# MAS1802: Problem Solving II (Statistical Computing with R)

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**School of Mathematics, Statistics & Physics**

Semester 2, 2018/2019

# Part V

# Random Number Generation

# Some thoughts...

- When writing big chunks of code, indent nicely! Generally, it is good practice for your code to be structured (bug-spotting, typos etc.). Certainly don't type everything onto a single line.
- `if/else` statements – feel free to put each `if` on a single line.
- Plus symbol in the console window – R is expecting something else – most likely a close bracket!
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# Some reminders...

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- Practical 3 due in **Friday, 11am**
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# 5.1 Randomness: quantifying uncertainty

- The concepts of uncertainty and randomness have intrigued humanity for a long time:
  - Chinese: formalised odds/chance some 3000 years ago
  - Greek philosophers discussed randomness at length
  - 16th Century: Italian mathematicians formalised odds associated with games of chance
  - 19th Century: Physics
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# 5.1 Randomness: quantifying uncertainty

- The world around us is not deterministic and we are faced continually with chance occurrences.
- Uncertainty is inherent in nature; for example, the behaviour of fundamental physical particles, genes and chromosomes in biology, and individuals in society under stress or strain.
- The methodology for exploring uncertainty involves the use of *random numbers*.

# 5.2 Pseudo–random numbers

Suppose we need to obtain a list of random digits $0, 1, 2, \ldots, 9$. How might we go about this? There are several options:

# Fair ten–sided die

If the sides are labelled from 0 to 9 then tosses of this die will yield the required digits.

# Decimal expansion of $\pi$

Irrational number – decimal expansion goes on forever, with no pattern!

$$\pi = 3.1415$$
$$92653589793$$
$$23846264338 3$$
$$2795028841971 69$$
$$3993751058209749 4$$
$$4592307816406286208998$$

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# Tosses of a fair coin

Toss a fair coin four times. The following equally likely outcomes could correspond to the integers shown:

| | | | |
|---|---|---|---|
| H H H H | 0 | H T H T | 5 |
| H H H T | 1 | H T T H | 6 |
| H H T H | 2 | H T T T | 7 |
| H H T T | 3 | T H H H | 8 |
| H T H H | 4 | T H H T | 9 |

The coin has no ‘memory’, and so each block of 4 tosses is independent of any other. If any outcome other than those listed occurs, we can ignore and toss a new set of 4.

This method is rather inefficient as a lot of the time a combination of outcomes is rejected!

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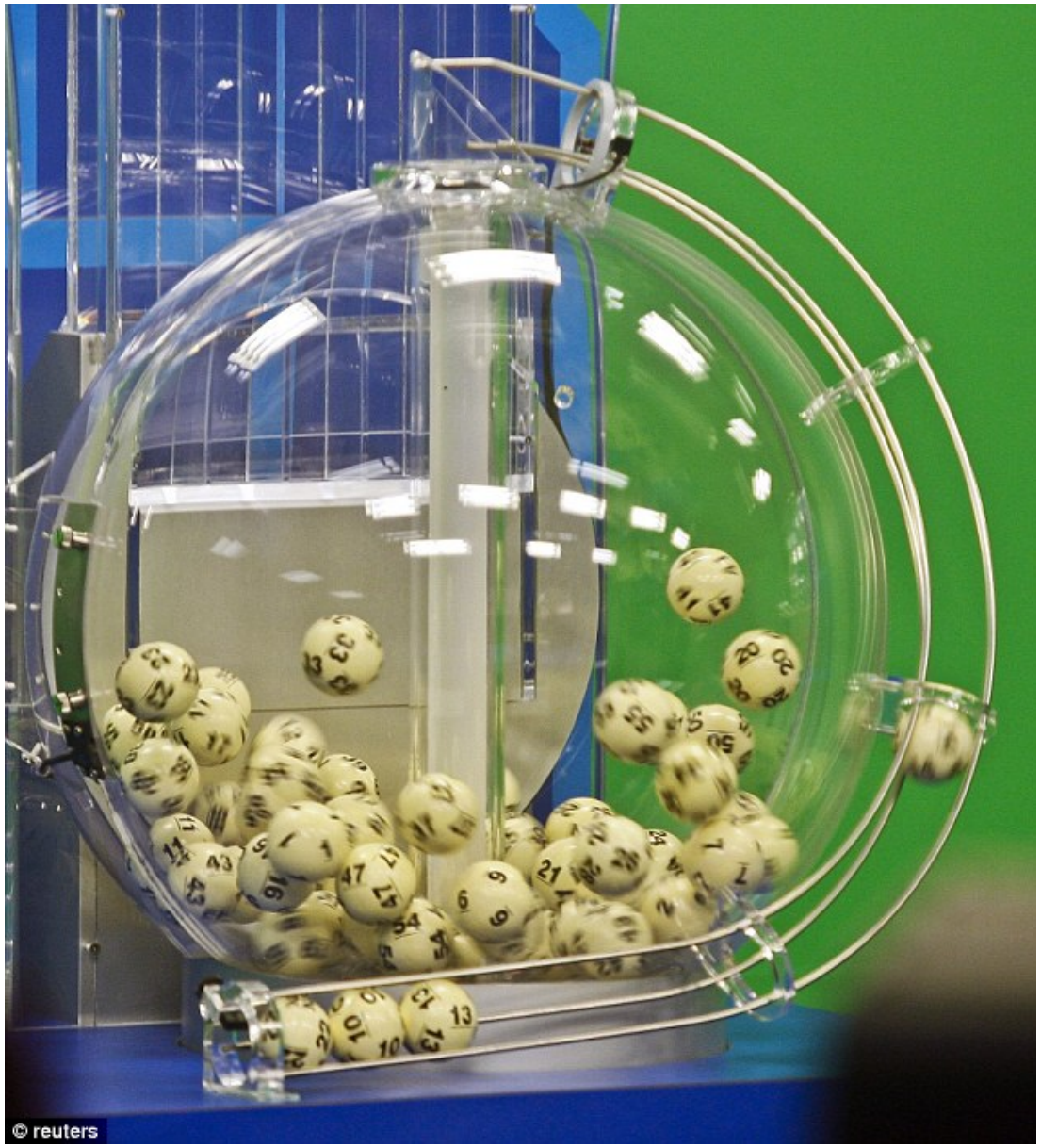
# Other physical devices: Wheels of fortune

