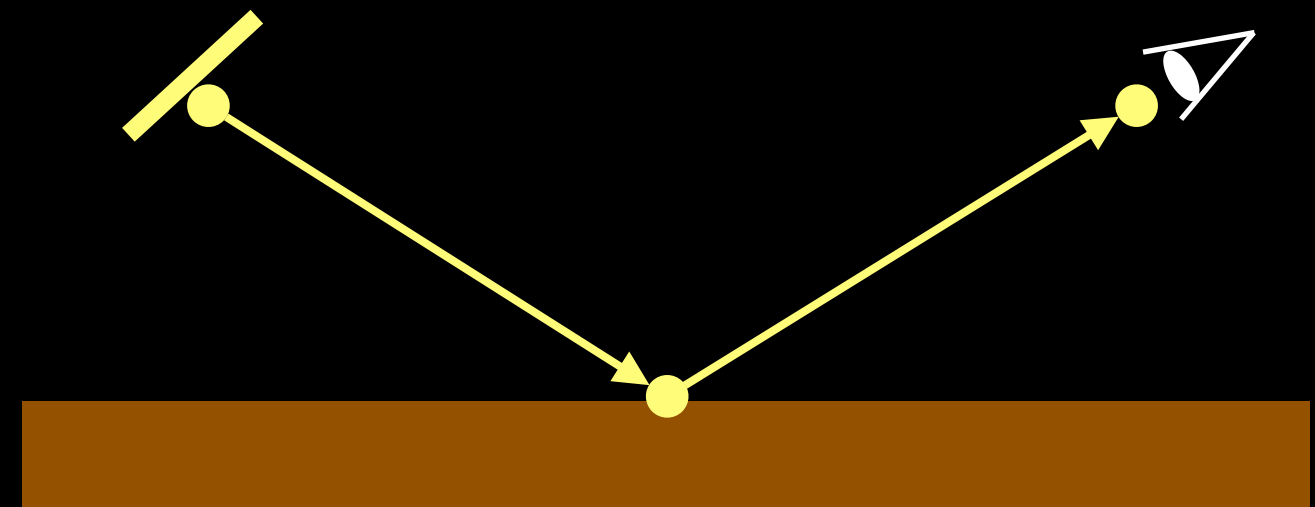
Primary sample space

- Hypercube of random numbers $\bar{U} \in]0, 1[^N$
 - Mapping from a point to the path = Inverse CDF
 - Introduced by Kelemen et al. [2002]



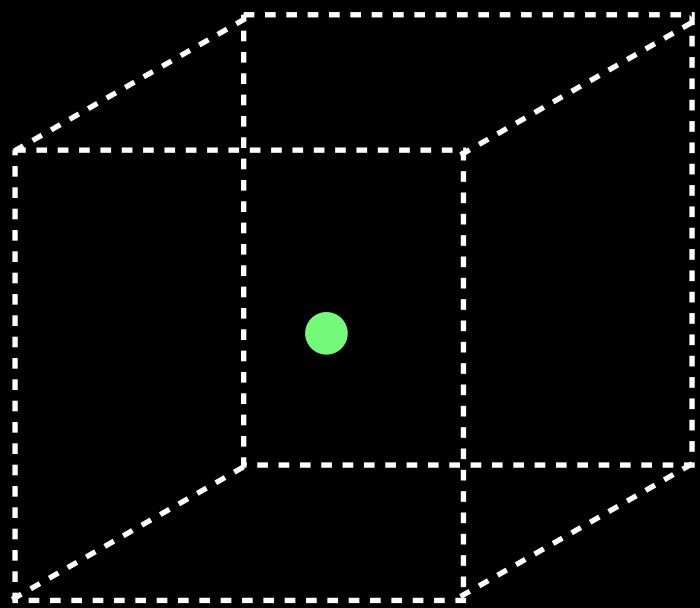
Point in the hypercube

$$\bar{X} = P^{-1}(\bar{U})$$


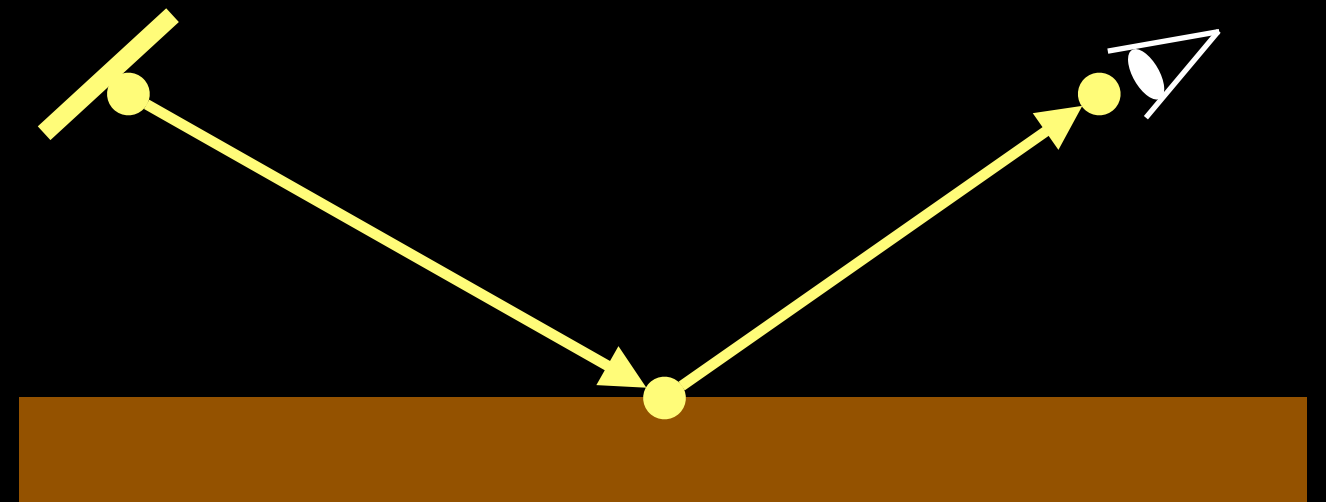
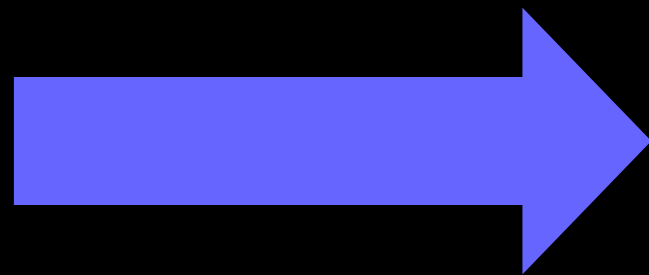


Path in the object space

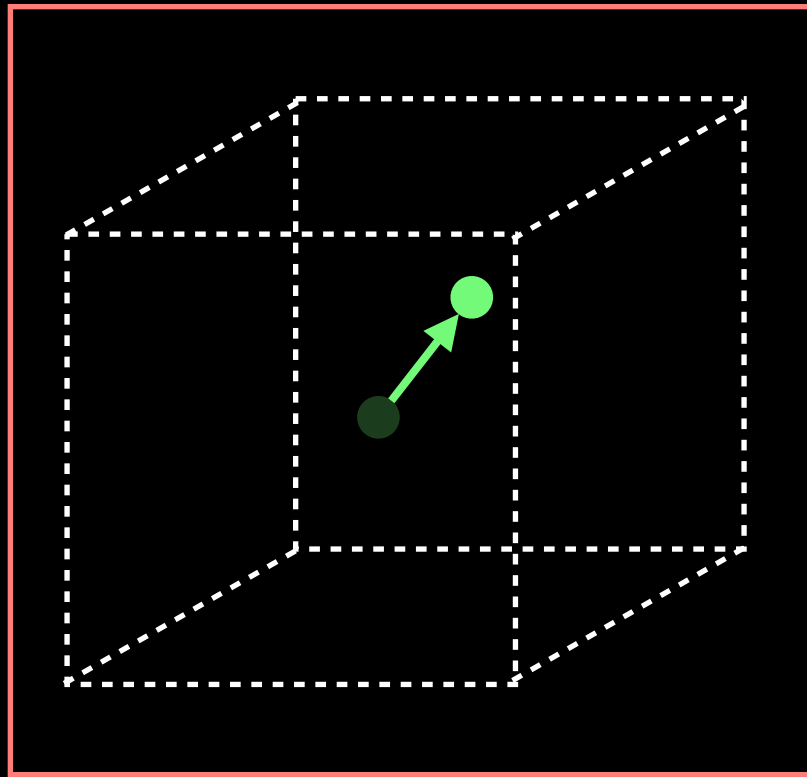
Primary sample space MLT



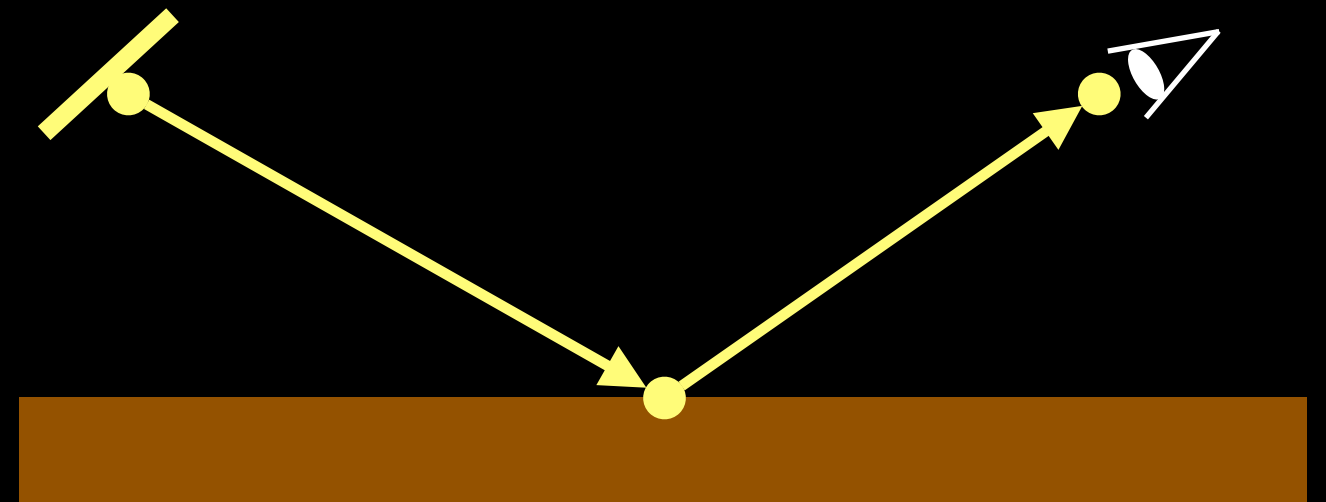
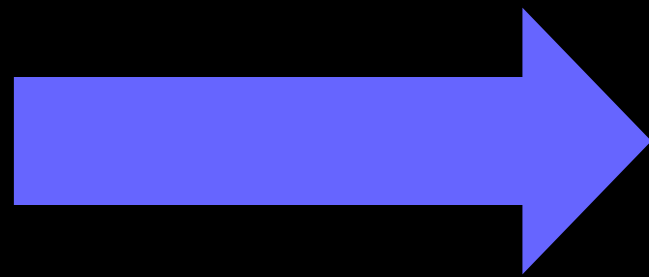
$$\bar{X} = P^{-1}(\bar{U})$$



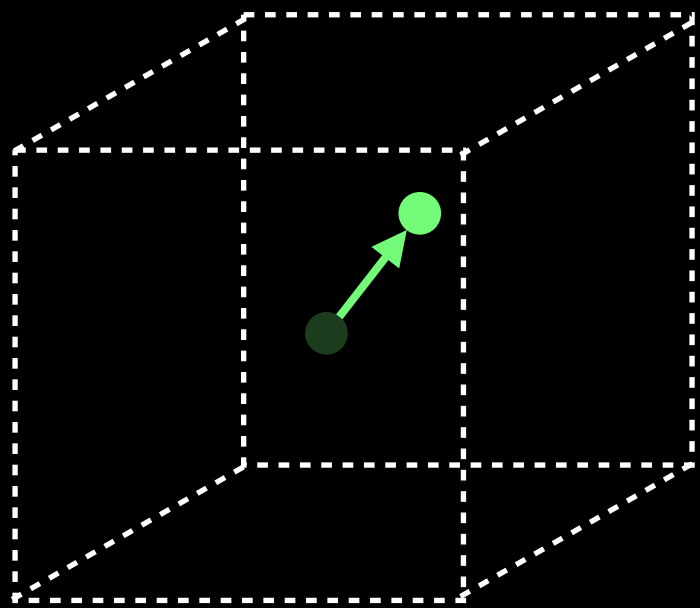
Primary sample space MLT



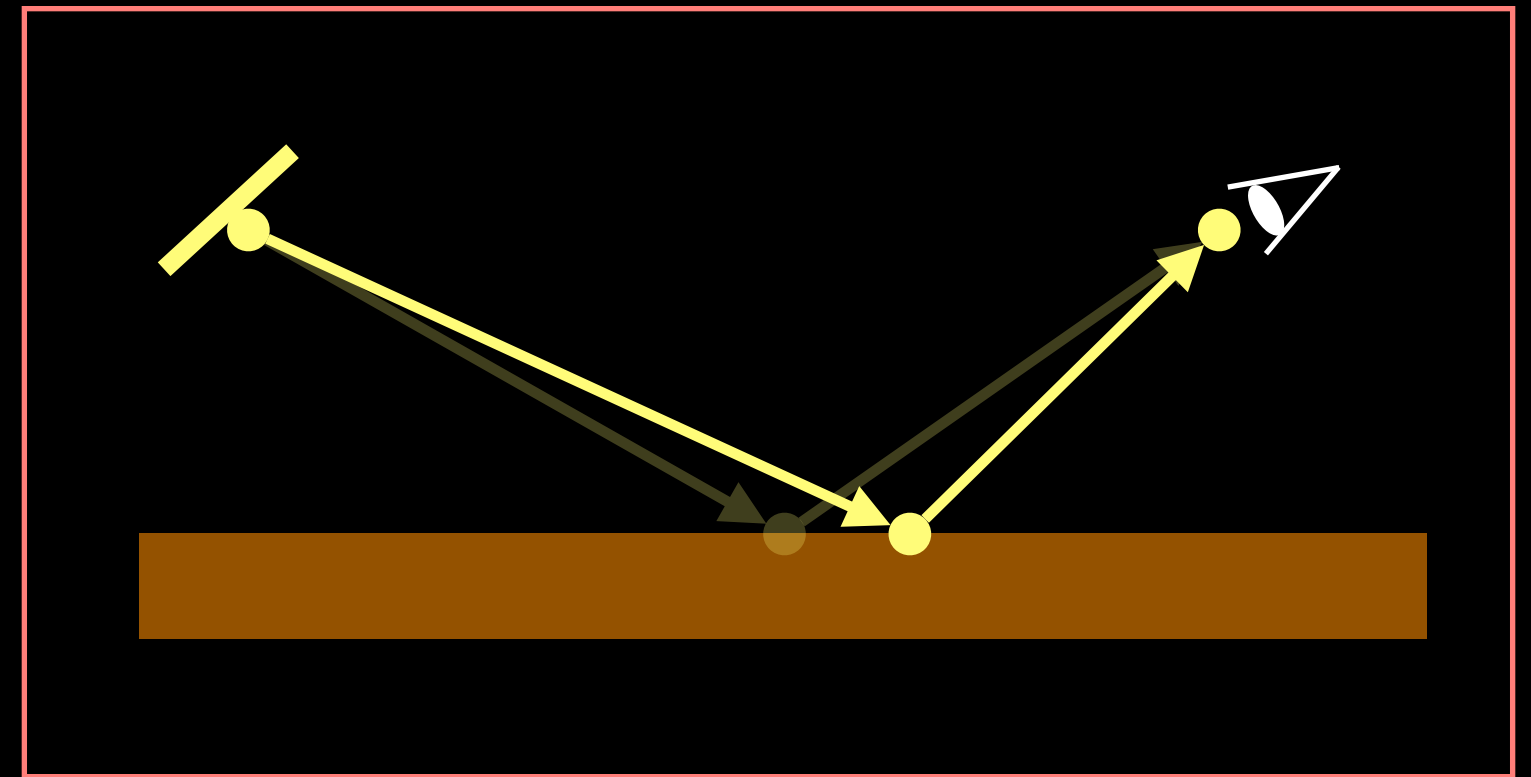
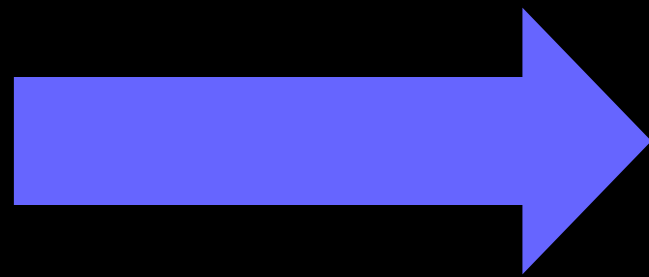
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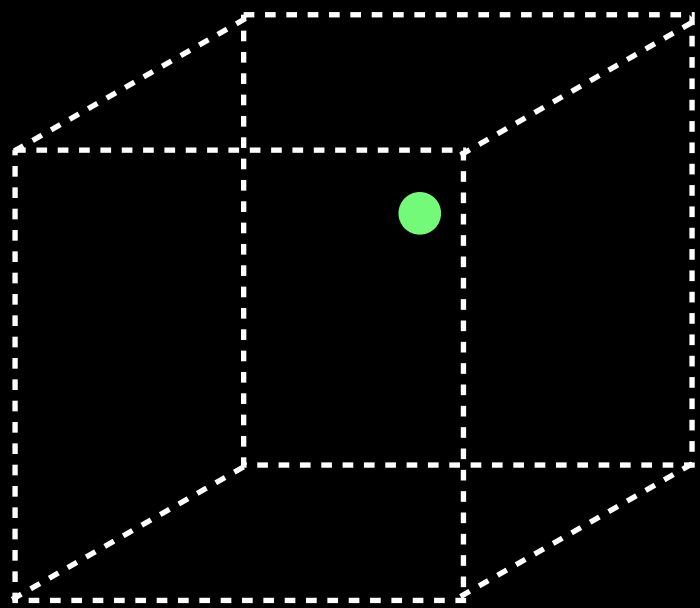
Primary sample space MLT



