

Better Numerical Integration through Randomness

Mark Huber¹ and Sarah Schott²

¹Department of Mathematics and Computer Science, Claremont McKenna
College

²Department of Mathematics, Duke University

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Randomness can be used for good or evil



Saturday Morning Breakfast Cereal 17 February, 2007

Numerical Integration

Numerical integration

Not just for those who can't master integration by parts

- ▶ Many integrands have no elementary antiderivatives
- ▶ Example:

$$\int_{-\infty}^a \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx$$

- ▶ Some antiderivatives exponentially large in input
- ▶ Example:

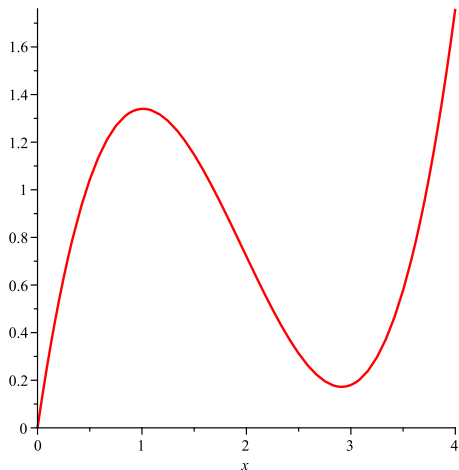
$$\int_0^a x^{1000000} \exp(-x) dx$$

- ▶ Antiderivative has a million (and one) terms!

1-D: easy

Fortunately, in 1-D numerical integration easy

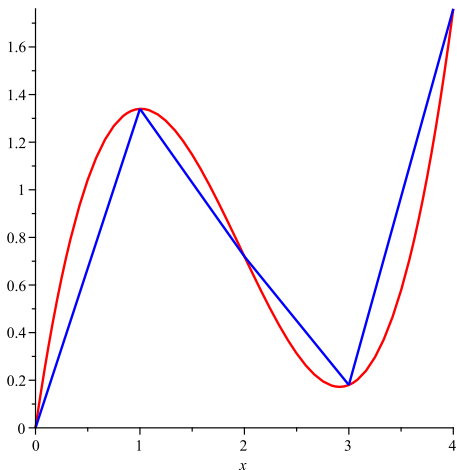
- ▶ Use rectangles, or trapezoidal rule, or Simpson's rule



1-D: easy

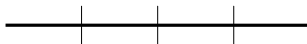
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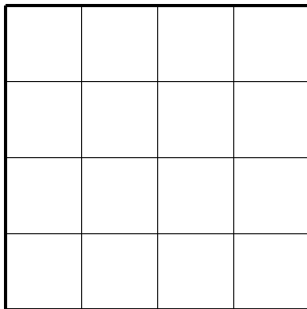


Higher dimensions, not so easy

In 1-D, k intervals



In 2-D, k^2 squares



Growth in d dimensions

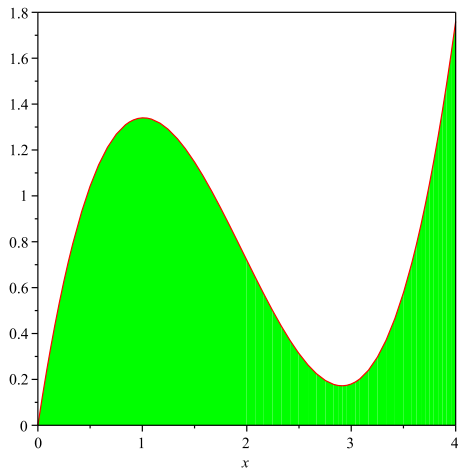
In d dimensions, need k^d squares

- ▶ Exponential growth in d
- ▶ Called “The curse of dimensionality”

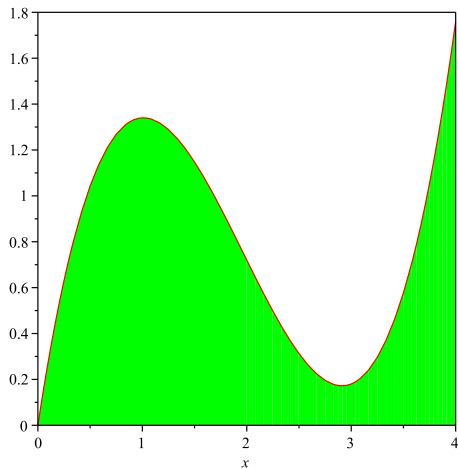
High dimensional integration arises often

