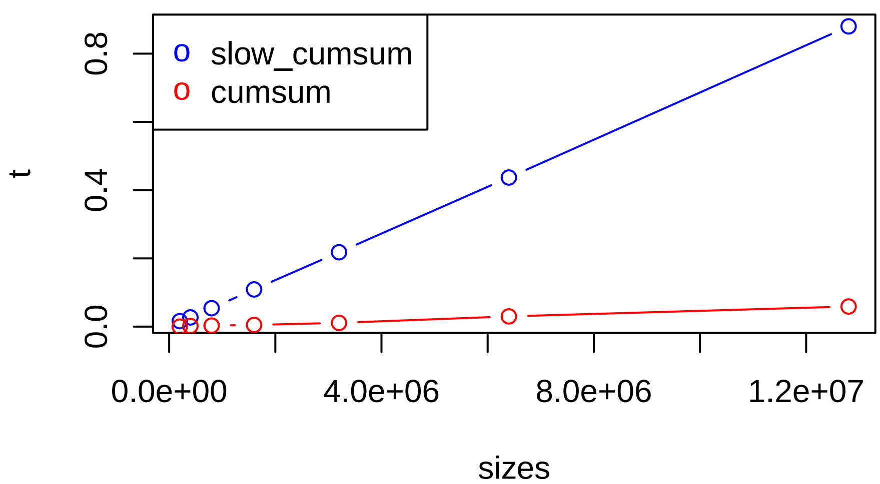
High Performance R exercises - day 1

1. CPU

Ex 1

Measure the execution time of `slow_cumsum()` and `cumsum()` with different sizes of the vector `x`. Plot the results for comparison.



Ex 2

The function below is even worse than `slow_cumsum()`:

```r
atrocious_cumsum <- function(x) {
  # we will "build up" the cumulative sum as we iterate over x
  result <- c()
  for (x_elem in x) {
    if (is.null(result)) {
      # if the result is empty, we start with just x[1]
      result <- x_elem
    } else {
      # otherwise we append to the result the sum of the current
      # element of x and the last element of result
      result <- c(result, result[length(result)]+x_elem)  # DON'T!!! ;(
    }
  }
  result
```

```
}
```

Profile this function. Where does it spend the most time?

Ex 3

Let x be a numeric matrix of size 10000×10000. Try adding random numbers to:

a) 100 randomly chosen **rows** of x,
b) 100 randomly chosen **columns** of x.

Benchmark both variants. Which one is faster? Why?

```
##      expr      min       lq     mean   median       uq      max neval
## 1 rowwise 76.86855 77.33351 82.26599 77.74423 78.36302 455.3232   100
## 2 colwise 60.38661 60.67199 62.10412 60.89400 61.74725  67.3331   100
```

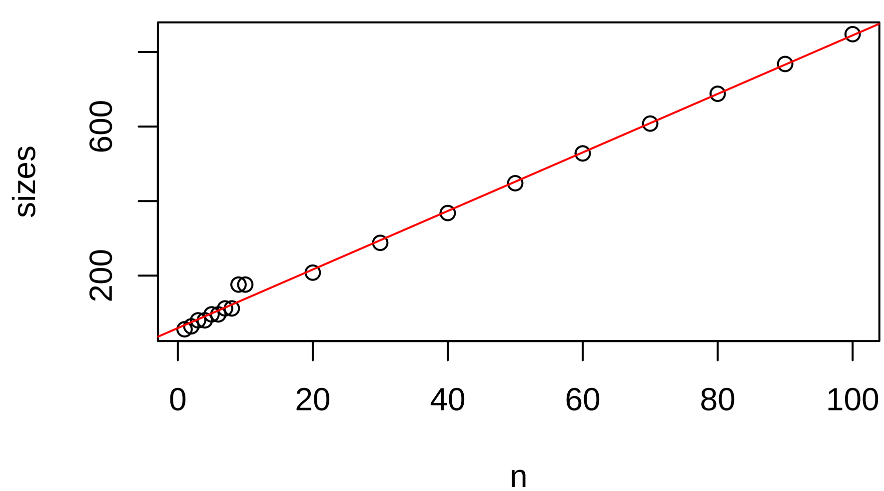
2. Memory

Ex 4

Generate vectors of random numbers of type `integer` and `float` and sizes from 1 to 1000. Try to determine:

- how many bytes does an individual element take?
- how large is the overhead per the entire vector?