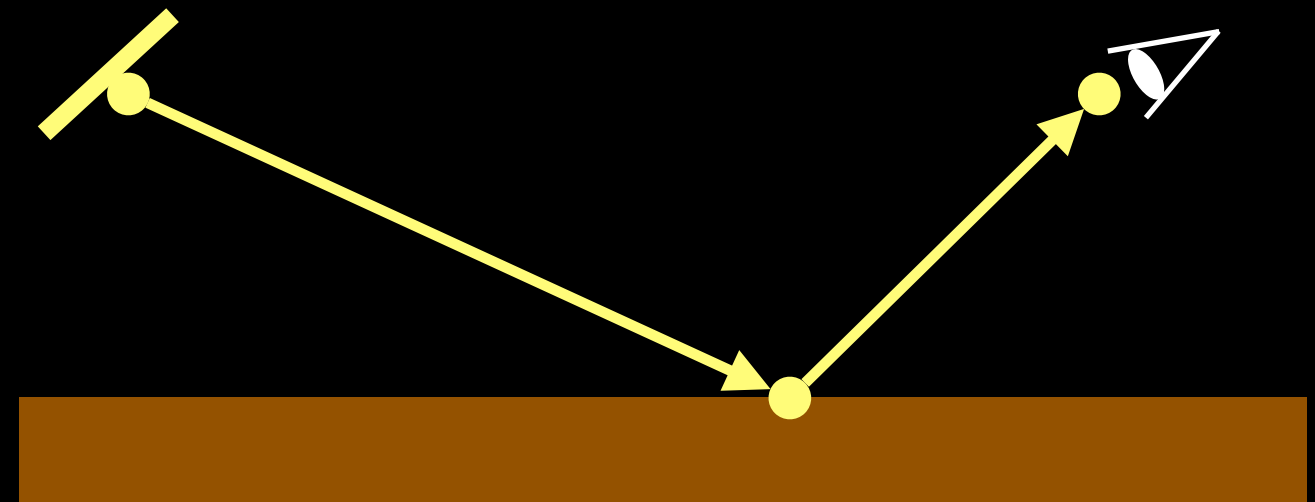
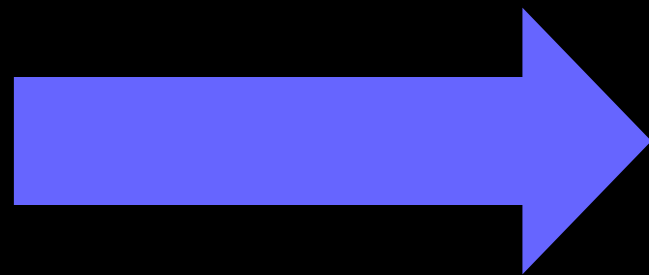
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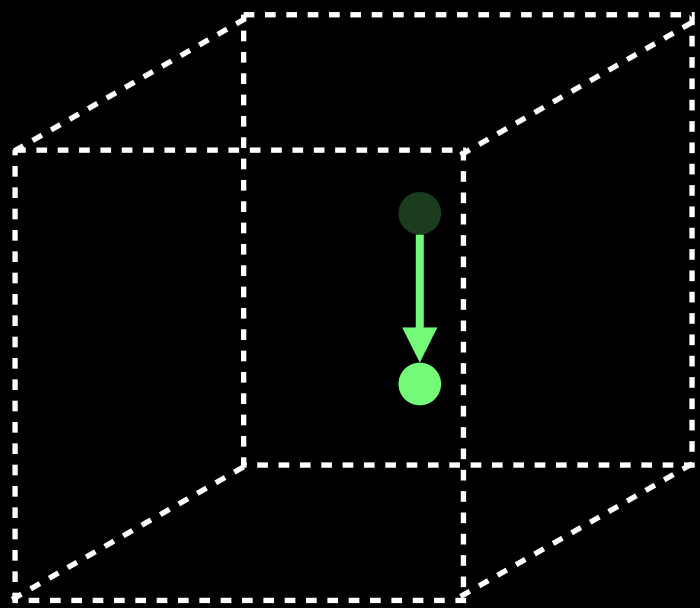
Primary sample space MLT



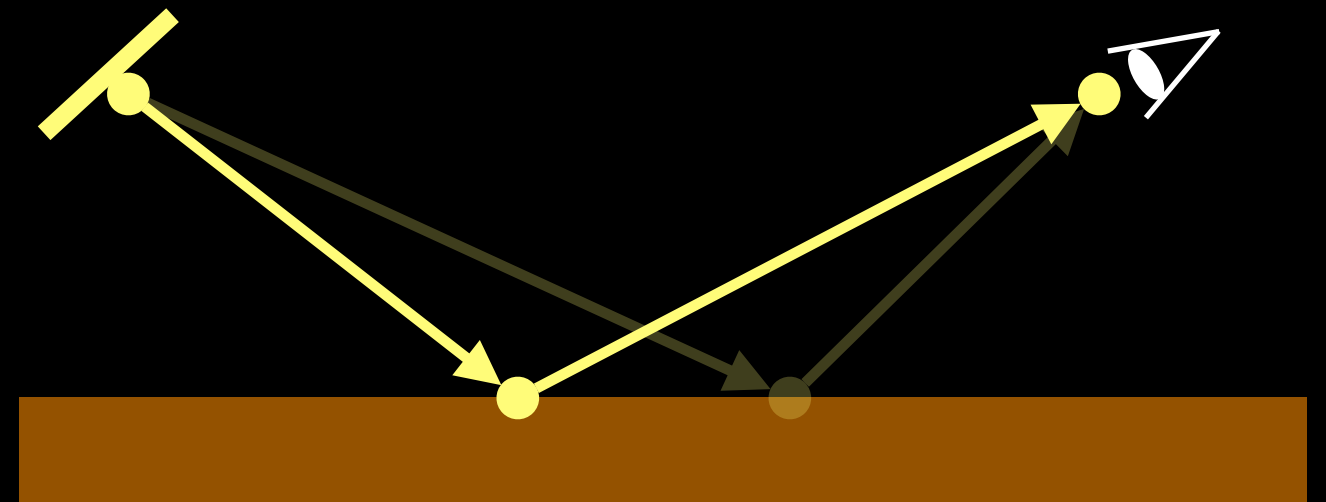
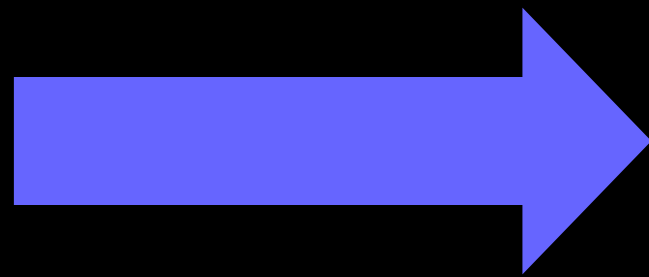
$$\bar{X} = P^{-1}(\bar{U})$$



Primary sample space MLT

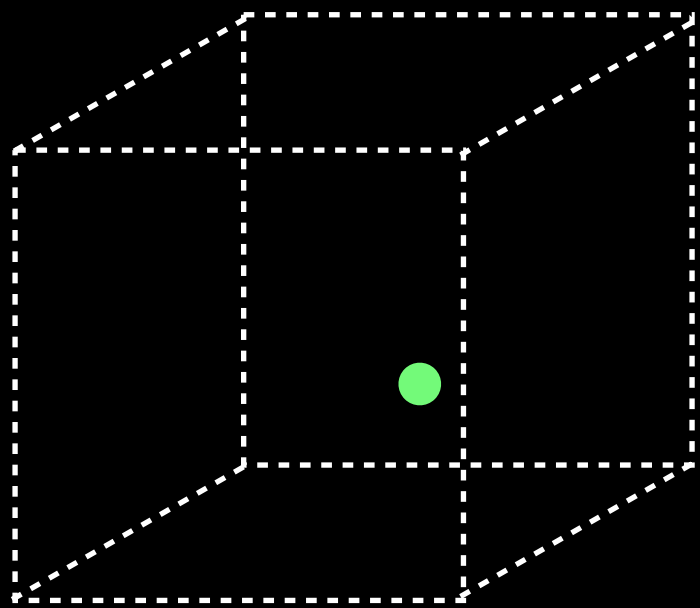


$$\bar{X} = P^{-1}(\bar{U})$$

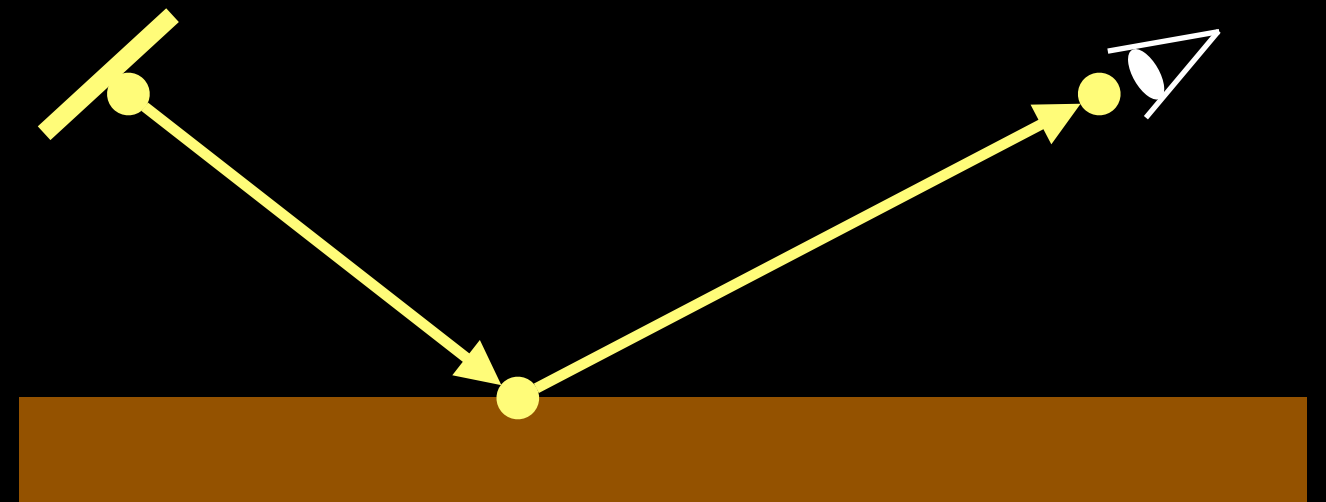
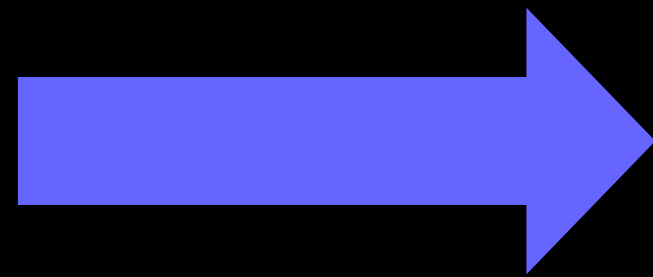