- ▶ In statistics, X_1, X_2, \dots, X_n are data values
- ▶ For $A \subseteq \mathbb{R}^n$, need to find $\mathbb{P}((X_1, \dots, X_n) \in A)$
- ▶ In combinatorics/CS, $\#P$ complete problems
- ▶ Graph with n nodes leads to n dimensional problem

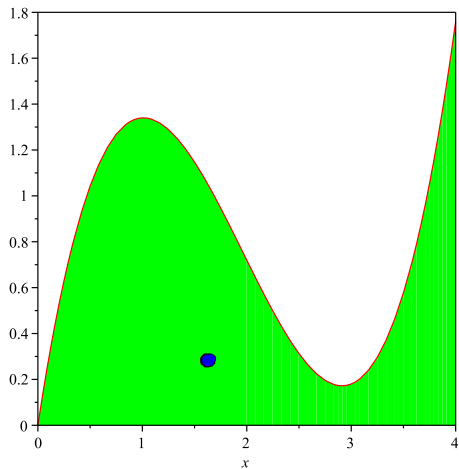
Solution: Shoot at it randomly



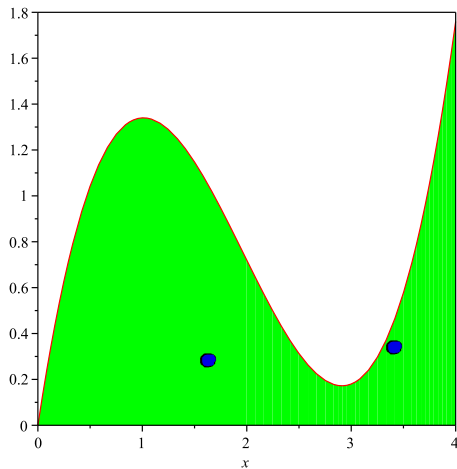
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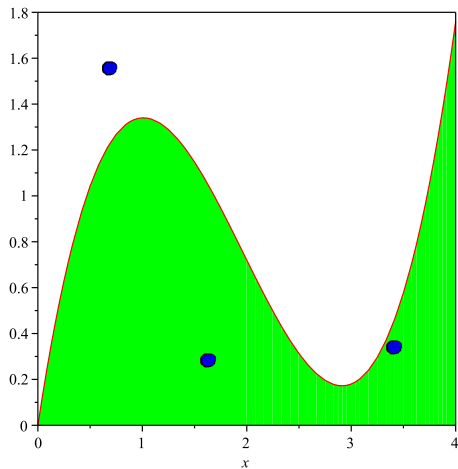
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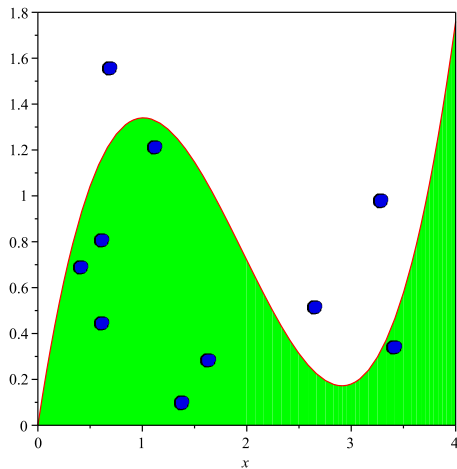
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Analyzing the algorithm

Algorithm

- ▶ Fire n times at box
- ▶ Say you hit H times

Analysis

- ▶ Let p be chance hit green region
- ▶ Then

$$p = \frac{\text{volume}(\text{region})}{\text{volume}(\text{box})}$$

- ▶ Estimate

$$\hat{p} = \frac{H}{n}, \quad \widehat{\text{volume}(\text{region})} = \frac{H}{n} \cdot \text{volume}(\text{box}).$$

How well does it work?

True answer: 3.0933...

- ▶ After 10 iterations 5.04
- ▶ After 10^3 iterations 2.8656
- ▶ After 10^5 iterations 3.0870
- ▶ After 10^7 iterations 3.0935

About a factor of 100 per extra digit

How well does it work?