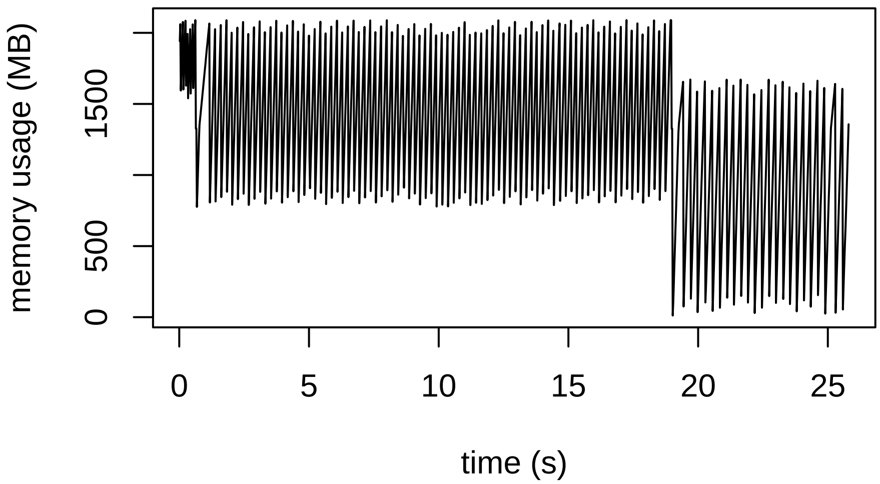
Plot the object size depending on length.




```
##
## Call:
## lm(formula = sizes ~ n)
##
## Coefficients:
## (Intercept)            n
##      59.250        7.856
```

Ex 5

Profile and plot the memory usage of `atrocious_cumsum()`. Explain the pattern.



Ex 6

Compare the memory usage of k-means clustering and hierarchical clustering (the latter together with the distance matrix calculation). Try different dataset sizes!

You can use the word embeddings dataset.

3. Functional programming

Note: In all the exercises in this section, use the functional programming style.

Ex 7

Write a function `powers(a, b)` that for two vectors a, b calculates a matrix C, with $c_{ij} = a_i^{b_j}$.

```
powers(c(2, 3, 5, 6), 1:3)
```

```
##      [,1] [,2] [,3]
## [1,]    2    4    8
## [2,]    3    9   27
## [3,]    5   25  125
## [4,]    6   36  216
```

Ex 8

Write a function `binary(x)` that for a vector of integers `x` returns a matrix of binary representations of numbers from `x`: each row is a sequence of zeros and ones.

```
binary(1:10)
```

```
##       [,1] [,2] [,3] [,4]
##  [1,]    1    0    0    0
##  [2,]    0    1    0    0
##  [3,]    1    1    0    0
##  [4,]    0    0    1    0
##  [5,]    1    0    1    0
##  [6,]    0    1    1    0
##  [7,]    1    1    1    0
##  [8,]    0    0    0    1
##  [9,]    1    0    0    1
## [10,]    0    1    0    1
```

Ex 9

Generalize the function from the previous exercise to `radix(x, base = 2)` which computes a representation with any base (2 = binary, 8 = octal etc.).

```r
radix(c(1, 8, 11, 16), base = 8)
```

```
##      [,1] [,2]
## [1,]    1    0
## [2,]    0    1
## [3,]    3    1
## [4,]    0    2
```

Ex 10

The "3 vs 2 dice" game from the lecture involves rolling 5 six-sided dice - the number of possible combinations is only $6^5 = 7776$.

Calculate the probability of winning with 3 dice brute-force - by enumerating all possible results.

Hint: use the `radix()` function to convert single numbers to results on five dice (five-"digit" numbers in representation with base 6).

```r
dice_game_bruteforce()
```

```
## [1] 0.7785494
```

Ex 11

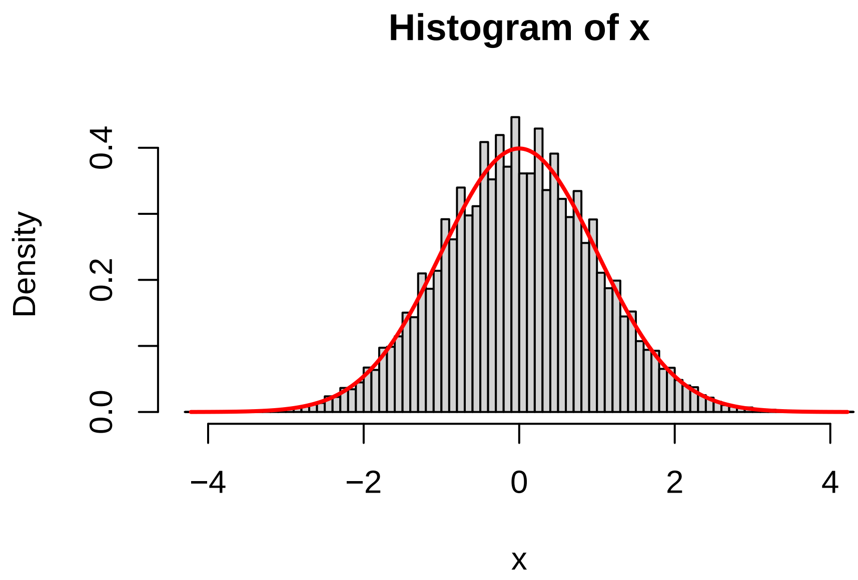
The Central Limit Theorem says that a standardized mean of n independent identically distributed random variables approaches the standard Normal distribution with increasing n. Let's test it!