Multiplexed primary sample space

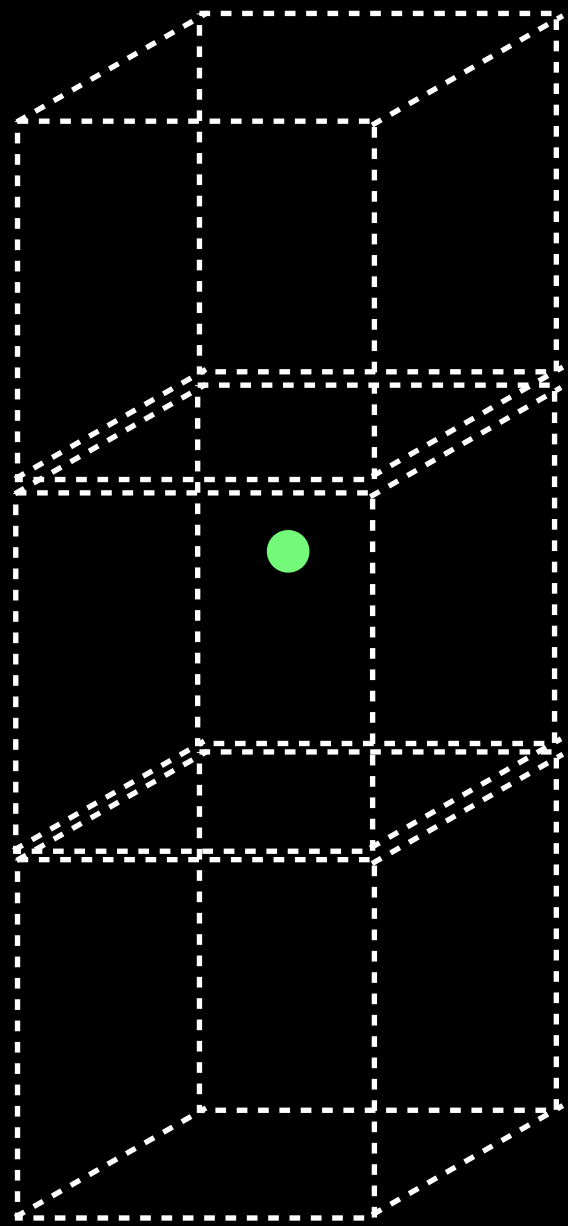
Multiplexed primary sample space



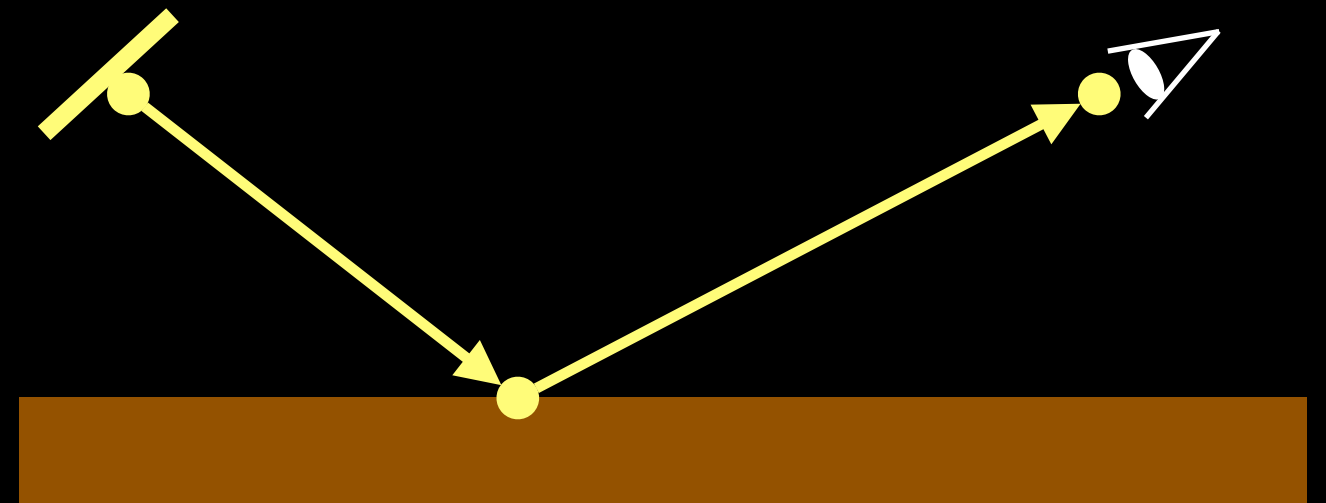
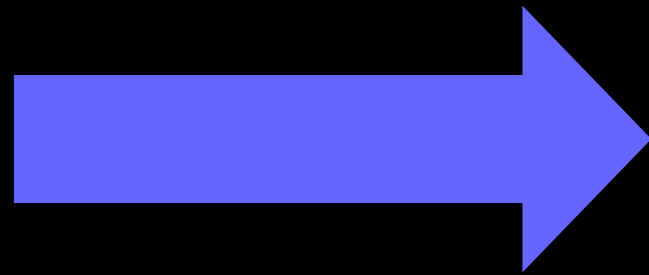
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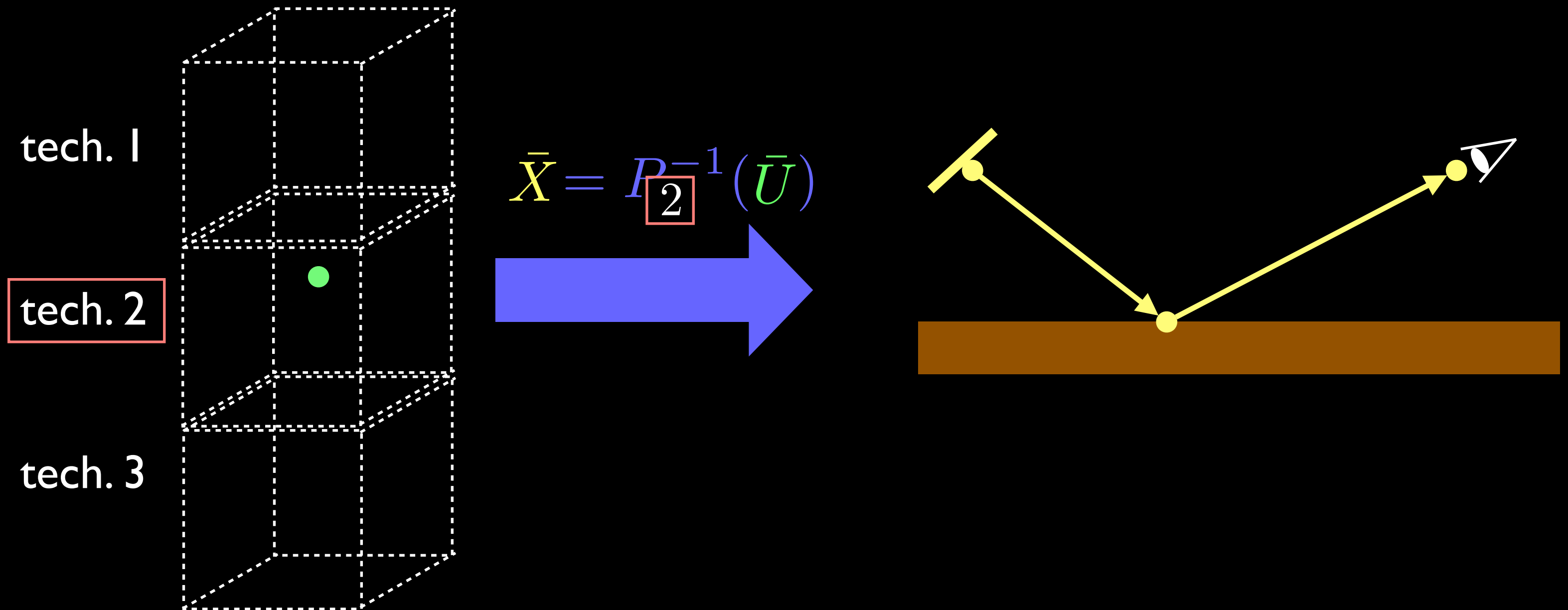
Multiplexed primary sample space



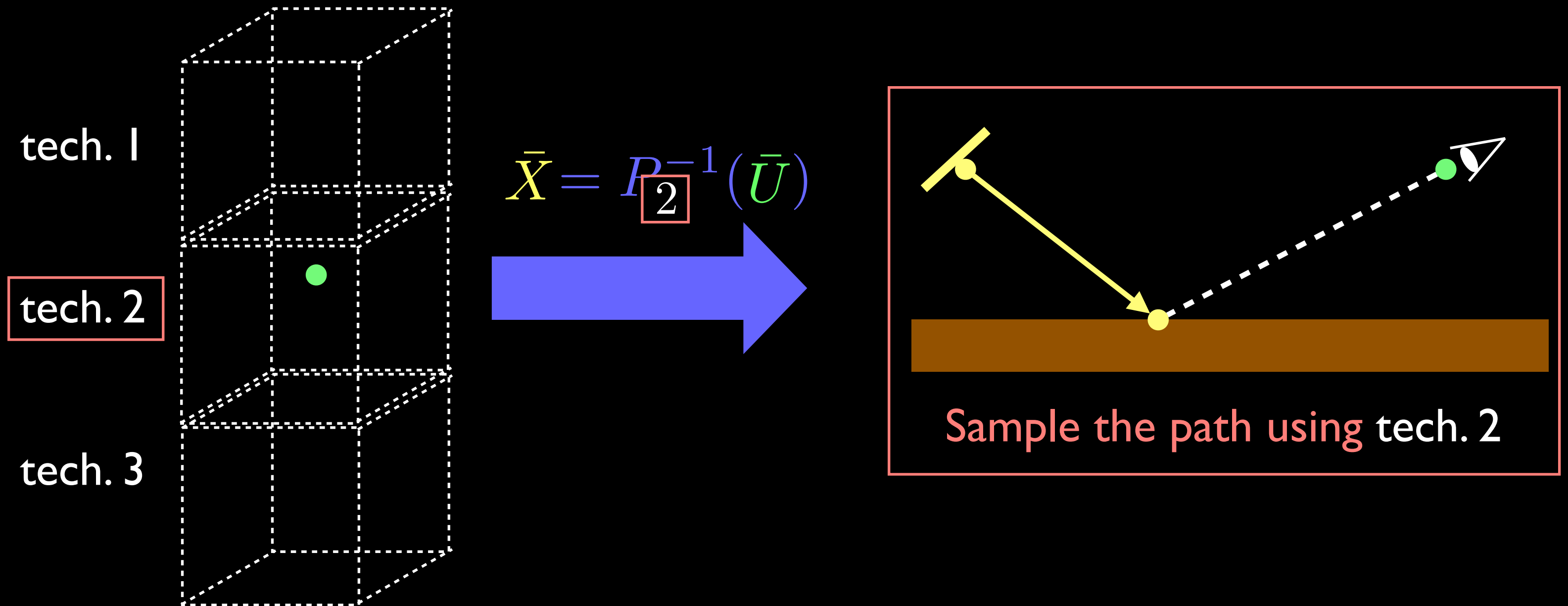
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Multiplexed primary sample space

