## Expected Values with Hard-to-Sample Distributions

Computing the sample mean requires samples from the distribution p(x) of the random variable X. What if such samples aren't available?

$$E[x] = \int x p(x) dx$$

$$= \sum_{i=1}^{x} x_i p(x) dx$$

$$\approx \sum_{i=1}^{y} \frac{s_i}{N}$$

$$E[f(x)] = \int f(x) p(x) dx$$

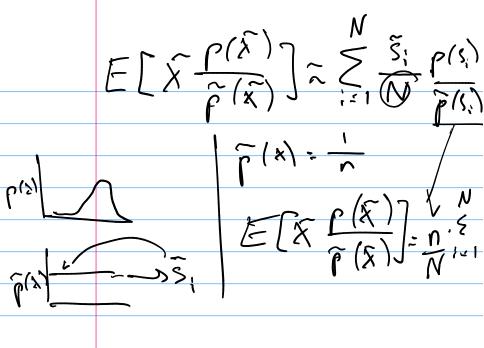
$$E[X] = \int_{X} p(x) dx$$

$$Sample from  $\tilde{p}(X)$$$

$$E[X] = \int_{X} \frac{p(x)}{\tilde{p}(x)} \tilde{p}(x) dx$$

$$= E[X] = \int_{X} \frac{p(x)}{\tilde{p}(x)} \tilde{p}(x) dx$$

$$= E[X] = \sum_{x} \frac{p(x)}{\tilde{p}(x)} \tilde{p}(x) dx$$



# Switching Distributions for Sampling

Found:

$$E[X] = E\left[\tilde{X} \cdot \frac{p(\tilde{X})}{\tilde{p}(\tilde{X})}\right]$$

Why is this useful for sampling?

**In-class activity:** Monte-Carlo Methods

## Expected Value: Example II

What is the expected snowfall in Illinois?

$$\int S_{NOW}(x,y) \cdot p(x,y) dx dy$$

$$\int S_{NOW}(r) dr \qquad \boxed{OQO}$$

$$IL$$

$$P(x,y) = \begin{cases} 0 : \text{otherwise} \end{cases}$$

# Dealing with Unknown Scaling

What if a distribution function is only known up to a constant factor, e.g.

$$p(x) = C \cdot \underbrace{ \left\{ \begin{array}{ll} 1 & \text{point } x \text{ is in IL,} \\ 0 & \text{it isn't.} \end{array} \right.}_{q(x)}$$

Typically  $\int_{\mathbb{R}} q \neq 1$ . We need to find C so that  $\int p = 1$ , i.e.

Idea: Use sampling.

$$\begin{cases}
\frac{q(x)}{p(x)} \stackrel{\sim}{p(x)} dx \\
\frac{1}{p(x)} = E \left[\frac{q(x)}{p(x)}\right] \\
\frac{1}{p(x)} = \frac{1}{p(x)} \int_{\mathbb{R}^{n}} q(x) \frac{1}{p(x)} dx$$

$$\approx N \stackrel{\sim}{>} q(x) = \frac{1}{p(x)} \int_{\mathbb{R}^{n}} q(x) \frac{1}{p(x)} dx$$

**Demo:** Computing  $\pi$  using Sampling

**Demo:** Errors in Sampling

### Sampling: Error

The Central Limit Theorem states that with

$$S_N := X_1 + X_2 + \dots + X_n$$

for the  $(X_i)$  independent and identically distributed according to random variable X with variance  $\sigma^2$ , we have that

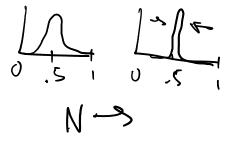
$$\frac{S_N - NE[X]}{\sqrt{\sigma^2 N}} \to \mathcal{N}(0, 1),$$

i.e. that term approaches the normal distribution. As we increase  $N,\ \sigma^2$  stays fixed, so the asymptotic behavior of the error is

$$\left| \frac{1}{N} S_N - E[X] \right| = O\left(\frac{1}{\sqrt{N}}\right).$$

#### Proof Intuition for Central Limit Theorem

The Central Limit Theorem uses the fact that given N identically distribution samples of random variable X with variance  $\sigma^2[X]$ , the average of the samples will have variance  $\sigma^2[X]/N$ . Since  $\sigma^2[X] = E[(E[X] - X)^2]$  is the expected square of the deviation, it tells us how far away the average of the samples is expected to be from the real mean. Why is this the case?



$$\sigma^{2}[X] = E[(X - E[X])]$$

$$= [X] - E[X]$$

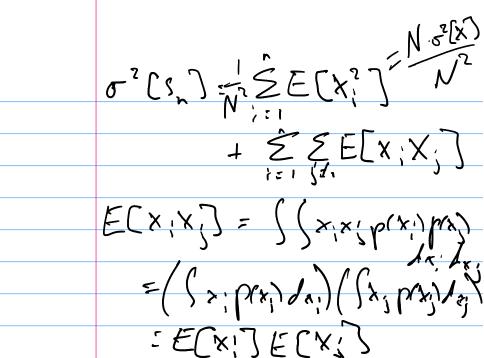
$$\sigma^{2}[X] = E[X]$$

$$S = [X]$$

$$S = [X]$$

$$S = [X]$$

$$S = [X]$$



### Monte Carlo Methods: The Good and the Bad

What are some advantages of MC methods?

What are some disadvantages of MC methods?

## Computers and Random Numbers

```
int getRandomNumber()
{
return 4; // chosen by fair dice roll.
// guaranteed to be random.
}
```

[from xkcd]

How can a computer make random numbers?

#### Random Numbers: What do we want?

#### What properties can 'random numbers' have?

- Have a specific distribution (e.g. 'uniform'-each value in given interval is equally likely)
- Real-valued/integer-valued
- ► Repeatable (i.e. you may ask to exactly reproduce a sequence)
- Unpredictable
  - V1: 'I have no idea what it's going to do next.'
  - V2: No amount of engineering effort can get me the next number.
- Uncorrelated with later parts of the sequence (Weaker: Doesn't repeat after a short time)
- Usable on parallel computers