# Other physical devices: Lottery machines



# Other physical devices: Gamma ray counters

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- **Idea:** Use a geiger counter to generate random numbers!

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# 5.2 Pseudo–random numbers

The German Federal Office for Information Security (*Bundesamt für Sicherheit in der Informationstechnik*, or BSI) has established criteria for quality RNG:

1. A sequence of random numbers has a high probability of containing no identical consecutive elements
2. A sequence of numbers which is indistinguishable from ‘true random’ numbers (tested using statistical tests)
3. It should be impossible to calculate – or guess – from any given sub-sequence, any previous or future values in the sequence
4. It should be impossible, for all practical purposes, for an attacker to calculate, or guess, the values used in the random number algorithm

Points 3 and 4 are crucial for many applications.

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# 5.2 Pseudo–random numbers

As we will see in this course, it is important to be able to reproduce a sequence of random numbers.

The advent of digital computers gave rise to a number of techniques that use a recursive relation, that is, the number $r_i$ in a sequence is a function of the preceding numbers $r_{i-1}, r_{i-2}, \ldots$.

Some of these PRNG's have quite cool names: for example,

- the *Super-Duper* PRNG
- the *Blum-Blum-Shub* PRNG (after Lenore Blum, Manuel Blum and Michael Shub)
- the *Mersenne-Twister* PRNG (as used by R)

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## 5.3.1 The `runif` function

```
> runif(n, min=0, max=1)
```

- This function will generate n random numbers between the values of `min` and `max`.
- If the arguments `min` or `max` are omitted, then the default values are 0 and 1 respectively.

# 5.3.1 The runif function

For example,

```
> runif(1)
[1] 0.2729965
> runif(1)
[1] 0.9990863
> runif(5)
[1] 0.8122783 0.9069950 0.1731072 0.3454292 0.6102412
> runif(1, 6, 7)
[1] 6.427512
```

# 5.3.1 The runif function

```
> set.seed(12345)
> runif(1)
[1] 0.7209039
> runif(1)
[1] 0.8757732
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```

## 5.3.2 The sample function

Another important R function that we will use is the sample function:

```
> sample(x, size, replace = FALSE, prob = NULL)
```

## 5.3.2 The `sample` function

This takes the following arguments

- `x`: a list of values
- `size`: non-negative integer giving the number of items to choose.
- `replace`: Should sampling be with replacement? Default: `FALSE`.
- `prob`: A vector of probability weights. Default: All values equally likely.

# 5.3.2 Example usage of `sample`

Suppose we wish to sample five numbers from $\{1, 2, 3, 4, 5, 6\}$, then

```
> set.seed(1)
> x = c(1, 2, 3, 4, 5, 6)
> sample(x, 5)
[1] 2 6 3 4 1
```

We can also sample with replacement:

```
> sample(x, 5, replace=TRUE)
[1] 6 6 4 4 1
```

This means that values **may** appear more than once.

## 5.3.3 Simulating the Captial One Cup draw

We are in the semi-finals of the *Capital One* Cup, and we need to organise the draw for the final stage. The remaining teams are:

Manchester Utd, Mancehster City, Sunderland, West Ham.

# 5.3.3 Simulating the Captial One Cup draw

Here's how we do this in R:

```
> set.seed(3)
> teams = c("Man Utd", "Man City", "Sunderland", "West
Ham")
> sample(teams, 4)
[1] "Man Utd"    "Sunderland" "West Ham"   "Man City"
```

So we have 'Man Utd vs Sunderland' and 'West Ham vs Man City'.

# 5.3.3 Simulating the Capital One Cup draw

However, if we think Sunderland are likely to get beaten by Man Utd, we can rig the voting:

```
> prob_weights = c(0.4, 0.4, 0.05, 0.2)
> sample(teams, 4, prob=prob_weights)
[1] "Man Utd"    "Man City"   "West Ham"
"Sunderland"
```

That's better!

# 5.3.3 Simulating the Capital One Cup draw

# 5.4 Simulating from discrete probability distributions

Suppose we want to simulate a discrete random variable $X$ which has probability mass function

$$\Pr[X = x_j] = p_j \quad \text{for } j = 1, 2, \ldots,$$

and where $\sum_{\text{all}} p_j = 1$.

# 5.4 Simulating from discrete probability distributions

To accomplish this we first simulate a value $u$ from a $U(0,1)$ distribution and set

$$x = \begin{cases} x_1 & \text{if } u < p_1 \\ x_2 & \text{if } p_1 \leq u < p_1 + p_2 \\ x_3 & \text{if } p_1 + p_2 \leq u < p_1 + p_2 + p_3 \\ \vdots & \vdots \\ x_j & \text{if } \sum_{i=1}^{j-1} p_i \leq u < \sum_{i=1}^{j} p_i \\ \vdots & \vdots \end{cases}$$

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# 5.4.1 Example

Simulate a random variable with the following probability mass function:

| $x$ | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| $\Pr[X = x]$ | 0.2 | 0.15 | 0.25 | 0.4 |

# 5.4.1 Solution

We calculate the CDF of the distribution:

| $x$ | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| $\Pr[X = x]$ | 0.2 | 0.15 | 0.25 | 0.4 |
| $\Pr[X \leq x]$ | 0.2 | 0.35 | 0.60 | 1.0 |

Then we generate an observation $u$ from $U \sim \mathrm{Uniform}(0, 1)$, so

- if $u < 0.2$, set $X = 1$;
- if $0.2 \leq u < (0.2 + 0.15) = 0.35$, set $X = 2$;
- if $0.35 \leq u < (0.2 + 0.15 + 0.25) = 0.6$, set $X = 3$;
- if $u \geq 0.6$, set $X = 4$.

Suppose $u = 0.821$. Then $X = 4$.

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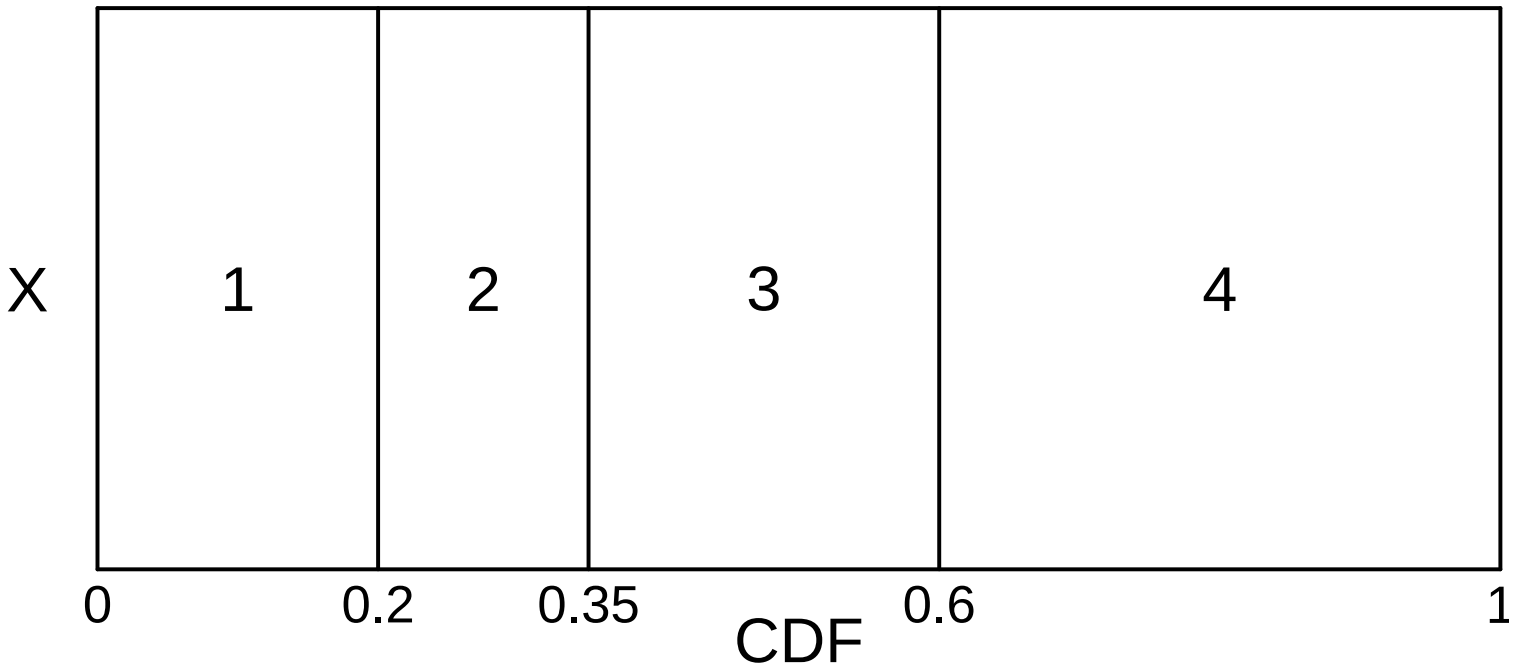


Figure: Simulating discrete random numbers.

# 5.4.1 Using R

To simulate from the above distribution in R, there are two (obvious) methods that we can use. We could use the `sample` command...