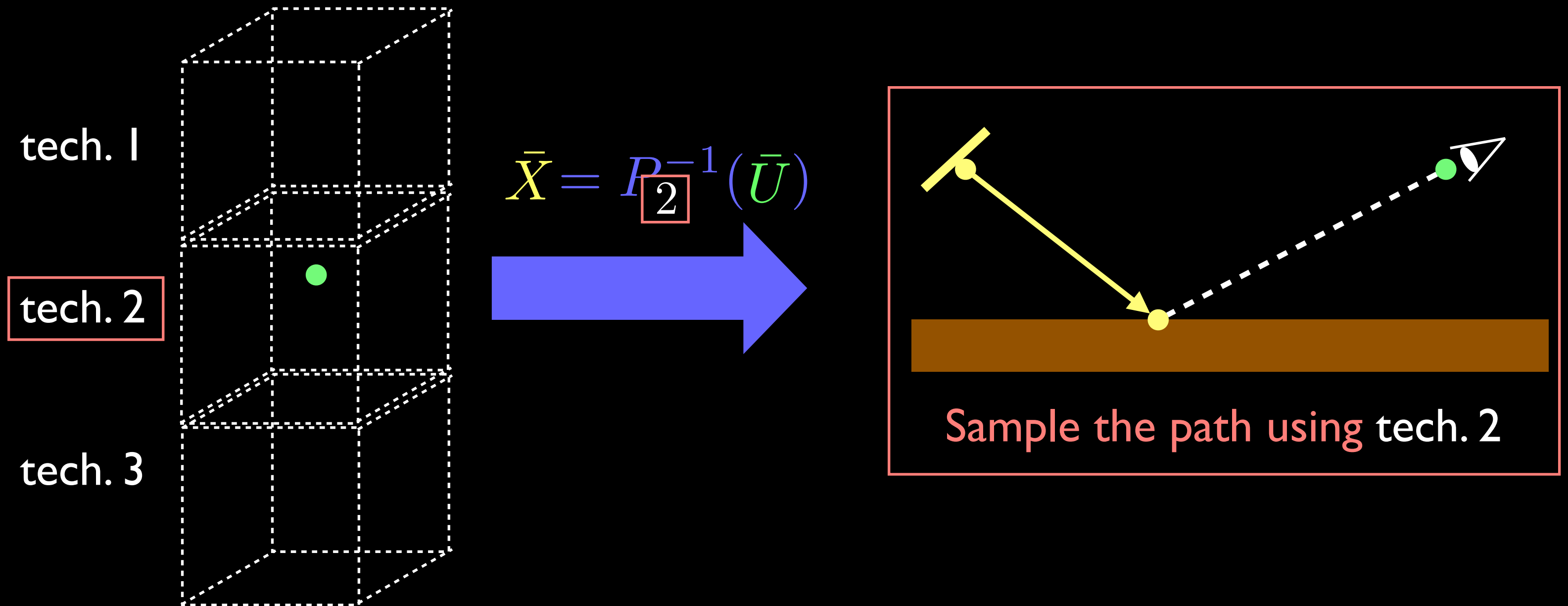


Multiplexed primary sample space



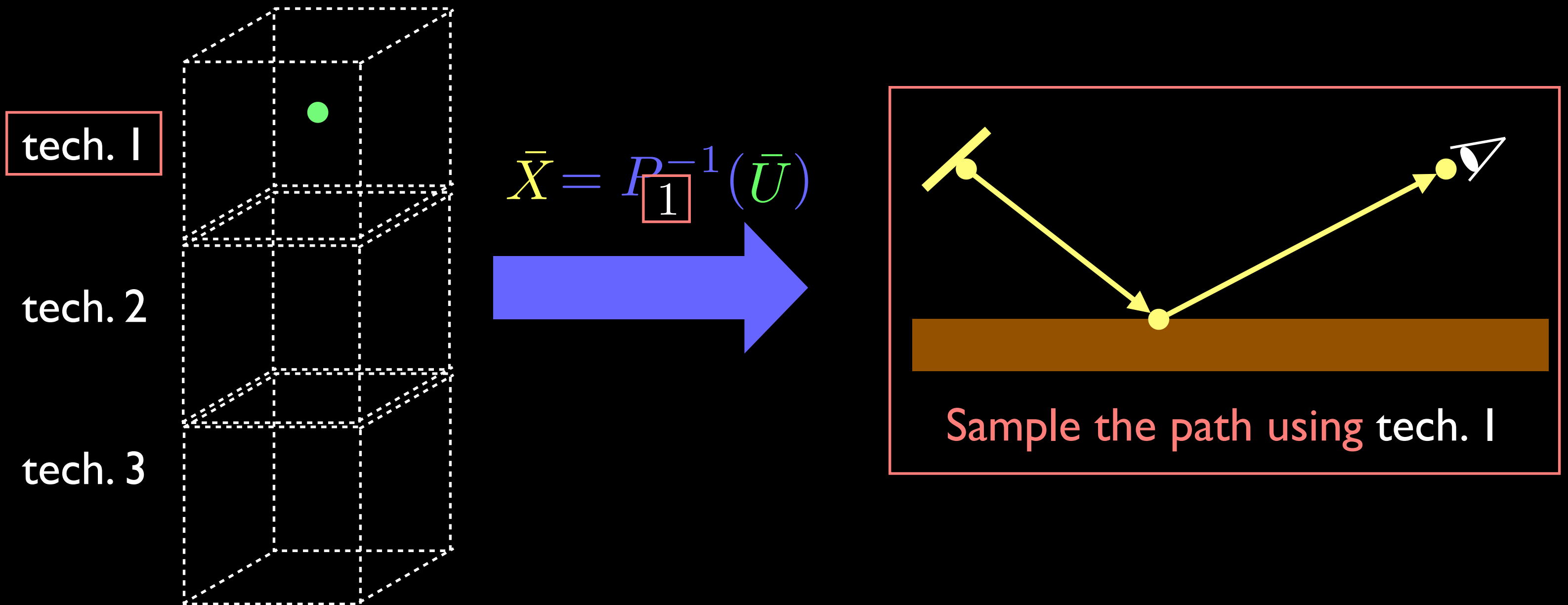
Multiplexed primary sample space

Extension of the primary sample space by technique index



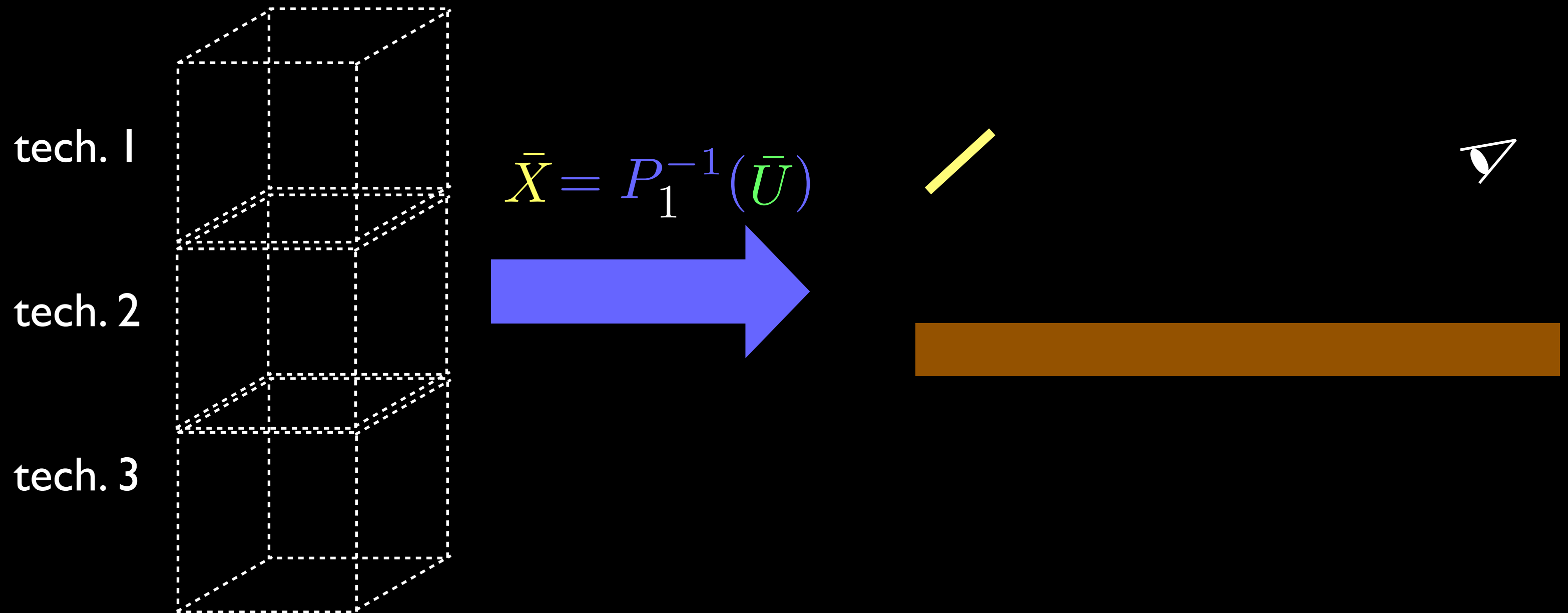
Multiplexed primary sample space

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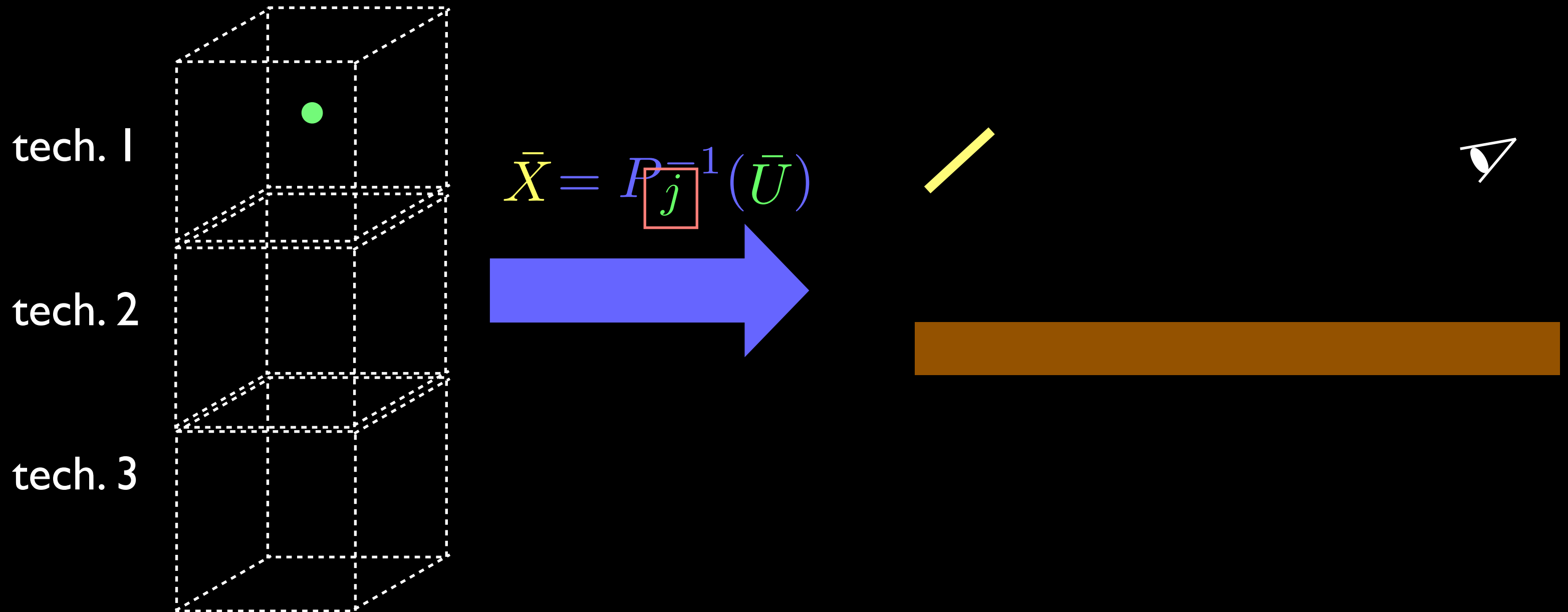
Multiplexed MLT

Markov chain states: (\bar{U})



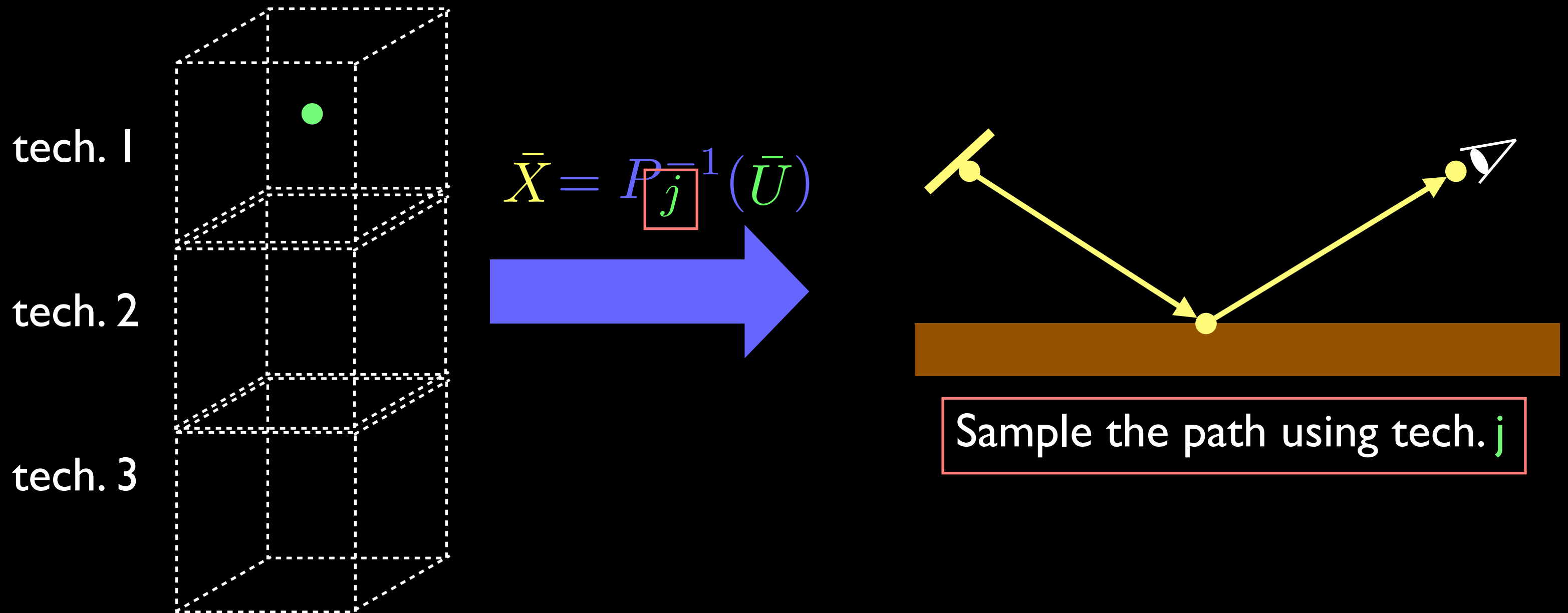
Multiplexed MLT

Markov chain states: (\bar{U}, j)



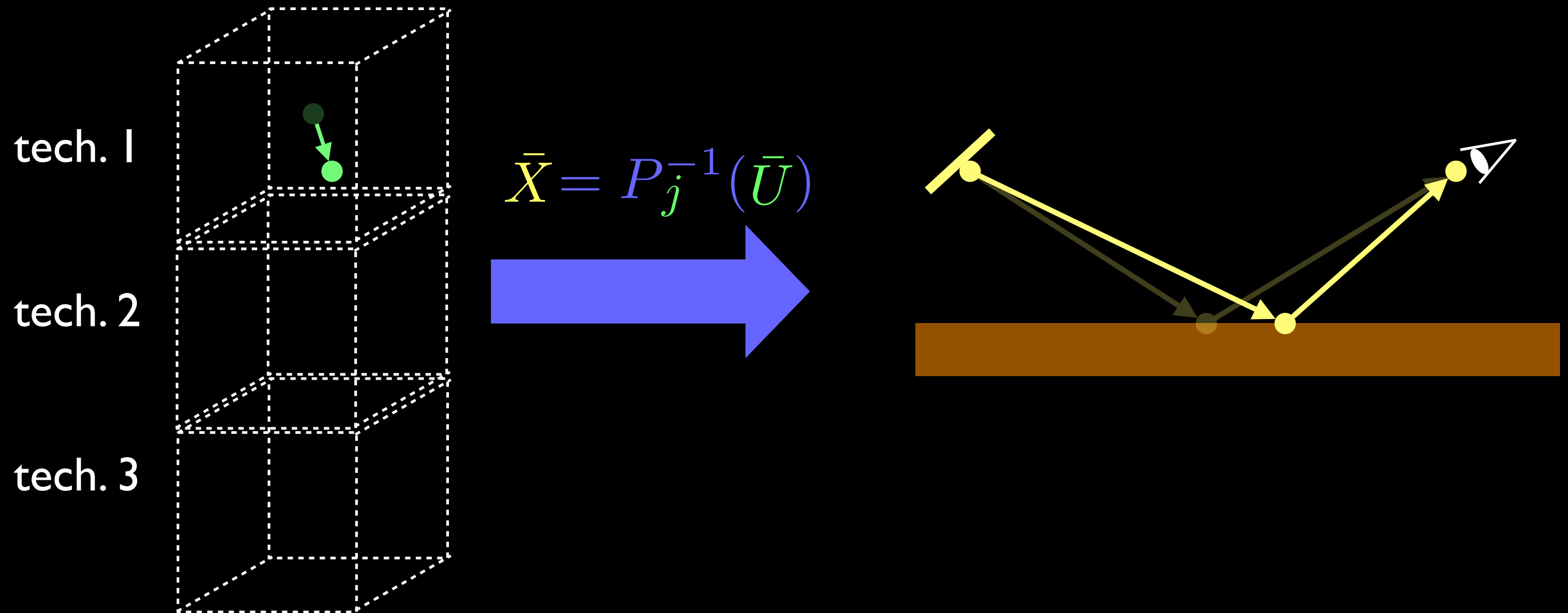
Multiplexed MLT

Markov chain states: (\bar{U}, j)



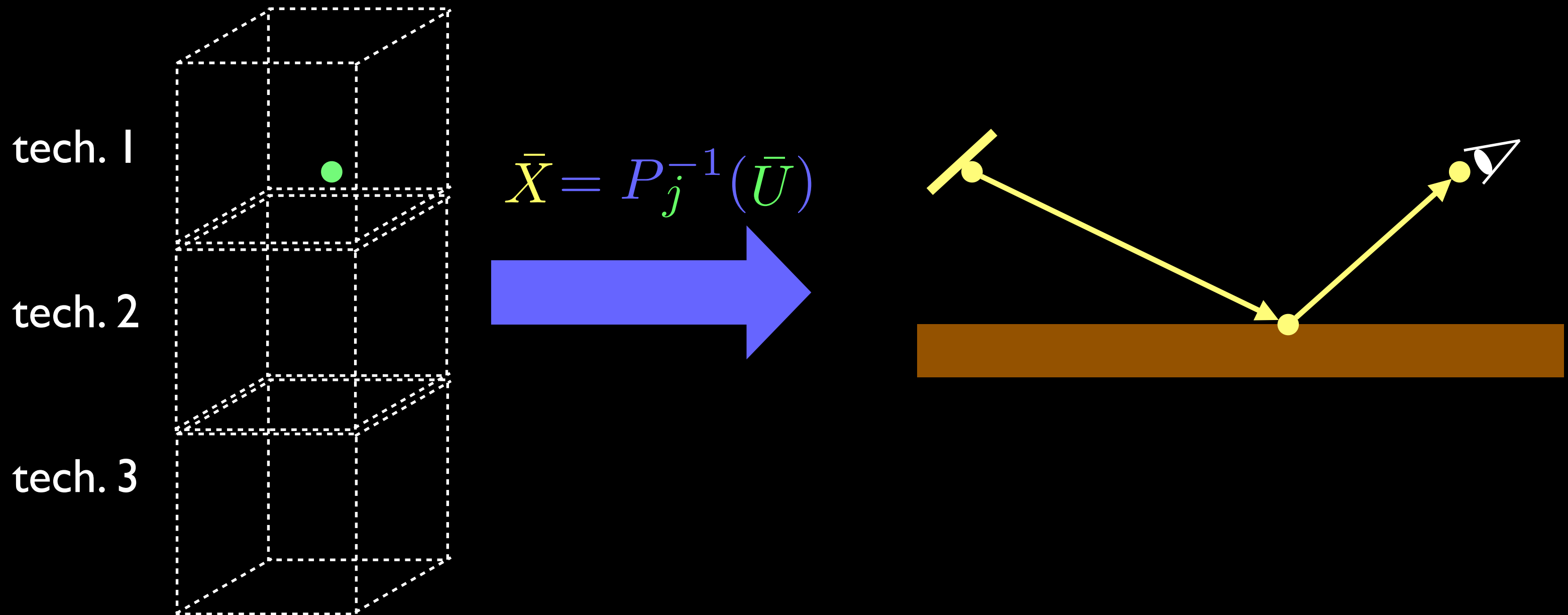
Multiplexed MLT

Markov chain states: (\bar{U}, j)



