Time-series processing methods for high-dimensional time-series: runstats R package

3rd webinar OSS developers in physical behavior field

Marta Karas Nov 5, 2019

Outline

- Fast time-series processing
 - Rolling statistics
 - Speed-up rolling mean/sd/var with 1-liner trick
 - Speed-up rolling cor/cov with convolution theorem
- runstats R package
 - CRAN: https://cran.r-project.org/web/packages/runstats/index.html
 - o GitHub: https://github.com/martakarass/runstats (considered in this presentation)

Fast time-series processing: motivation

Recall: raw accelerometry data is voluminous

Example: raw accelerometry data collected from 1 patient, 1 week,
 frequency=100Hz yields 3 * 100 * 60 * 60 * 24 * 7 = 181,440,000 float values

Some often used operations:

- Smoothing (e.g. running window average)
- Running variance, running correlation (with some short signal)

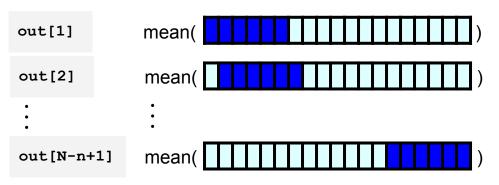
must be done fast

Example 1: running window average (running mean)

Input:



Output:



Simple R is not fast: running window average

```
## Running window average of a time-series
RunningMean.sapply <- function(x, win n) {</pre>
  1 \times < - length(x)
  sapply (1: (1 \times - win n + 1), function(i) {
    mean(x[i:(i + win_n - 1)])
  })
N <- 10000000 # 10,000,000
                                           ~18h of fs=100Hz 1-dimensional time-series
x <- runif(N)
win n <- 100
system.time({
  RunningMean.sapply(x, win n)
})
    user system elapsed
                                           ~ 1.25 minute of execution
# 75.880 3.545 79.678
```

Example 2: running correlation

out[N-n+1]

Simple R is not fast: running correlation

```
## Running covariance of long time-series x and short(er) y
RunningCor.sapply <- function(x, y) {</pre>
  1 \times < - length(x)
  l y <- length(y)</pre>
  sapply(1:(1_x - 1_y + 1), function(i){
    cor(x[i:(i+l y-1)], y)
  })
N <- 10000000 # 10,000,000
                                           ~18h of fs=100Hz 1-dimensional time-series
n < -100
x <- runif(N)
y <- runif(n)
system.time({
  RunningCor.sapply(x, y)
})
     user system elapsed
                                           ~ 8.5 minutes of execution
# 516.994 2.554 519.946
```

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1-liner trick implemented in runstats R package

Goal: compute x vector running average over moving window of length w

```
runningMean(x, W) {
    diff(c(0, cumsum(x)), lag = W) / W
}
```

Acknowledgement: this piece is the most recent improvement contributed by **Lacey Etzkorn** (PhD student at JHU Biostat); previously it had been previously implemented also via FFT.

runstats R package: running window average

```
## Running window average of a time-series
RunningMean.sapply <- function(x, win n) {</pre>
  1 \times <- length(x)
  sapply (1: (1 \times - win n + 1), function(i) {
    mean(x[i:(i + win n - 1)])
  })
                                        ~18h of fs=100Hz 1-dimensional time-series
N <- 10000000 # 10,000,000
x <- runif(N)
win n <-100
system.time({
  RunningMean.sapply(x, win_n)
})
    user system elapsed
                                        ~ 1.25 minute of execution
# 75.880 3.545 79.678
system.time({
  runstats::RunningMean(x, win n)
 user system elapsed
                                        ~ 0.2 seconds of execution (~350x faster)
# 0.216 0.019
                 0.237
```

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Speed-up computing with convolution theorem [1/]

Convolution

Convolution is a mathematical operation on two functions, denote f and g, defined as the integral of the product of the two functions after one is reversed and shifted:

$$(f*g)(t) = \int_{-\infty}^{\infty} f(\tau)g(t-\tau)d\tau. \tag{1}$$

Discrete convolution

For functions x, h defined on the set \mathbb{Z} of integers, the discrete convolution of x and h is given by

$$(x*h)[n] = \sum_{i=-\infty}^{\infty} x[i]h[n-i], \quad n \in \mathbb{Z}.$$
 (2)

Speed-up computing with convolution theorem [2/]

Discrete convolution, finite support

Consider x, h defined on the finite set:

$$x[n], \ 0 \le n \le M - 1, \ len(x) = M,$$
 (3)

$$h[n], \ 0 \le n \le N-1, \ len(h) = N.$$
 (4)

Then

$$(x*h)[n] = \sum_{i=0}^{M-1} x[i]h[n-i] = \sum_{i=0}^{N-1} h[i]x[n-i], \quad 0 \le n < M+N-1.$$
(5)

Running product of two vectors

Consider denoting:

- x a (longer) numeric vector of length M, for which we want to compute running window average with window length m,
- y a (shorter) numeric vector of length m, m < M.