```
> x = c(1, 2, 3, 4)
> prob = c(0.2, 0.15, 0.25, 0.4)
> sum(prob)
[1] 1
> sample(x, 1, prob, replace=TRUE)
[1] 4
```

# 5.4.1 Using R

... or we could use a bunch of `if` statements (Monopoly!):

```
> u = runif(1)
> if(u <= 0.2) {
+   X = 1
+ } else if(u <= (0.2+0.15)) {
+   X = 2
+ } else if(u <= (0.2+0.15+0.25)) {
+   X = 3
+ } else {
+   X = 4
+ }
```

# 5.4.2 Simulating a Poisson random variable

For the uniform random numbers

$$0.253,\ 0.588,\ 0.789,$$

simulate three random numbers from a Poisson distribution with mean $\lambda = 2$.

# 5.4.2 Solution

The pdf of the Poisson distribution is

$$Pr[X = x] = \frac{e^{-\lambda}\lambda^x}{x!}$$

where $\lambda > 0$. So we have

| $x$ | 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| $\Pr[X = x]$ | 0.135 | 0.271 | 0.271 | 0.180 | 0.090 |
| $\Pr[X \leq x]$ | 0.135 | 0.406 | 0.677 | 0.857 | 0.947 |

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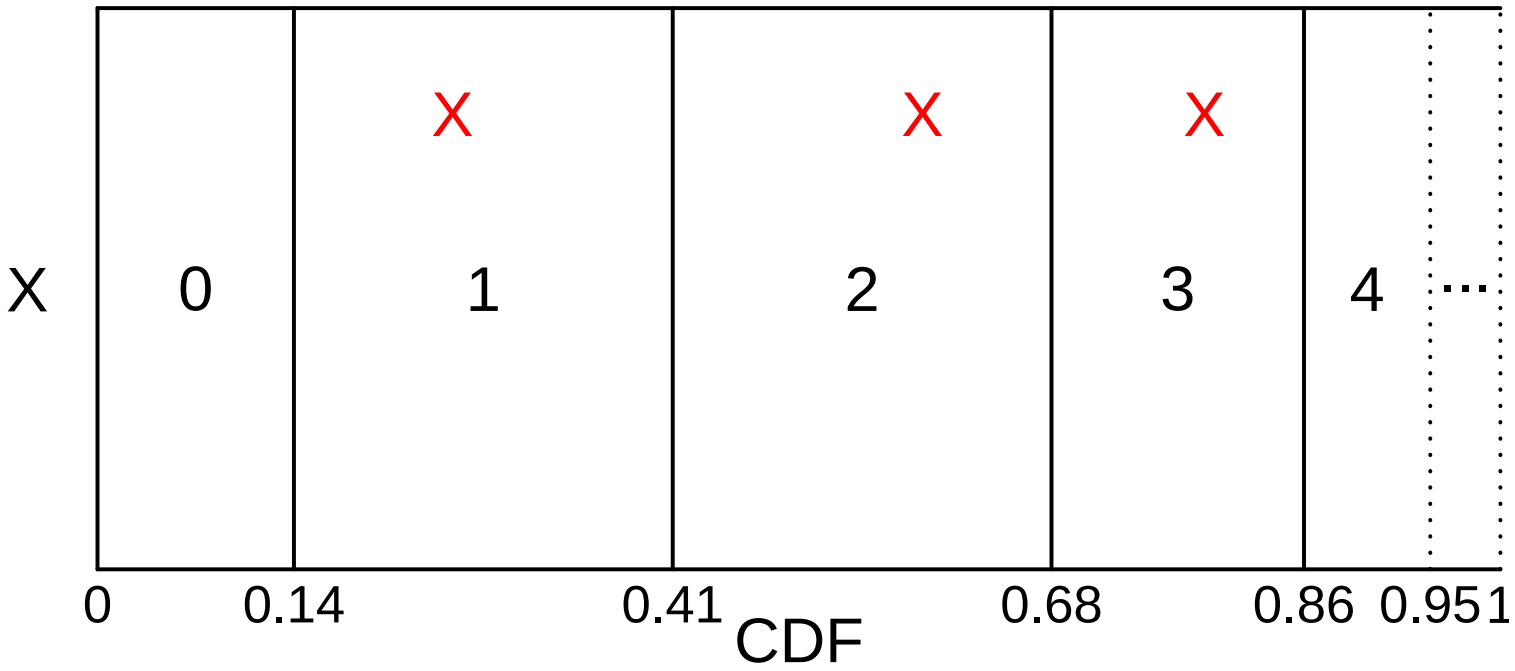


Figure: Diagram illustrating on simulating discrete random numbers from the Poisson distribution.

Hence our random numbers are 1, 2 and 3.

# 5.4.2 Using R