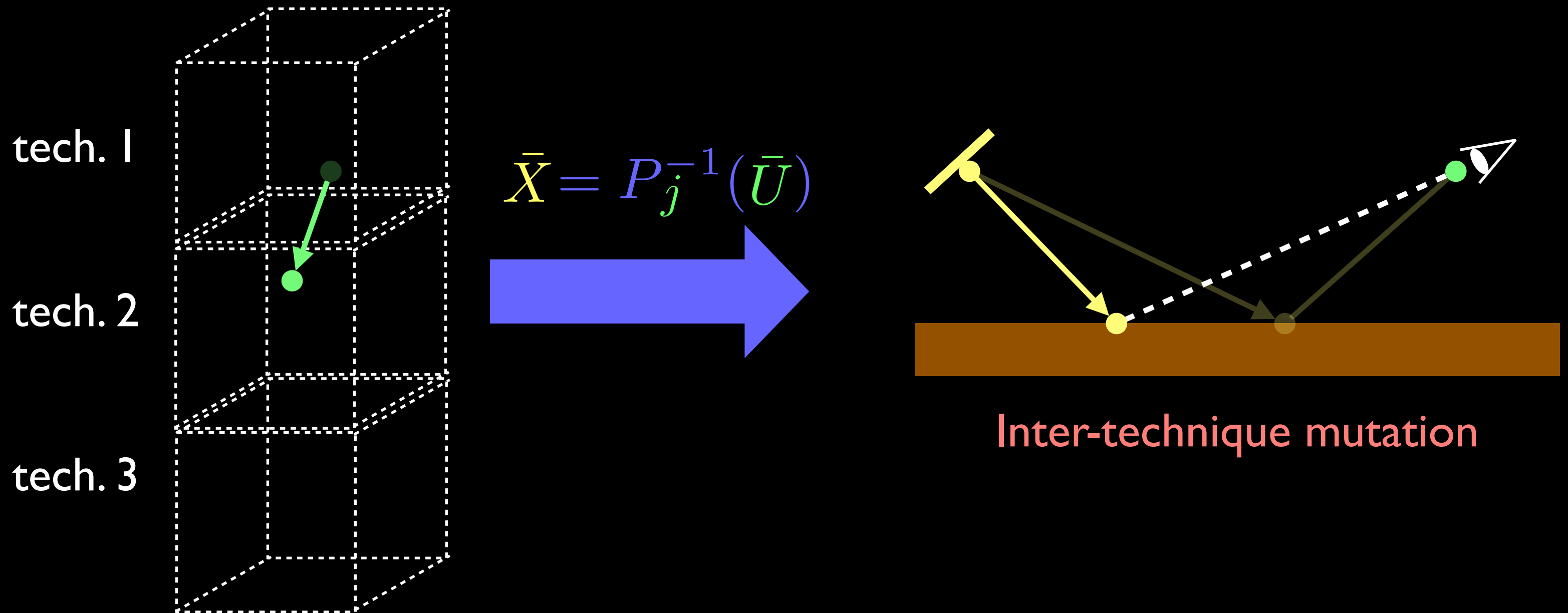
Multiplexed MLT

Markov chain states: (\bar{U}, j)



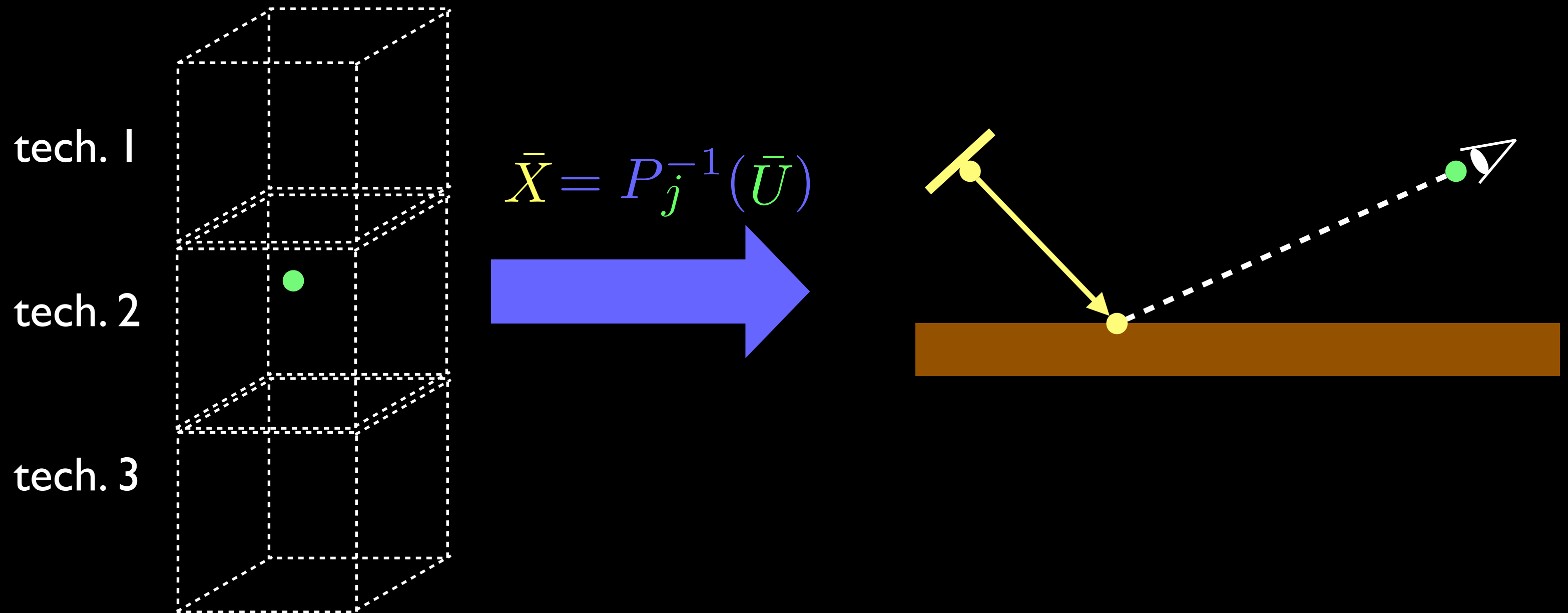
Multiplexed MLT

Markov chain states: (\bar{U}, j)



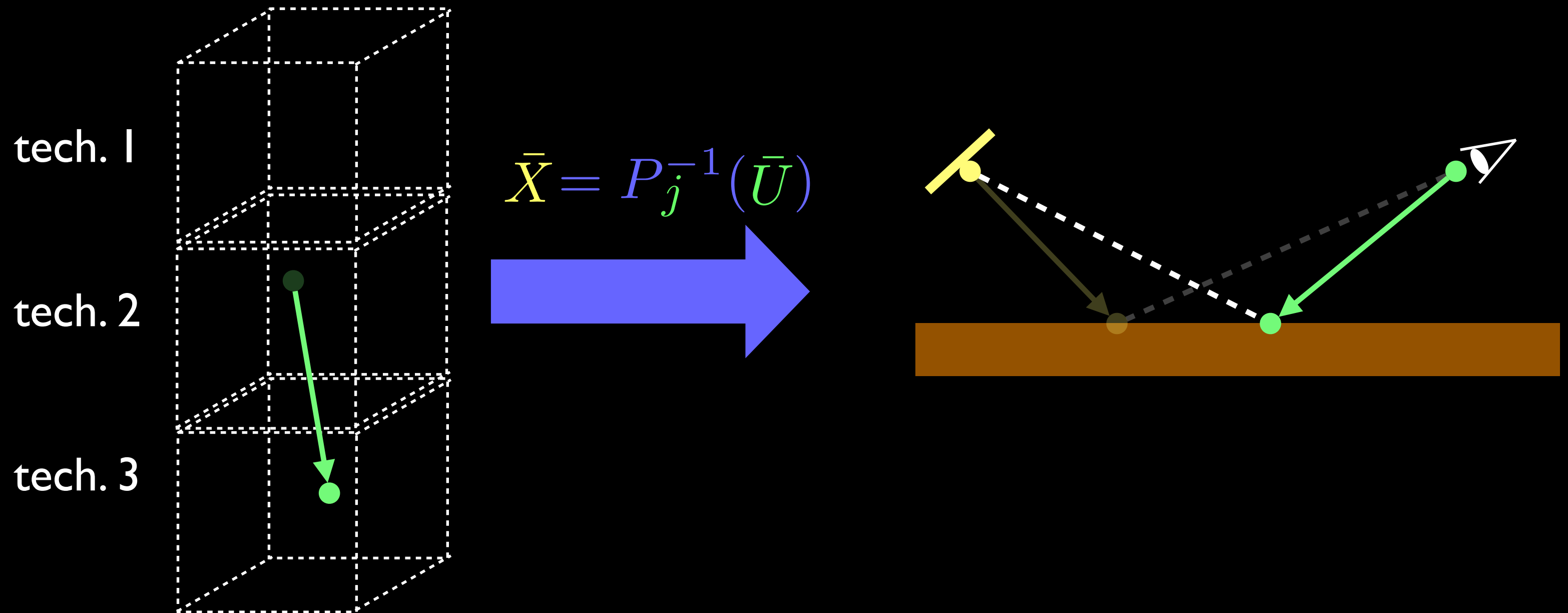
Multiplexed MLT

Markov chain states: (\bar{U}, j)

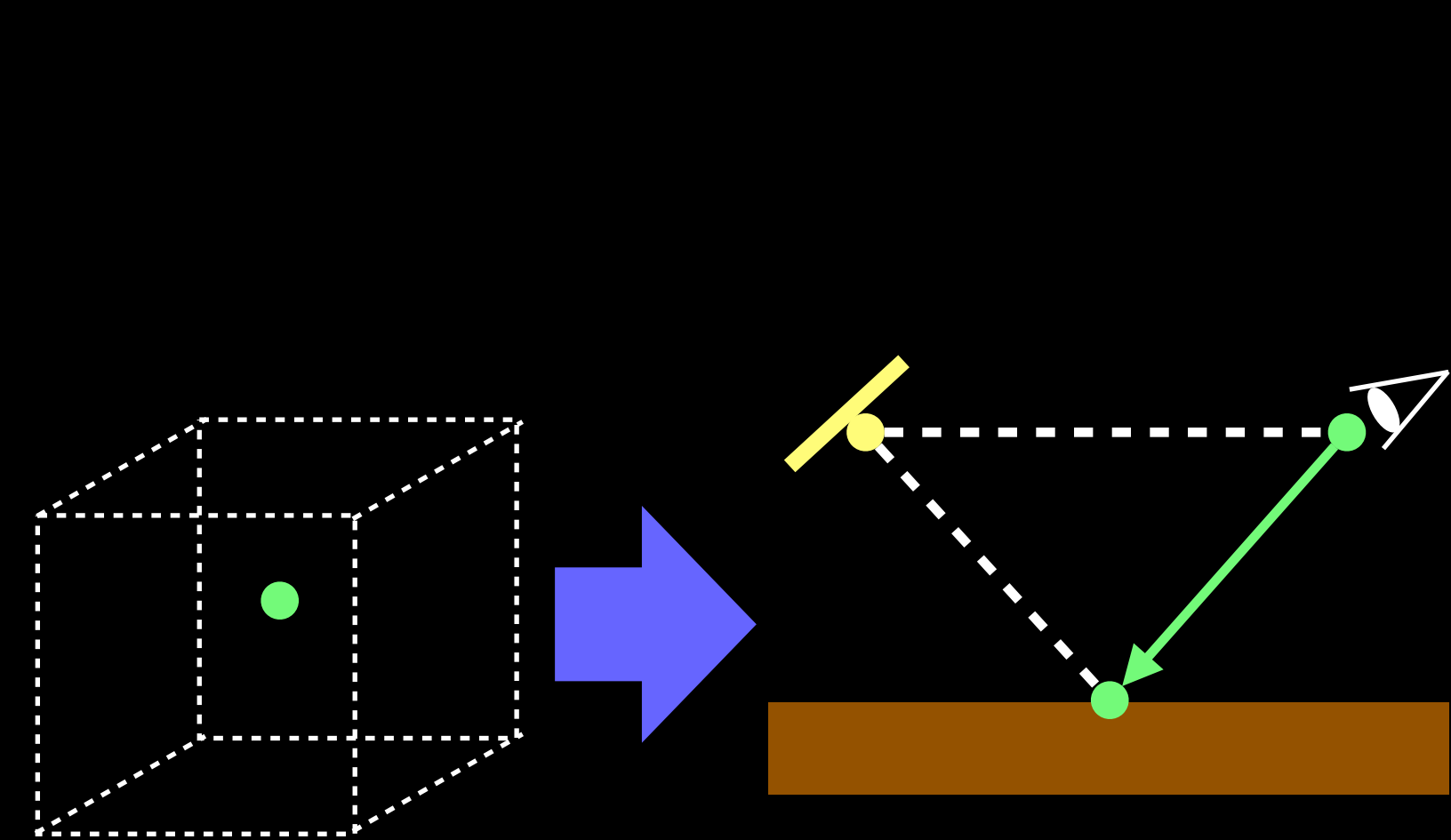


Multiplexed MLT

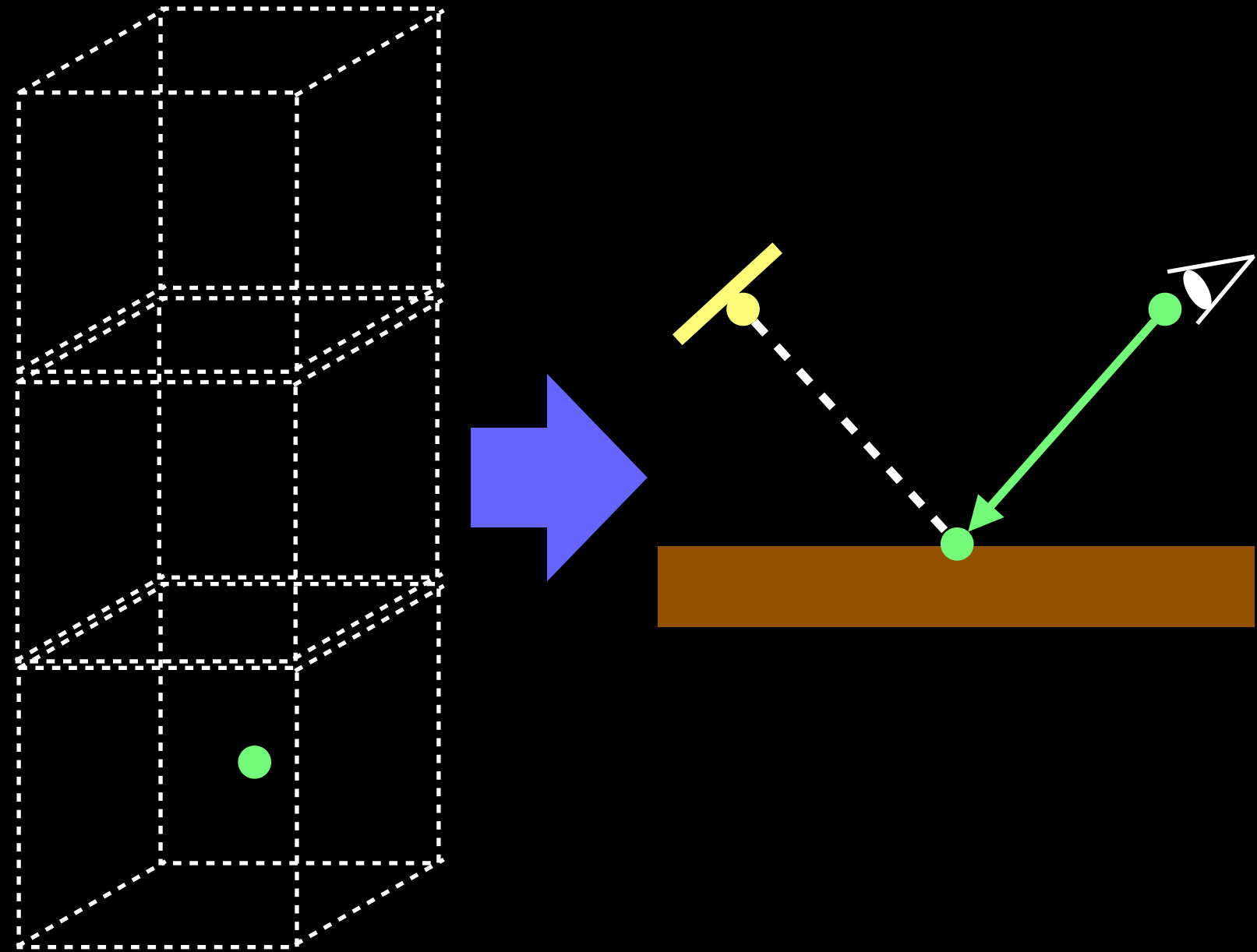
Markov chain states: (\bar{U}, j)