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About a factor of 100 per extra digit

Probability explanation

Mean value = average = expected value

$$\mathbb{E}[\hat{p}] = p$$

Standard deviation

$$SD[\hat{p}] = \sqrt{\frac{p(1-p)}{n}}$$

Relative error

$$\frac{SD(\hat{p})}{p} = \sqrt{\frac{1-p}{np}} \leq \epsilon$$

Bounding error

Get relative error below ϵ

$$n \approx \frac{1-p}{p} \cdot \frac{1}{\epsilon^2}$$

- ▶ The $1/\epsilon^2$ effect called “Monte Carlo” error
- ▶ Best you can do in general
- ▶ Independent of the dimension!

Solution: Use “interior” rather than “exterior” sampling

- ▶ Need ability to sample from green region rather than box
- ▶ The algorithm is called “TPA”
- ▶ Combines “product estimator” [1] with “nested sampling” [3]

The Algorithm

The Tootsie Pop Algorithm

What is a Tootsie Pop?

- ▶ Hard candy lollipops with a tootsie roll (chewy chocolate) at the center

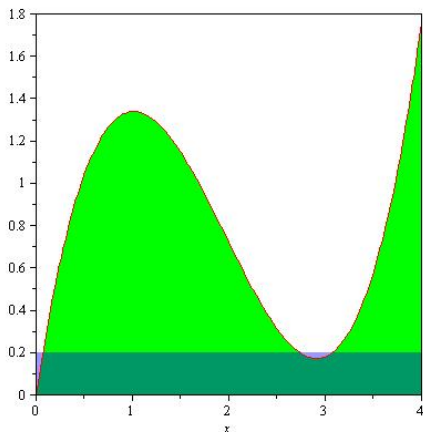


In 1970, Mr. Owl was asked the question:

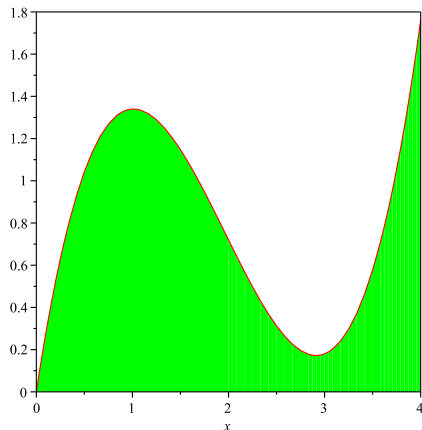
- ▶ How many licks does it take to get to the center of a Tootsie Pop?

The chocolate chewy center

- ▶ Area under .2 line almost all green
- ▶ That's our chewy center
- ▶ Hard candy is original green region
- ▶ Next question: how do we lick?

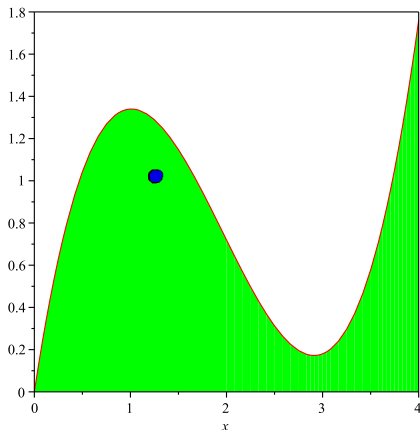


Only shoot at the green part



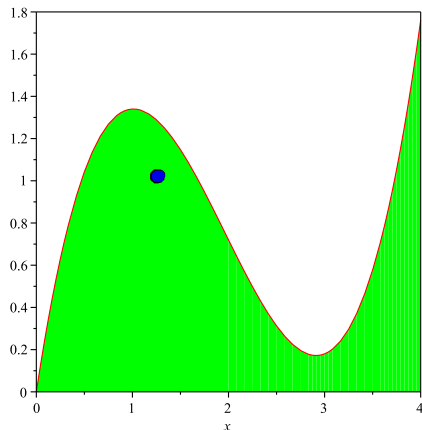
- ▶ Don't shoot bounding box
- ▶ Only shoot at green region
- ▶ Easier: don't need to maximize function!
- ▶ Usually done in high dimensions using Markov chains

Only shoot at the green part



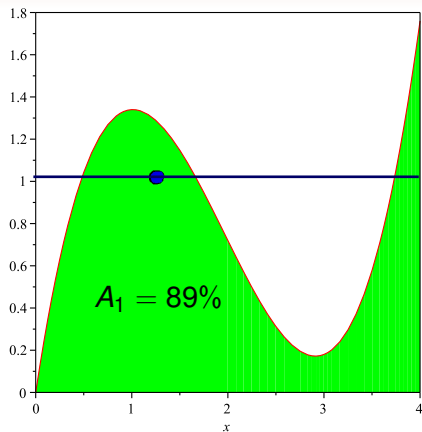
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Only consider region below point