```
> rpois(1,2)
[1] 3
```

```
> rpois(10,2)
[1] 0 1 2 0 0 0 2 1 3 1
```

# 5.4.3 Simulating from other distributions

Simulating random values from other standard probability distributions is easy in R.

Just as we have seen the intrinsic functions `runif` and `rpois`, there are other functions such as `rgeom` and `rbinom`.

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# 5.4.3 Simulating from other distributions

For example, suppose $X \sim \mathrm{Bin}(6, 0.2)$ and $Y \sim \mathrm{Geom}(0.75)$, and we want to simulate 5 random values from $X$ and 3 random values from $Y$:

```
> (X=rbinom(5,6,0.2))
[1] 0 1 1 3 0
```

```
> (Y=rgeom(3,0.75))
[1] 2 0 1
```

# 5.4.3 Variations on a theme

We have seen, for example, `runif`, `rpois`, `rbinom` and `rgeom`.

Replacing the `r` prefix with:

- d, calculates the density of the distribution at a particular value.
  For example, `dpois(1,2)` would find $Pr[X = 1]$ when $X \sim Po(2)$
- p, calculates the distribution function at a particular value.
  For example, `pbinom(2,6,0.2)` would find
  $Pr[X \leq 2] = Pr[X = 0] + Pr[X = 1] + Pr[X = 2]$ when
  $X \sim \mathrm{Bin}(6, 0.2)$
- q, finds quantiles of a distribution for a particular probability.
  For example, `qnorm(0.7,0,1)` finds $x$ such that $Pr[X \leq x] = 0.7$, when
  $X \sim N(0, 1)$

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  $X \sim \mathrm{Bin}(6, 0.2)$
- q, finds quantiles of a distribution for a particular probability.
  For example, `qnorm(0.7,0,1)` finds $x$ such that $Pr[X \leq x] = 0.7$, when
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# 5.4.3 Variations on a theme

We have seen, for example, `runif`, `rpois`, `rbinom` and `rgeom`.

Replacing the `r` prefix with:

- d, calculates the density of the distribution at a particular value.
  For example, `dpois(1,2)` would find $Pr[X = 1]$ when $X \sim Po(2)$
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# Monopoly: Some hints

- **Debugging**
  - For question 2, do each part (a)–(h) one at a time, checking the graph at each stage...
  - ...then, if you get something weird, you'll have more idea where you went wrong
  - Each time you edit your code, do so in a different script, so you don't screw up the code that you know works!
  - Indent your code – the Rstudio text editor usually does this automatically – indenting makes your code more structured and easier to spot where things might be wrong
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- **What to look for**
  - Initially, all probabilities should hover around 1/40