Kelemen MLT + BDPT \neq MMLT

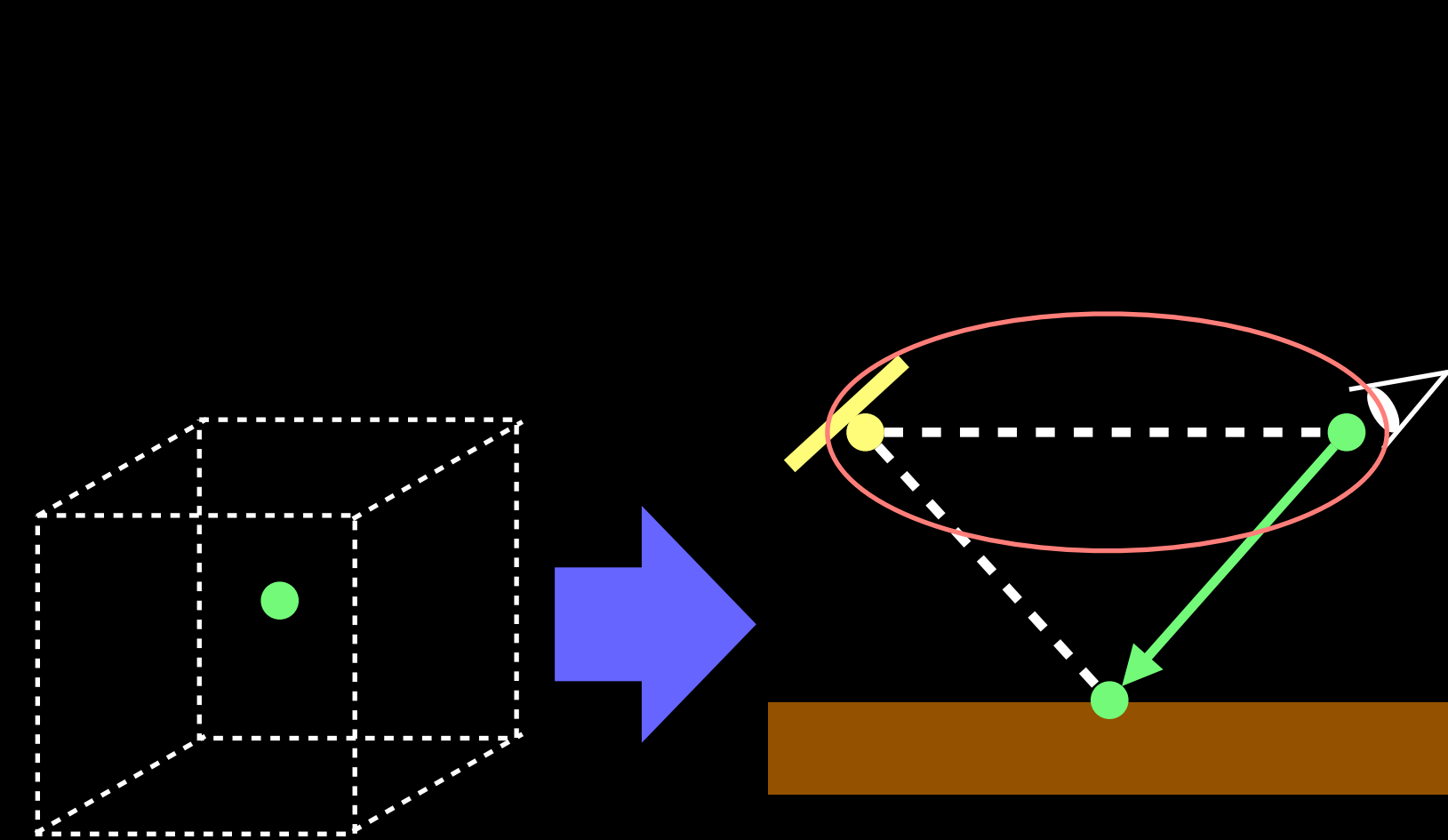


Kelemen MLT + BDPT



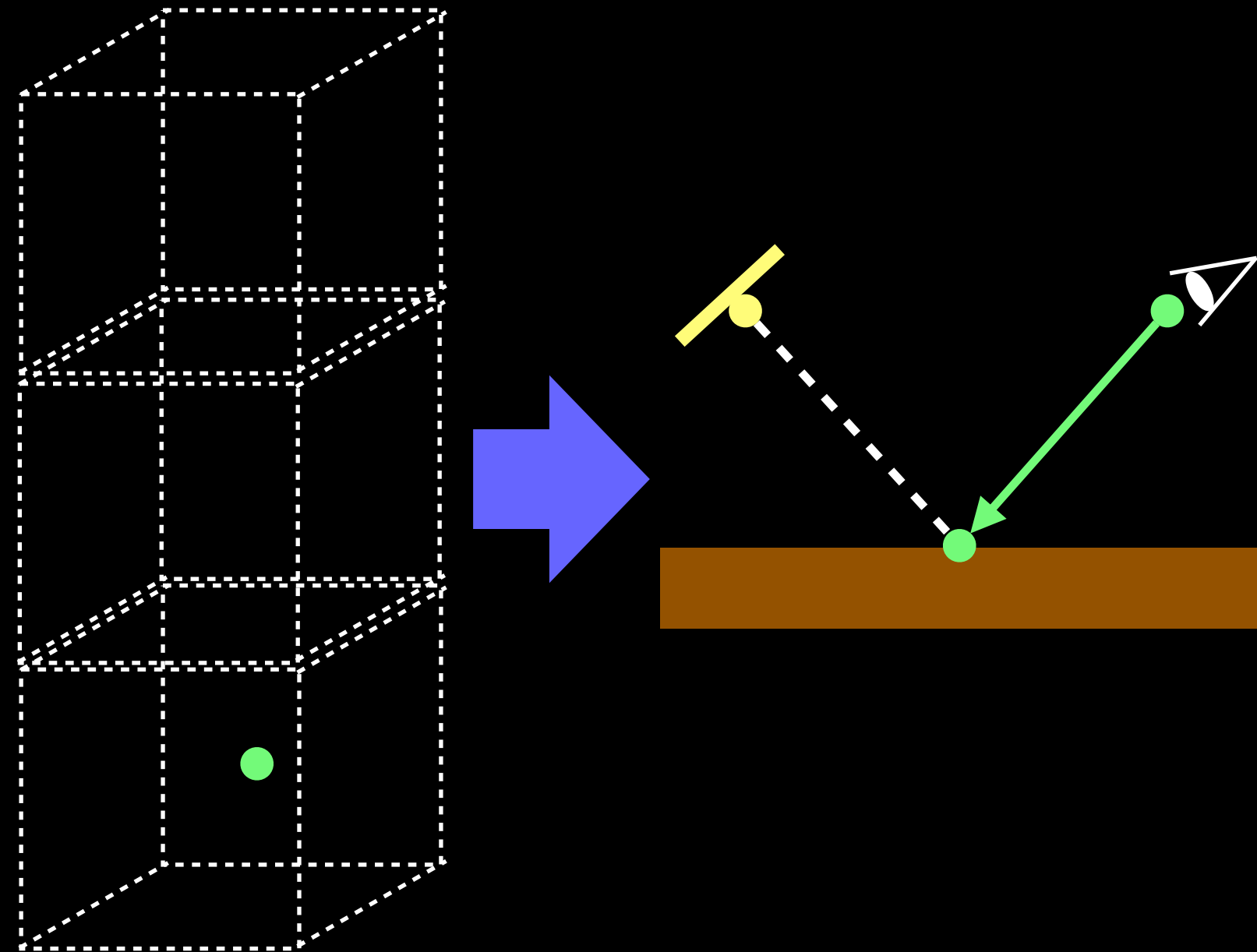
MMLT

Kelemen MLT + BDPT \neq MMLT



Kelemen MLT + BDPT

One sample = Set of BDPT connections



MMLT

One sample = One path

Kelemen MLT + BDPT \neq MMLT

tech. 1

tech. 2

tech. 3

all

Kelemen



Multiplexed



Kelemen MLT + BDPT \neq MMLT



of samples with MMLT

\approx



Actual relative contributions

Results

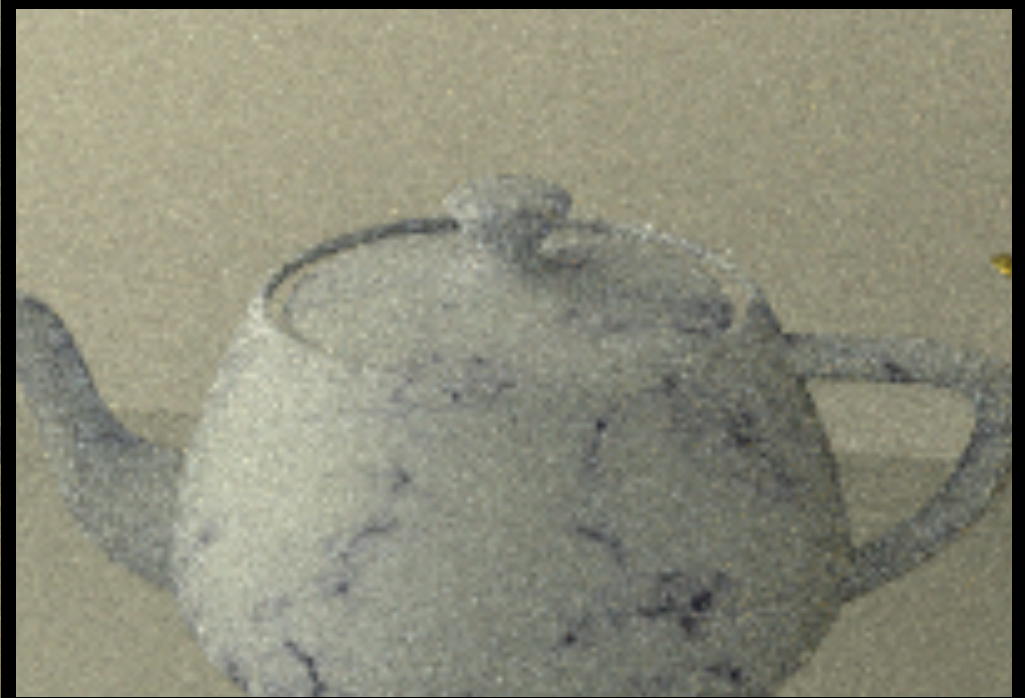
Comparisons

- All the comparisons are equal-time
- Proprietary rendering system
 - BDPT, Veach MLT, Kelemen MLT, Multiplexed MLT
- Mitsuba [Jakob 10]
 - Manifold exploration