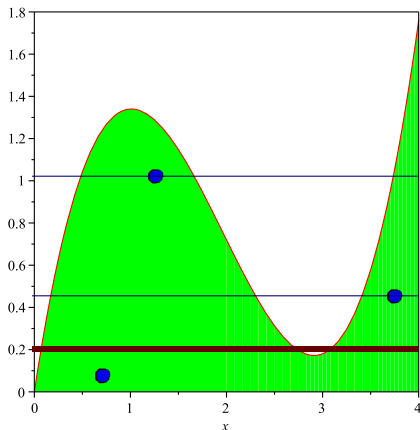


Let A_1 denote the percentage of green region below the point

Note $\mathbb{P}(A_1 \leq 1/2) = 1/2$

For all $a \in [0, 1]$, $\mathbb{P}(A_i \leq a) = a$, call A_1 *uniform* on $[0, 1]$

Keep on licking!



- ▶ After choosing first point
- ▶ Draw next point from region below first point
- ▶ Continue “licking” until reach “center”
- ▶ In example, three licks

The number of licks

Let

N = the number of licks

Set

$$r = \frac{\text{volume}(\text{chewy center})}{\text{volume}(\text{green region})}, \quad A_1, A_2, \dots \stackrel{\text{iid}}{\sim} \text{Unif}([0, 1])$$

In terms of A_i :

N = smallest value of n such that $A_1 A_2 A_3 \cdots A_n \leq r$

Multiplication to addition

Multiplication is hard:

$N =$ smallest value of n such that $\ln A_1 + \ln A_2 + \cdots + \ln A_n \leq \ln r$

Note $\ln x < 0$ for $x \in (0, 1)$

$N =$ smallest n such that $(-\ln A_1) + (-\ln A_2) + \cdots + (-\ln A_n) \leq -\ln r$

A day at the races



0

$-\ln r$

Roll A_1 , move horse forward ($-\ln A_i$)
Count how many steps to reach $-\ln r$
steps A_i $-\ln A_i$

A day at the races



Roll A_1 , move horse forward ($-\ln A_1$)
Count how many steps to reach $-\ln r$

steps	A_i	$-\ln A_i$
1	.23	1.469

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A day at the races



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Count how many steps to reach $-\ln r$

steps	A_i	$-\ln A_i$
1	.23	1.469
2	.48	.7339
3	.33	1.1086

Poisson process

This particular “race” is called a Poisson Process

- ▶ Very well studied process
- ▶ Again let N be number of steps until reach center
- ▶

$$\mathbb{P}(N = 1) = r, \quad \mathbb{P}(N = i) = r \frac{(-\ln r)^{i-1}}{(i-1)!}$$

- ▶ Average value of N is $(-\ln r) + 1$
- ▶ Standard deviation of N is $\sqrt{-\ln r}$

Want to estimate r , not $-\ln r$

Repeat experiment k times

$$N_1, N_2, \dots, N_k$$

Estimate r :

$$S = \frac{N_1 + N_2 + \dots + N_k - k}{k}, \quad \hat{r} = e^{-S}$$

For this estimate:

$$\mathbb{E}[\hat{r}] = r, \quad \text{relative error} = \frac{-\ln r}{\sqrt{k}} = \frac{\ln(1/r)}{\sqrt{k}}.$$

The result

Basic Monte Carlo

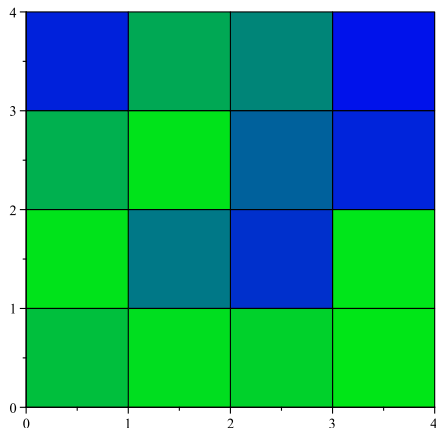
$$\# \text{ of samples} = \frac{1}{\epsilon^2} \cdot \frac{1-r}{r}$$