  - Once you start adding in extra layers (chance, community chest etc) this will change for some squares
  - Lots of things send you to Jail! So expect a spike here...
- **Rolling doubles – this bit is hard!**
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# Rolling doubles

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> df = data.frame(d1=sample(1:6,3,replace=TRUE),d2=sample(1:6,3,replace=TRUE))
> df$Total = apply(df,1,sum)
> df$IsDouble = df$d1==df$d2
> df
  d1 d2 Total IsDouble
1  6  3     9    FALSE
2  4  3     7    FALSE
3  2  2     4     TRUE
```

```
> if(df$IsDouble[1]==TRUE & df$IsDouble[2]==TRUE & df$IsDouble[3]==TRUE) {
      current = 11 #Go To Jail
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# Sticker album: Some hints

Ultimate goals:

- Find out how many packets of stickers are needed to fill the album!
- How much will this cost?
- Histograms and other numerical summaries...

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# Part VI

# Monte Carlo Methods

# Feedback on Assignment 2: Overall

- Generally marks are good – people know how to plot!
- Lots of people dropped marks for minor errors, though
- A constant problem was **failing to annotate graphs correctly** – headers, axis labels etc.!
- Another issue was **comments**, including them where they weren't needed (Q1 & Q3) and not including them where they were (Q2 & Q4)
- General rule – **make sure you answer the question** ("which group did better?" can't be answered by a plot itself...)

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- General rule – **make sure you answer the question** ("which group did better?" can't be answered by a plot itself...)

# Feedback on Assignment 2: Question 1

- Most people did fine here
- Lots of people dropped marks for **lack of headers** on their scatterplot
- Some lost marks for failing to make their standard deviations a **different line type** from their mean line (although some tried a different colour)
- P.S.: If you claim something is the “red line", please print in colour!

# Feedback on Assignment 2: Question 2

- Please repeat 1,000 times: **“Boxplots show the median, NOT the mean"**
- Labelling issues occurred again – lots of **plots missing headings**
- Lots of students also had each group in a separate plot, as opposed to having a single plot showing the three groups
- While the comments were generally good – a common issue was failing to actually say which group performed best, and thus **not actually answering the question**