Veach MLT



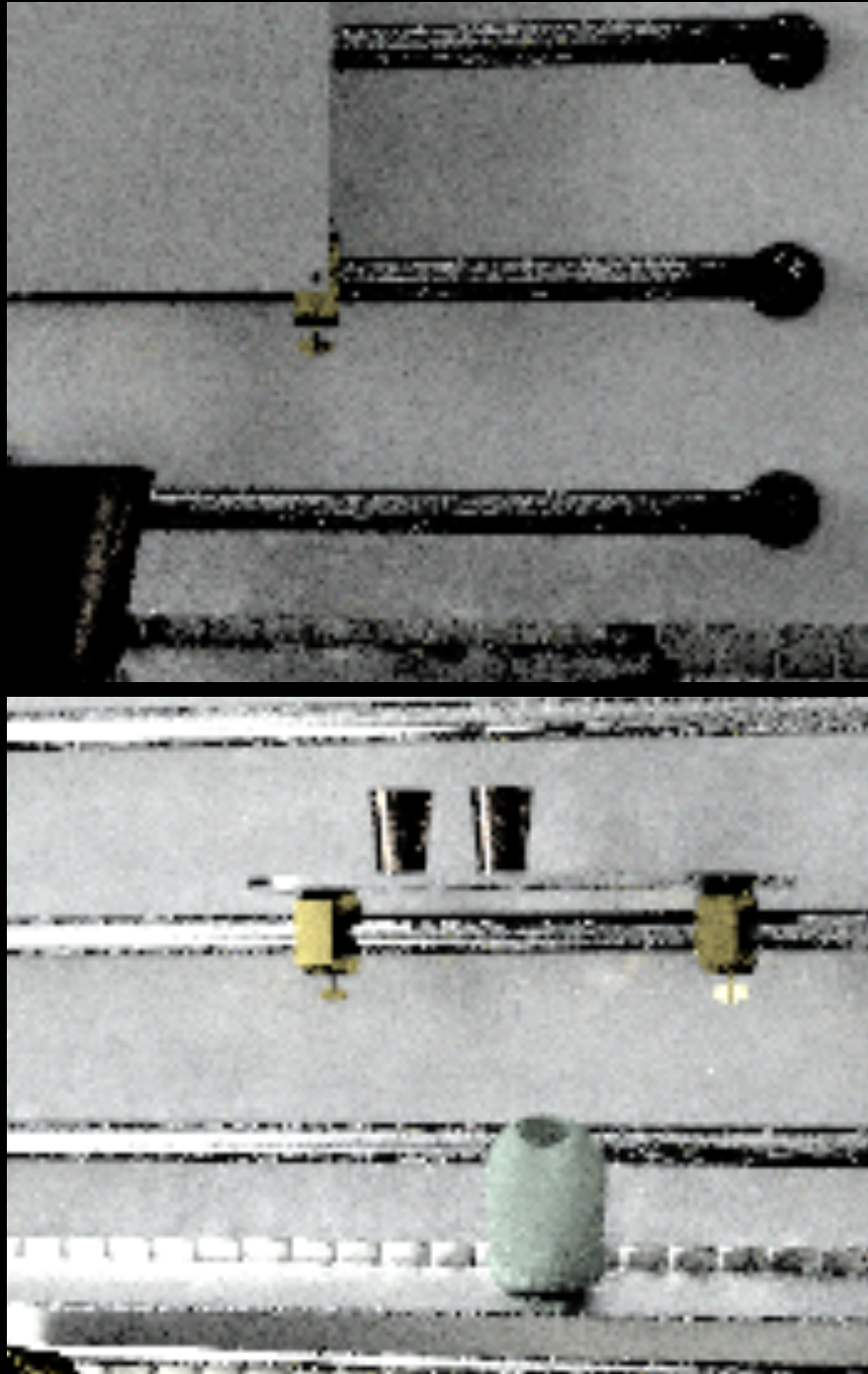
Kelemen MLT



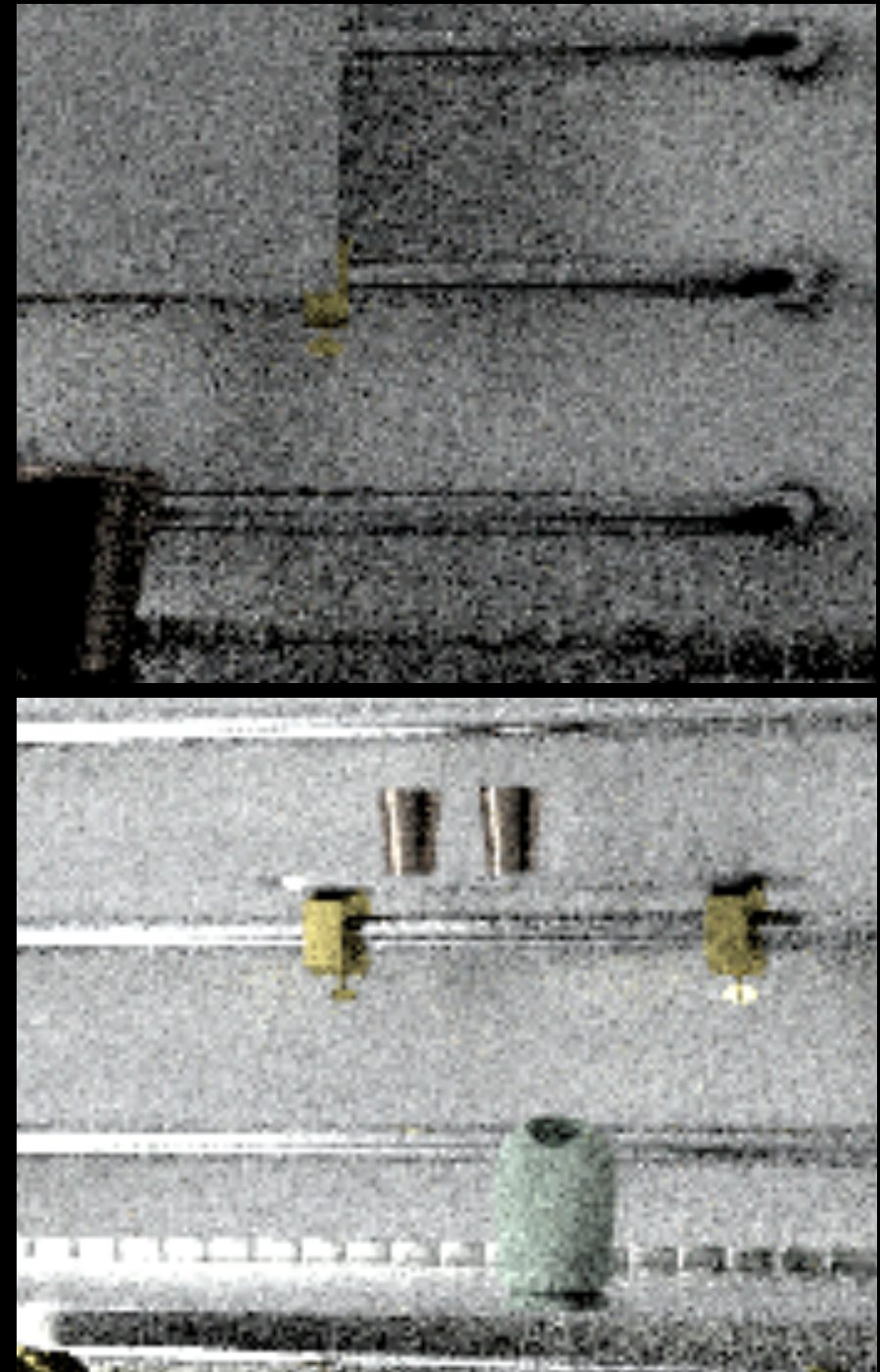
Multiplexed MLT



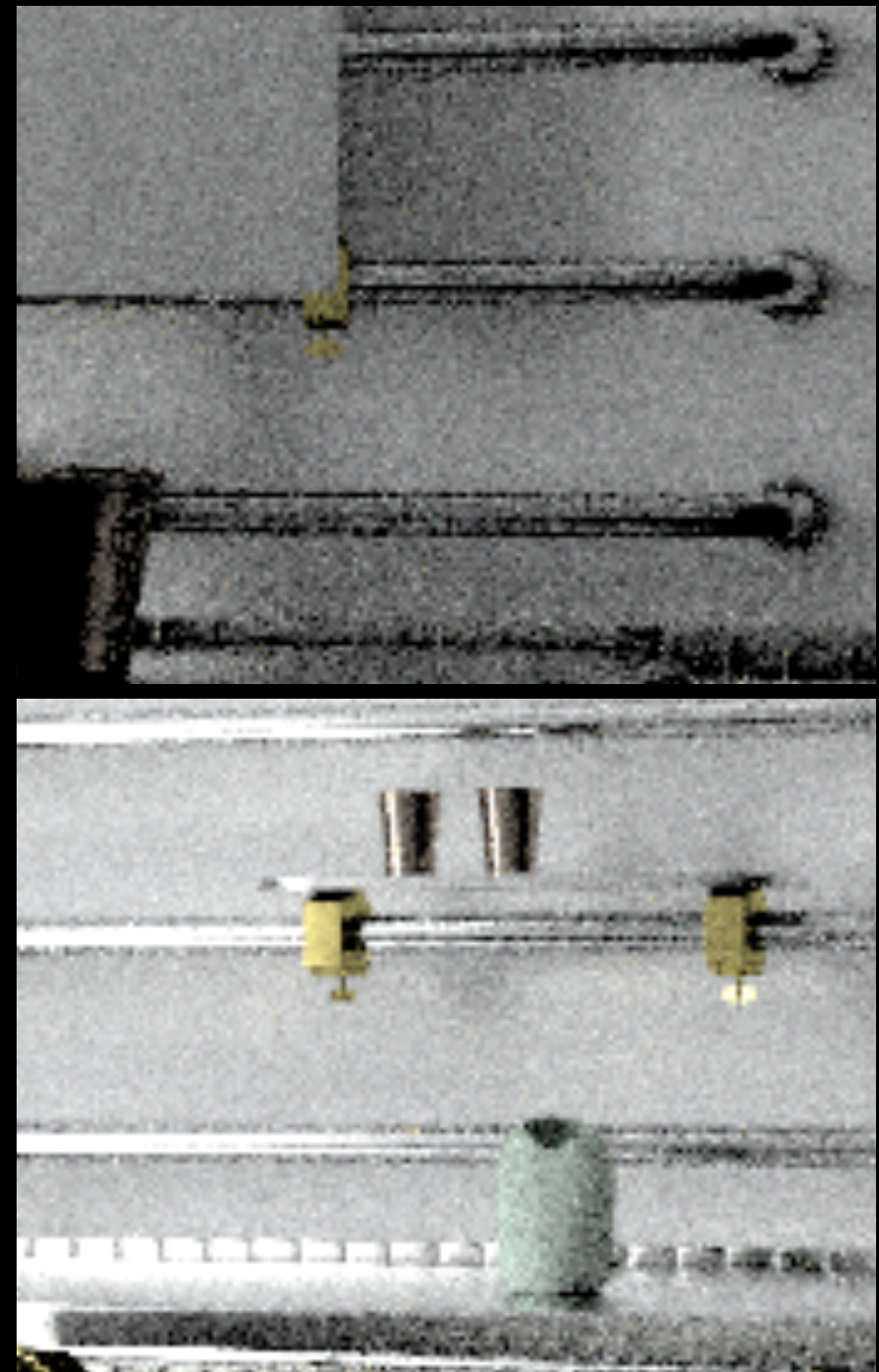
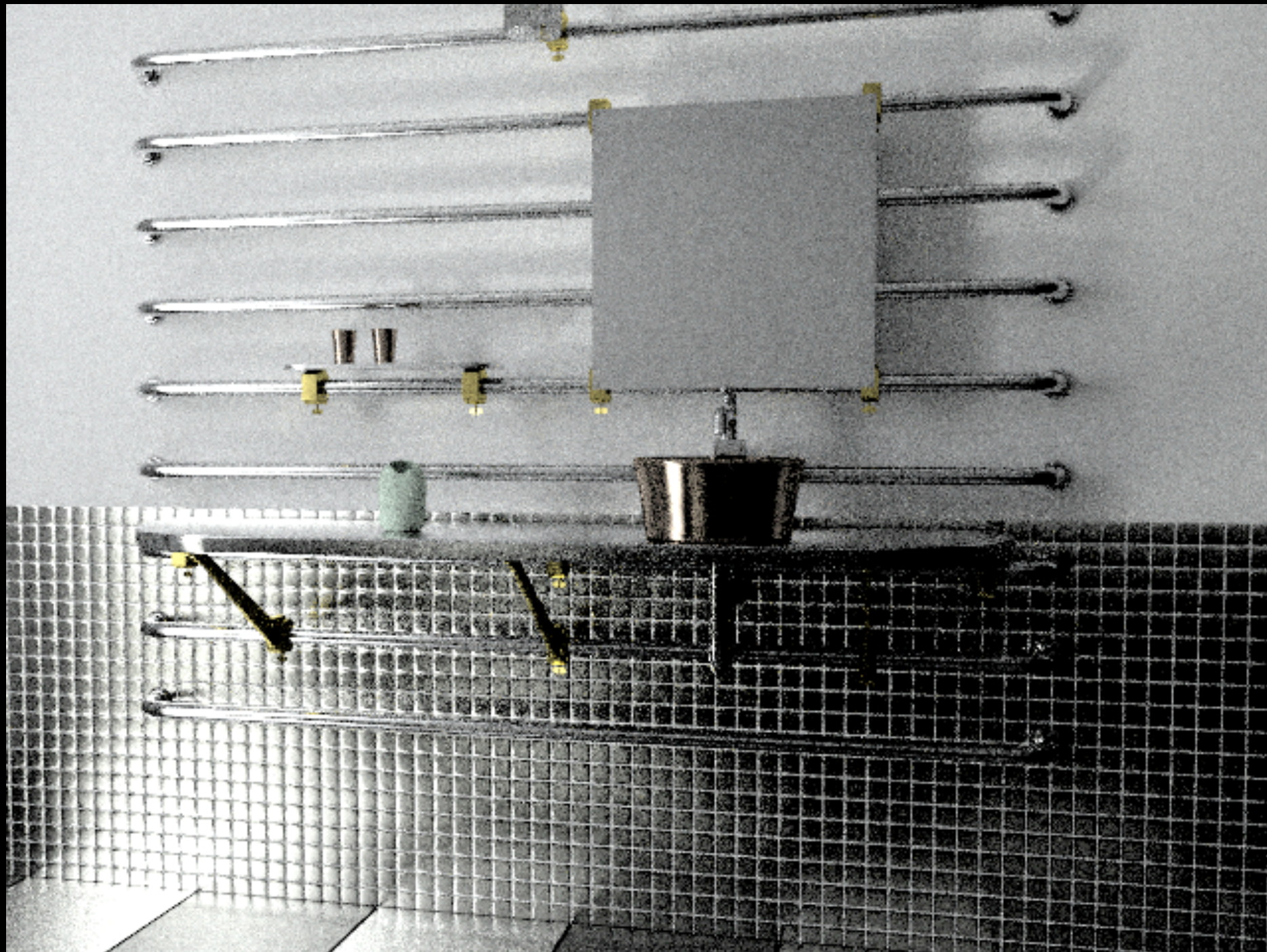
Veach MLT