Define a function `sample_dice(n, m)` that does the following:

- generate n experiments of m dice rolls each,
- for each experiment, calculate the mean score,
- standardize: subtract $\frac{7}{2}$ (mean) and divide by $\sqrt{\frac{105}{36}m^{-1}}$ (standard deviation).

Plot a histogram of the sample and draw the standard Normal distribution for reference.

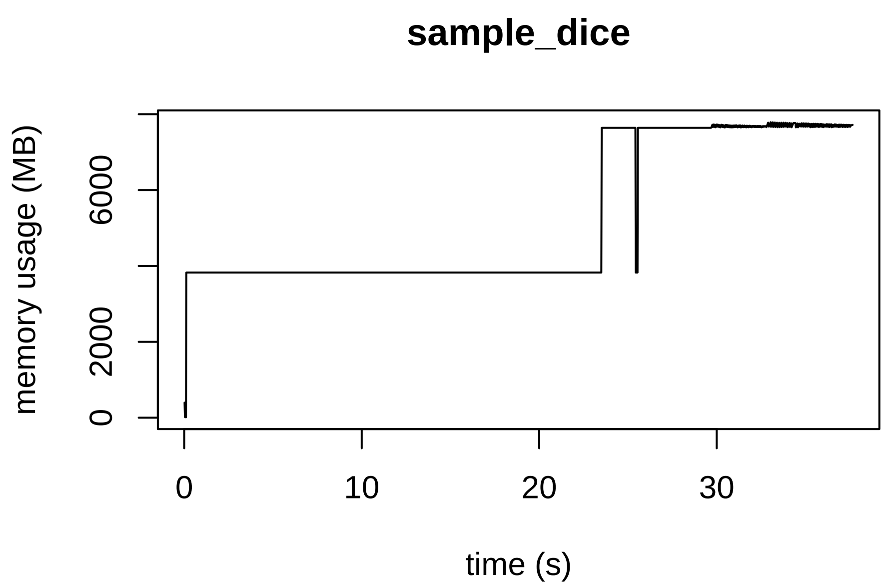
```r
x <- sample_dice(100000, 1000)
hist(x, probability=T, breaks=100)
nx <- seq(min(x), max(x), length.out=1000)
lines(nx, dnorm(nx), lwd=2, col='red')
```

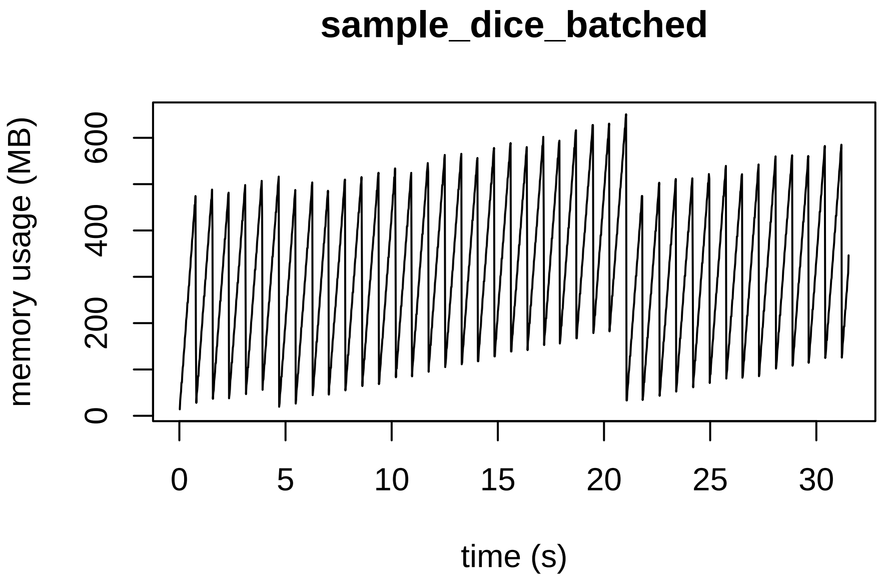


Ex 12

For large samples, the function `sample_dice()` has high memory consumption - it generates all dice rolls at once. Write a function `sample_dice_batched(n, m, batch_size)` that generates `n` experiments in total, but only up to `batch_size` at once.

Profile the memory usage of both functions!





sample_dice_batched
memory usage (MB)
0
200
400
600
0
5
10
15
20
25
30
time (s)