TPA

$$\# \text{ of samples} = \frac{1}{\epsilon^2} \cdot \left(\ln \frac{1}{r} \right)^2$$

Applications

The Autonormal model



- ▶ Spatial model
- ▶ Soil quality for each square
- ▶ Quality between 0 (blue) and 1 (green)
- ▶ Want more likely close squares close quality

Autonormal model assigns probabilities

For vector $\vec{x} \in [0, 1]^{16}$:

$$\mathbb{P}(\{d\vec{x}\}) = \frac{w_{\beta}(\mathbf{x})}{Z(\beta)} d\vec{x}, \quad w_{\beta}(\mathbf{x}) = \prod_{i,j \text{ adjacent}} \exp(-\beta(x(i) - x(j))^2/2)$$

where

$$Z(\beta) = \int_0^1 \int_0^1 \cdots \int_0^1 w(\mathbf{x}) dx(1) dx(2) \cdots dx(16)$$

Goal: given data x , find β that maximizes $w_{\beta}(x)/Z(\beta)$
(Called the maximum likelihood estimator.)

TPA for Autonormal

Ingredients

- ▶ $Z(0) = 1$ is hard candy shell (let $\beta_0 = 0$)
- ▶ $Z(\beta)$ is chewy center
- ▶ Note $Z(\beta')$ shrinks as β' grows
- ▶ Gives nested volumes
- ▶ At β_i , sample X uniformly from volume
- ▶ Let β_{i+1} be smallest β' so X still in volume

Bayesian inference

Theorem (Bayes' Rule)

$$\mathbb{P}(A|B) = \frac{\mathbb{P}(B|A)\mathbb{P}(A)}{\mathbb{P}(B)}$$

Basic outline

- ▶ Parameters are themselves random variables with probabilities
- ▶ Take data
- ▶ Use data + Bayes' rule to update probabilities

Bayesian Example: Autnormal

Initial probabilities (called *prior*)

- ▶ Example prior: $\mathbb{P}(\beta = 1) = 1/2$, $\mathbb{P}(\beta = 0) = 1/2$
- ▶ Data $X = x$, suppose $w(x) = 4.523$
- ▶ Bayes' Rule:

$$\begin{aligned}\mathbb{P}(\beta = 1 | X \in d\vec{x}) &= \frac{\mathbb{P}(X \in d\vec{x} | \beta = 1) \mathbb{P}(\beta = 1)}{\mathbb{P}(X \in d\vec{x})} \\ &= \frac{(w_1(\vec{x})/Z(1))(1/2)}{(w_1(\vec{x})/Z(1))(1/2) + (w_0(\vec{x})/Z(0))(1/2)}\end{aligned}$$

- ▶ Need to know $Z(0)$ and $Z(1)$

$\#P$ complete problems

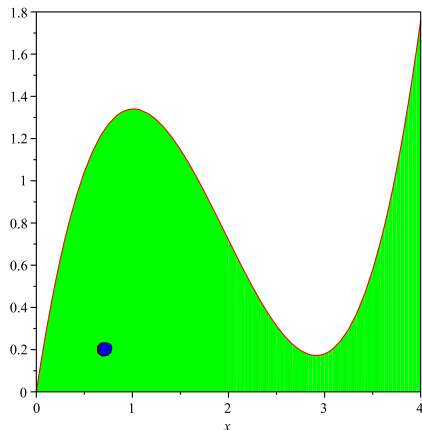
Computational Complexity

- ▶ Example: Traveling Salesman Problem
- ▶ Problem in NP : Is there a TSP path of length ≤ 60 ?
- ▶ Problem in $\#P$: How many TSP paths of length ≤ 60 ?

Some $\#P$ problems where TPA is applicable:

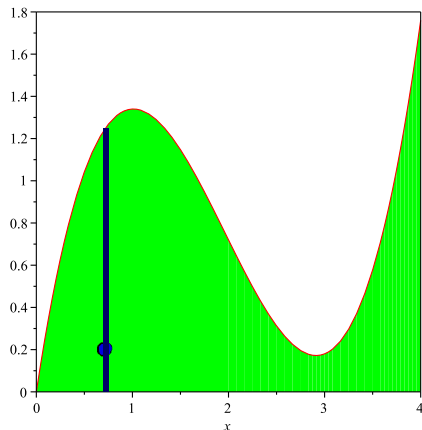
- ▶ Volume of a convex body
- ▶ Counting linear extensions of a poset
- ▶ Partition function for the Ising model

How to generate samples from green region?