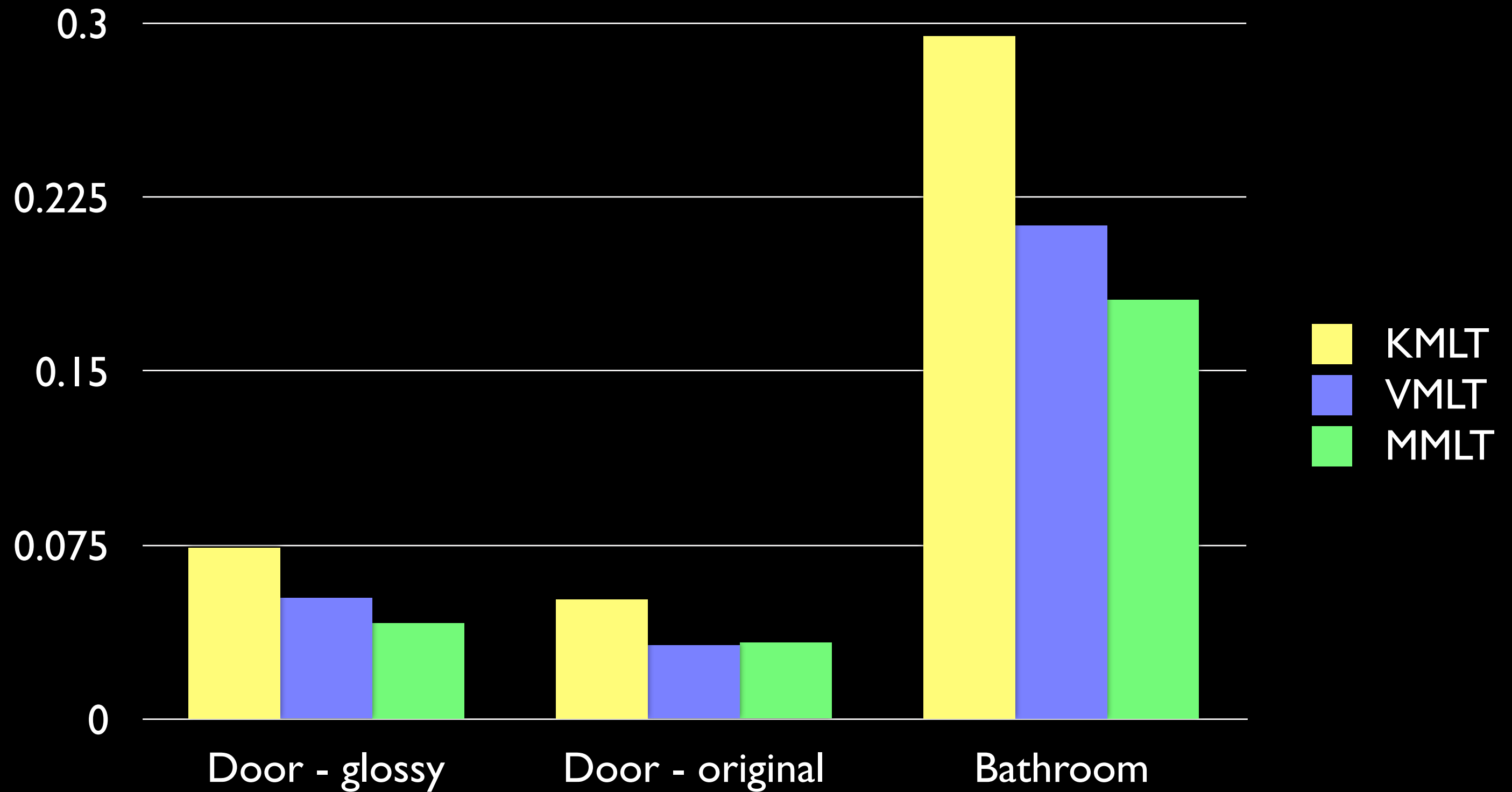
Kelemen MLT



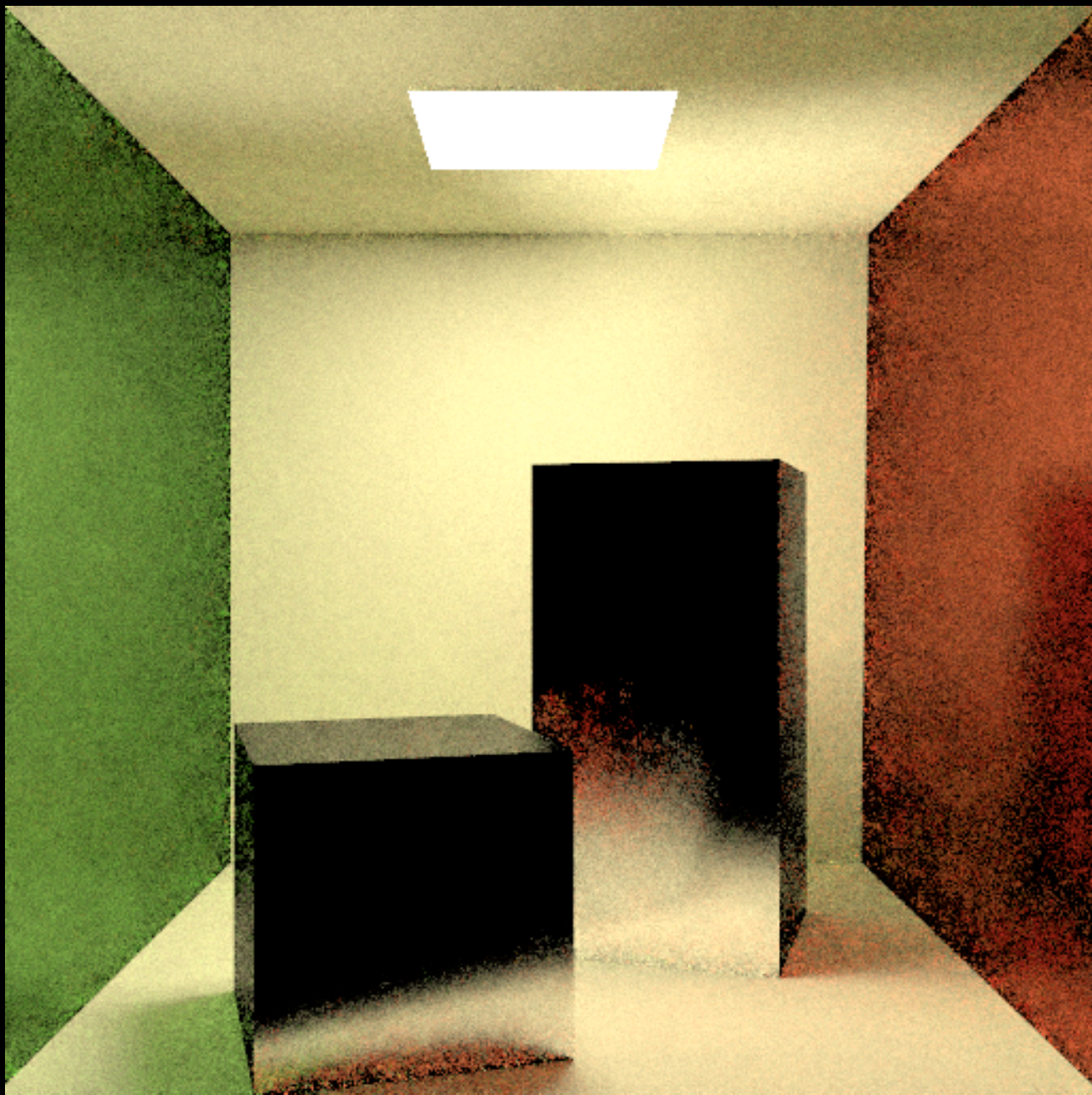
Multiplexed MLT



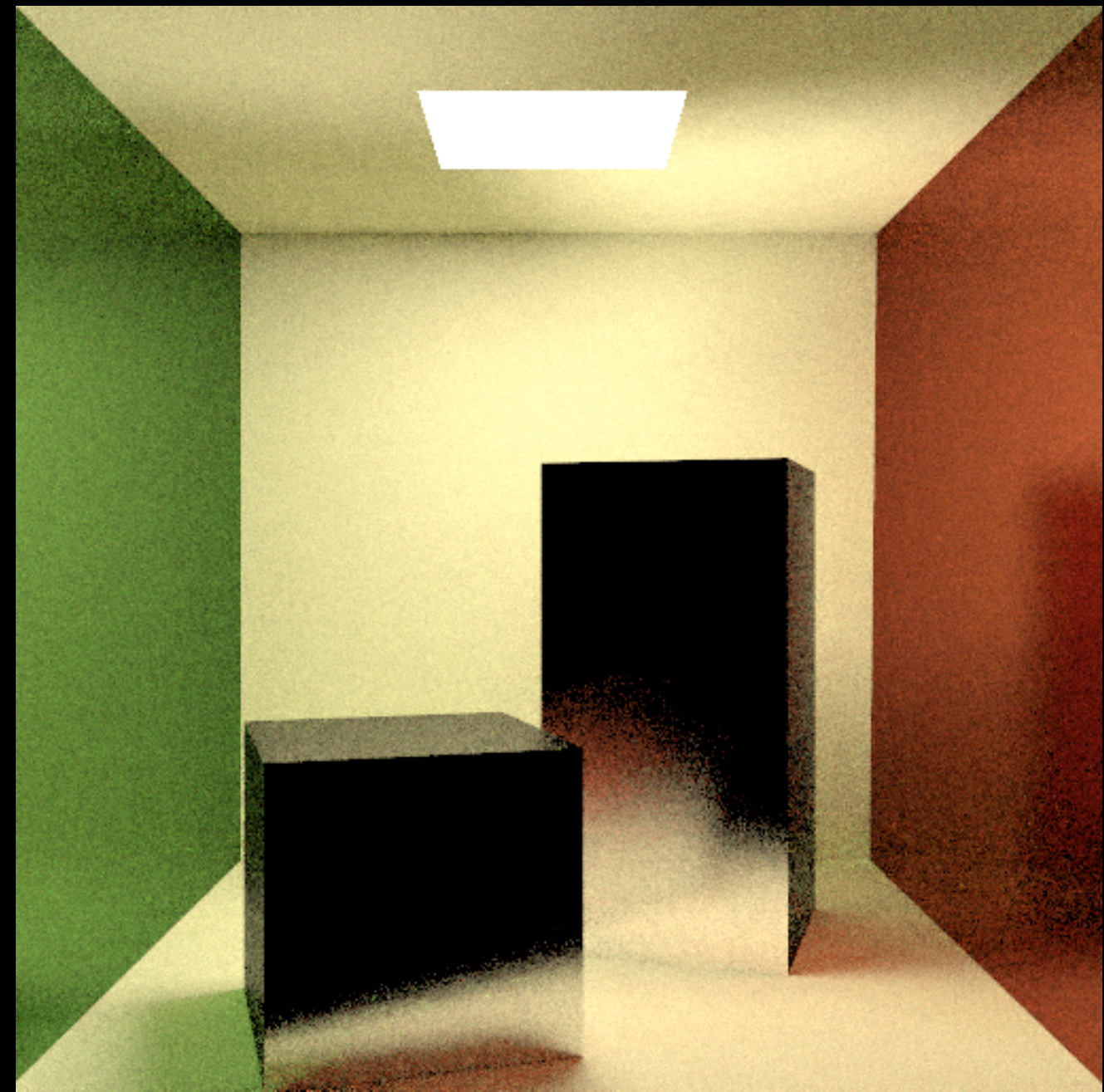
RMS errors



Comparison with manifold exploration

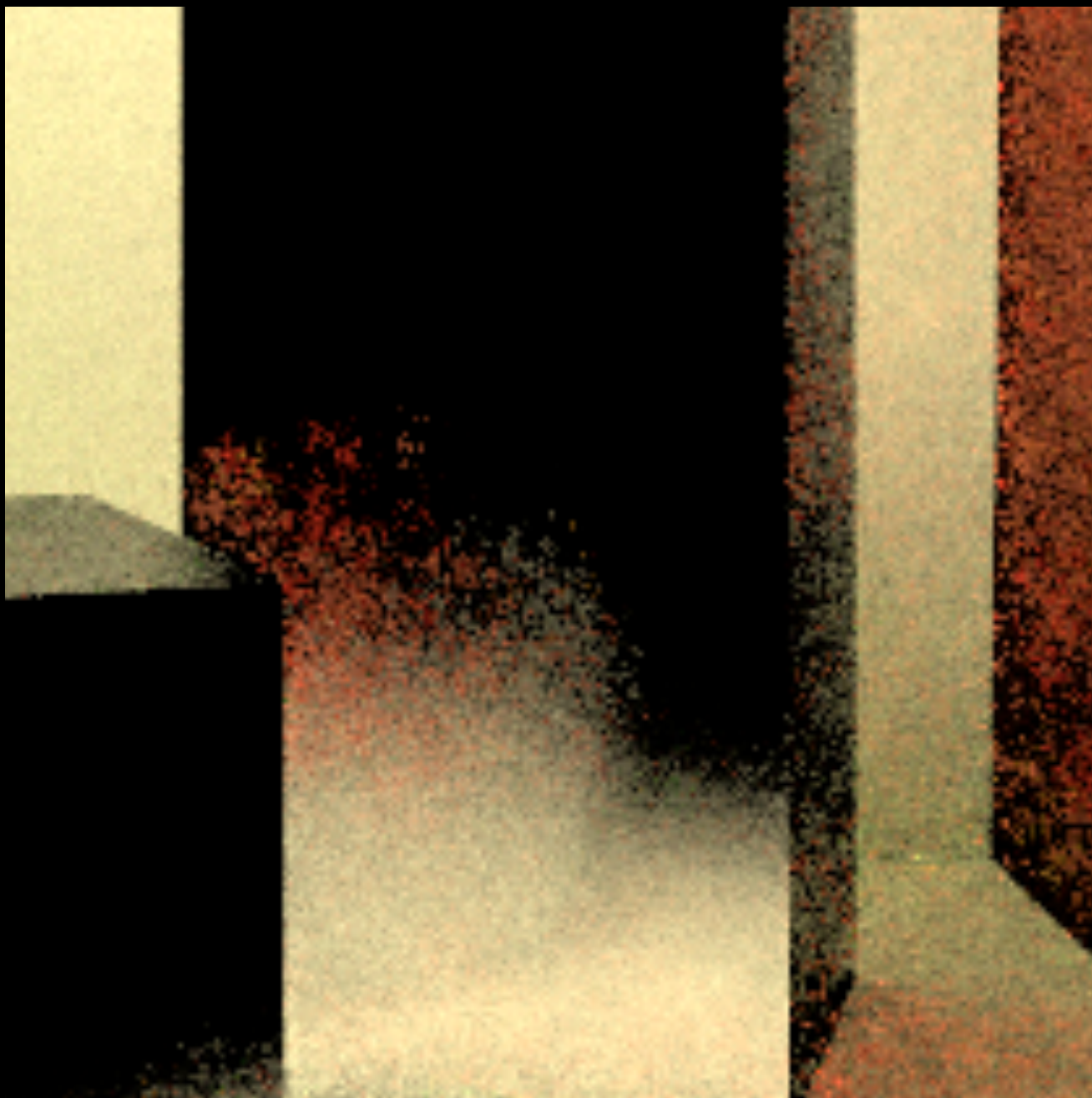


MEMLT (RMSE: 0.1374)

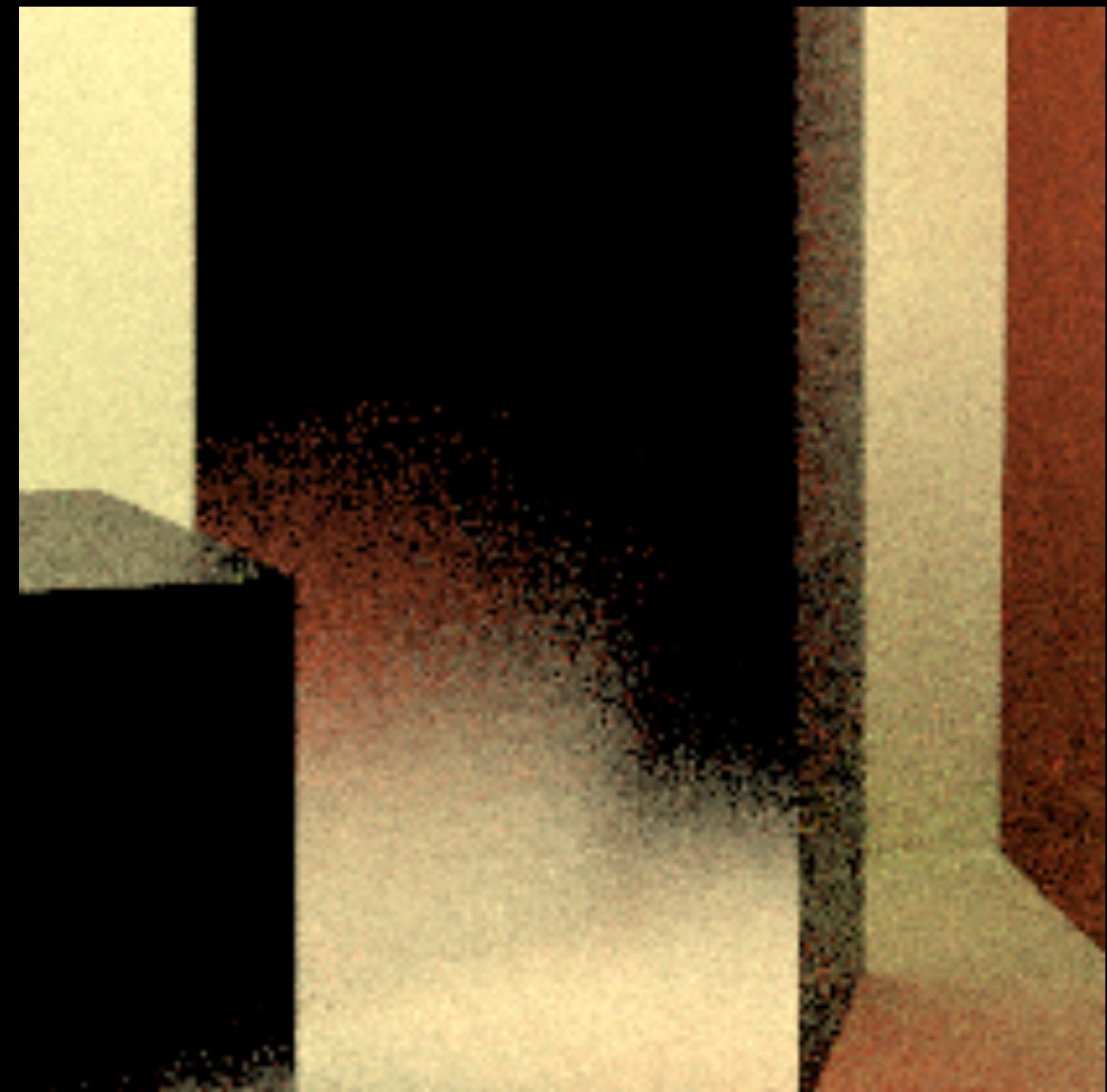


MMLT (RMSE: 0.1529)

Comparison with manifold exploration



MEMLT (RMSE: 0.1374)



MMLT (RMSE: 0.1529)

Limitations

- Common limitations as other MCMC methods
 - Lack of stratification, undesirable low frequency artifact, no reliable convergence test etc.
- Specular-diffuse-specular paths cannot be captured
 - Potential combination with UPS/VCM in future

Summary

Conclusion

- **First** fusion of Markov chain MC and multiple importance sampling
 - MC chain explores both technique and sample spaces
 - Automatically switch to proper sampling techniques

Multiplexed MLT is **very** practical

If your rendering system already uses Kelemen MLT and BDPT, there is basically no reason not to use multiplexed MLT!

- **Easy** to implement on top of Kelemen MLT + BDPT
- Works reasonably well across **many** scenes
- Example code is **available** on my webpage

<http://www.ci.i.u-tokyo.ac.jp/~hachisuka/smallmmlt.cpp>