# Feedback on Assignment 2: Question 3

- Most students got full marks here
- The main issue was not ensuring all plots had the **same x-axis limits** – important for comparisons!
- A few students also forgot to include their group guesses as a line on each histogram

# Feedback on Assignment 2: Question 4

- Generally, plots were good and relevant – though some students failed to include both years' version of a plot which makes comparison dificult
- Lots of students failed to include any **numerical summaries/summary statistics** – and immediately lost 2 out of the 5 marks!
- The issue of failing to actually **state which year peformed best** in the comments also cost some students a mark

# 6.1 Introduction

- The term “Monte Carlo” is used to describe any simulation study which involves random numbers.
- The name is a reference to the famous Monte Carlo Casino in Monaco, where repetition of random events is the order of the day!

# 6.2 What is a simulation study?

- For our purposes, a simulation study is any study where we study the properties of a system using random numbers.
- We have already seen a simulation study: for example, the monopoly exercise in your project.
- In general, suppose we do an experiment which has the event $A$ as one possible outcome.
- We would like to estimate the probability of $A$, denoted by $\Pr[A]$.

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# 6.2 What is a simulation study?

- Then by repeatedly simulating the experiment, it is simple to estimate $\Pr[A]$, the probability of the event $A$, using $P_F(A)$, where:

$$P_F(A) = \frac{\text{No. of times } A \text{ occurs}}{\text{Number of times experiment simulated}}.$$

- Here $P_F(A)$ is the *frequency estimate* of $\Pr[A]$.
- Why does this work?

# 6.2 What is a simulation study?

- Well suppose we denote the number of times we simulate the experiment by $n$, then $P_F(A)$ has the following important property:

$$\text{as } n \to \infty, \text{ then } P_F(A) \to \Pr[A].$$

- This means that the more simulations we do, the more *accurate* our estimate of $\Pr[A]$.

# 6.3 Monte Carlo Integration

- We would like to evaluate $\int_0^1 f(x)\,dx$, but the function may be too complicated to integrate.
- We can find an approximate answer by noting that the integral is equal to the area under the curve, and using Monte Carlo methods.
- We design an experiment which would work in general, even if the function was defined on a general range $(a, b)$, and if $f(x) \in (0, c)$, for any positive value $c$.

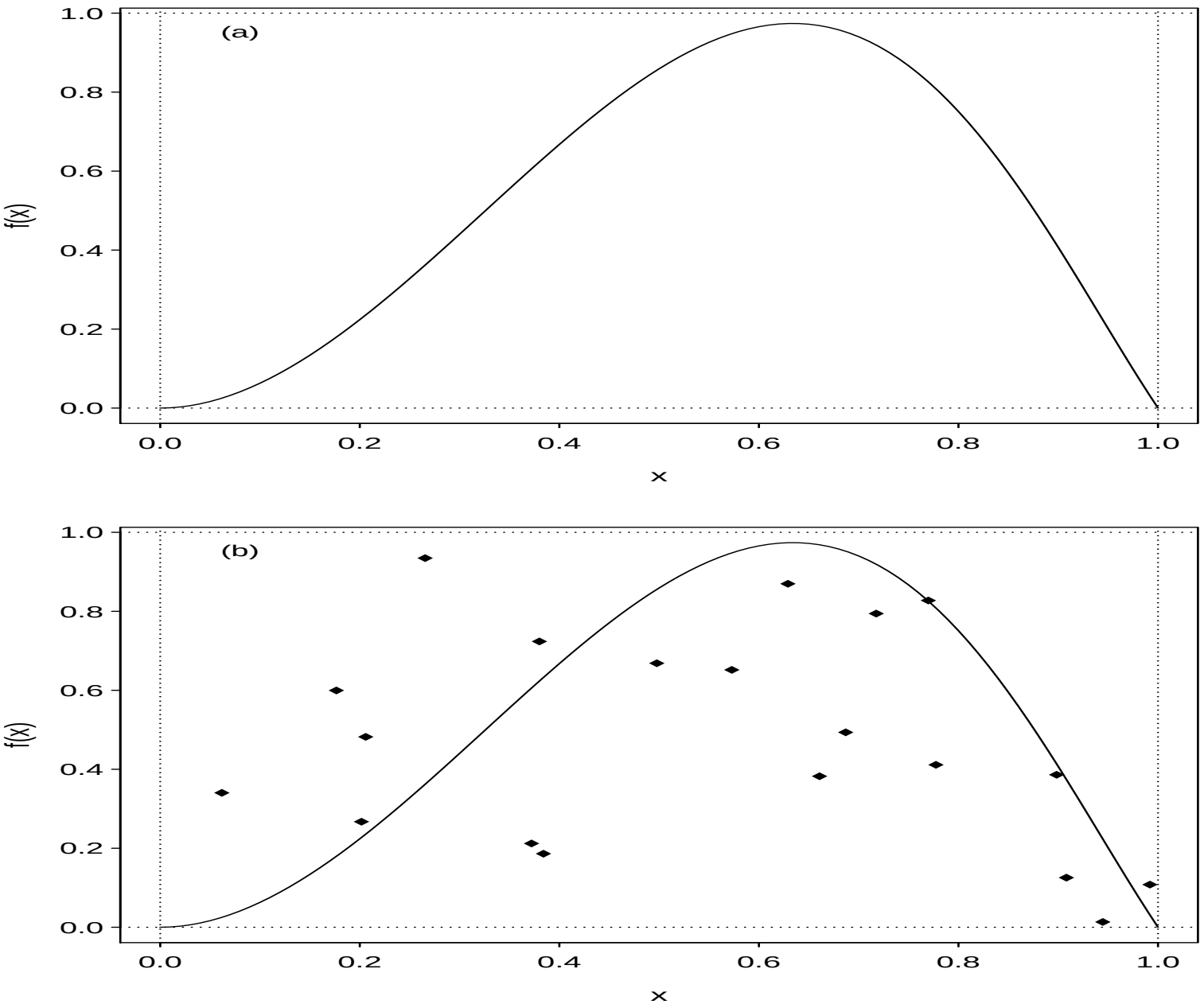