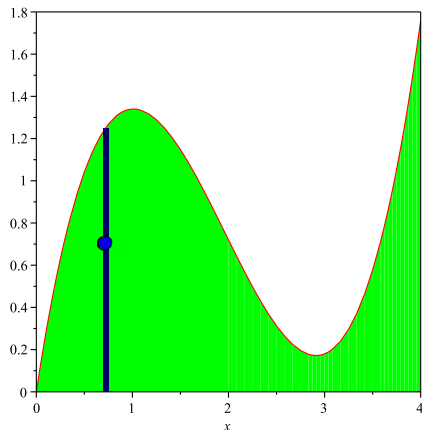
- ▶ Markov chains
- ▶ Take random steps from starting state
- ▶ Ex: Choose random vertical value
- ▶ Then choose random horizontal value

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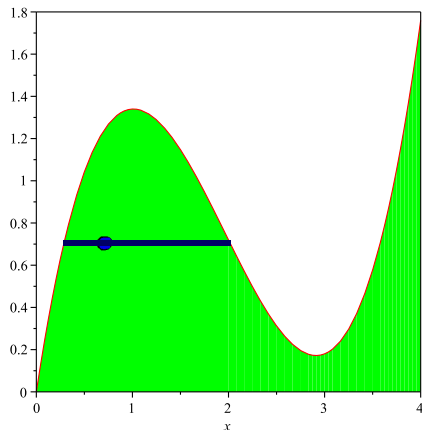
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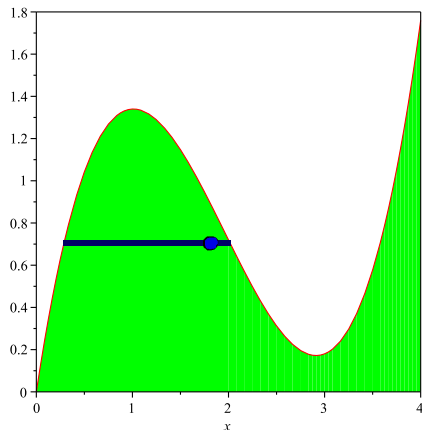
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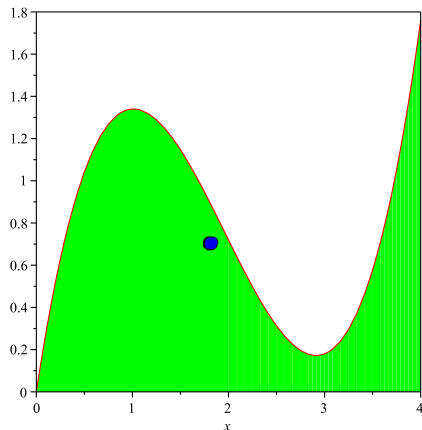
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Raises further questions

For a Markov chain

- ▶ How many steps until state close to random?
- ▶ (How many times must a deck of cards be riffle shuffled?)
- ▶ How best to design Markov chain?
- ▶ Markov chain Monte Carlo (MCMC) most popular method, there are others

But a more important question...

How many licks does it take to get the center of a Toosie Pop?

- ▶ Purdue created a licking machine, 364 licks
- ▶ Purdue also ran human experiments: 252 licks
- ▶ U. Michagan created a licking machine, 411 licks
- ▶ Swarthmore Junior HS ran human experiment: 144 licks

Summary: results and future work

The Tootsie Pop algorithm

- ▶ Interior rather than exterior sampling
- ▶ No need for bounding box
- ▶ Do need a chewy center (usually easy to find)
- ▶ Many applications!

Open questions

- ▶ Associated sampling problems
- ▶ Exponential families need # of samples equal to

$$\frac{1}{\epsilon^2} \left(\ln \frac{1}{r} \right)$$

Can TPA match this?

References



M. Jerrum, L. Valiant, and V. Vazirani.

Random generation of combinatorial structures from a uniform distribution
Theoret. Comput. Sci., **43**, 169–188, 1986



M. Huber and S. Schott

Improving the product estimator by using a random cooling schedule
preprint



J. Skilling,

Nested sampling for general Bayesian computation,
Bayesian Anal., **1**(4), 833–860, 2006