Figure: (a) An example function. (b) Twenty points randomly placed on the graph.

# 6.3 Monte Carlo Integration

We generate a random data point from a *simulation grid*. Let

$$A = \{\text{the data point lies below the curve}\}.$$

Then

$$\Pr[A] = \frac{\text{area under curve}}{\text{area of simulation grid}},$$

so that

$$\begin{aligned}\int_a^b f(x)\,dx &= [\text{area under curve}] \\ &= \Pr[A] \times [\text{area of simulation grid}].\end{aligned}$$

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# 6.3.1 Example

- Consider the function we saw earlier in Figure 6.1, defined on $(0, 1)$, and with $f(x) \in (0, 1)$.
- Estimate $\int_0^1 f(x)dx$ using Monte Carlo methods.

# 6.3.1 Solution: Step 1

We simulate $n$ data points from the simulation grid; here this is the unit square $(0, 1) \times (0, 1)$.

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Each of the coordinates $x$ and $y$ are generated using a $U(0,1)$ random variable. Note the fact that

$$A = \{\text{data point } (x, y) \text{ lies below the curve}\} = \{y < f(x)\}.$$

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# 6.3.1 Solution: Step 3

If $r$ points lie below the curve, then $\Pr[A] \simeq P_F(A) = r/n$, and thus

$$\begin{aligned}
\int_0^1 f(x)\,dx &= \Pr[A] \times [\text{area of simulation grid}] \\
&= \Pr[A] \times 1 \\
&= \Pr[A] \\
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# 6.3.1 Solution: Step 4

In our case, from the figure above we estimate:

$$\int_0^1 f(x)\,dx \simeq \frac{r}{n} = \frac{12}{20} = 0.6\ .$$

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# 6.3.2 Example using R

We can also easily implement the above algorithm in R. As an extreme example, consider the function

$$f(x) = \left| \sin\{\sin[\sin(x^4)]\} \right| .$$

We wish to calculate

$$\int_0^2 f(x)\, dx = \int_0^2 \left| \sin\{\sin[\sin(x^4)]\} \right| dx ,$$

(which evaluates to approximately 0.71875). First plot the function to determine the necessary region:

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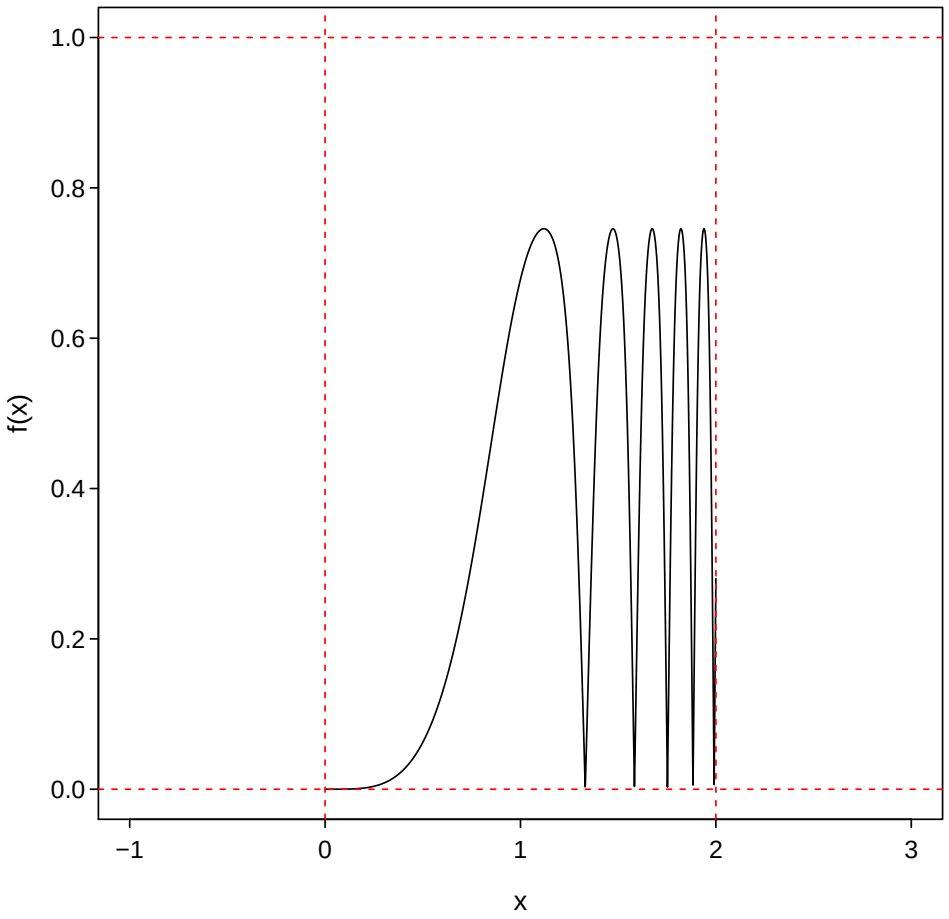


Figure: A plot of $|\sin\{\sin[\sin(x^4)]\}|$ with the sampling region.

# 6.3.2 Example using R

The plot generated in the code above is shown in figure 6.2. Then we use a `for` loop to simulate lots of random numbers:

```
> set.seed(1)
> N = 100000
> no_of_hits = 0
> for(i in 1:N) {
+   x = runif(1, 0, 2); y = runif(1)
+   if(abs(sin(sin(sin(x^4)))) > y) {
+     no_of_hits = no_of_hits + 1
+   }
+ }
> area_under_curve = no_of_hits/N*2
> area_under_curve
```