Then

$$(x*y)[n] = \sum_{i=0}^{m-1} y[i]x[n-i] = \sum_{i=0}^{m-1} y[i]x'[i]$$
 (7)

is a product of vector y and vector x' which is a (reverse of) part of x starting from x's index i = (n - m + 1) to i = n.

Computing whole convolution function (x * y)[n] gives values of product of subsequent windows of x and vector y.

Convolution theorem (where the speed-up comes from)

The convolution theorem states that, under suitable conditions, the Fourier transform of a convolution of two functions f,g is the pointwise product of their Fourier transforms:

$$\mathcal{F}\{f * g\} = \mathcal{F}\{f\} \cdot \mathcal{F}\{g\} \tag{8}$$

where:

- $\mathcal{F}\{f * g\}$, $\mathcal{F}\{f\}$ and $\mathcal{F}\{g\}$ Fourier transform operators for f * g, f and g, respectively,
- $\mathcal{F}\{f\}(\xi) = \int_{-\infty}^{\infty} f(x)e^{-2\pi ix\xi}dx$ Fourier transform of a function f.

By applying the inverse Fourier transform, we get

$$f * g = \mathcal{F}^{-1} \{ \mathcal{F} \{ f \} \cdot \mathcal{F} \{ g \} \}. \tag{9}$$

Speed-up computing with convolution theorem [5/]

The convolution representation given by RHS of

$$f * g = \mathcal{F}^{-1} \{ \mathcal{F} \{ f \} \cdot \mathcal{F} \{ g \} \}.$$

can be used for fast implementation of convolution:

- The standard convolution algorithm has quadratic computational complexity, $O\left(n^2\right)$.
- Using above result, and using a fast Fourier transform (FFT) algorithm that computes the discrete Fourier transform of a sequence, the complexity of the convolution can be reduced to $O(n \log n)$.

Goal: compute rolling covariance between (longer) x and (shorter) y

```
RunningCov(x, y) {
    # (...)
    covxy <- (conv(x, y) - W * meanx * meany)/(W - 1)
}</pre>
```

Goal: compute rolling covariance between (longer) x and (shorter) y

```
RunningCov(x, y) {
    # (...)
    covxy <- (conv(x, y) - W * meanx * meany)/(W - 1)
}</pre>
```

Equivalent formulas for unbiased sample covariance estimator

$$\left(\frac{1}{n-1}\left(\sum_{i=1}^{n} x_i y_i - n\overline{x}\overline{y}\right)\right) = \frac{1}{n-1}\sum_{i=1}^{n} \left(x_i - \overline{x}\right)\left(y_i - \overline{y}\right)$$

Goal: compute rolling covariance between (longer) x and (shorter) y

```
RunningCov(x, y) {

# (...)

covxy <- (conv(x, y) - W * meanx * meany)/(W - 1)
}

convolution of (longer) x and (shorter) y
:= "rolling product" of x and y</pre>
(precomputed) rolling mean of x
```

Goal: compute rolling covariance between (longer) \times and (shorter) y

```
RunningCov(x, y) {
    # (...)
    covxy <- ( conv(x, y)
                                     - W * meanx * meany) / (W - 1)
convolution of (longer) x and (shorter) y
                                              (precomputed) rolling mean of x
:= "rolling product" of x and y
Computing whole convolution function (x * y)[n] gives values of product of
subsequent windows of x and vector y.
```

runstats R package: running correlation

```
## Running covariance of long time-series x and short(er) y
RunningCor.sapply <- function(x, y) {</pre>
  1 \times < - length(x)
  1 y <- length(y)
  sapply (1: (1 \times - 1 y + 1), function(i) {
    cor(x[i:(i+l y-1)], y)
  })
                                            ~18h of fs=100Hz 1-dimensional time-series
N <- 10000000 # 10,000,000
n < -100
x <- runif(N)
y <- runif(n)
system.time({
  RunningCor.sapply(x, y)
})
     user system elapsed
                                            ~ 8.5 minutes of execution
# 516.994 2.554 519.946
system.time({
  runstats::RunningCor(x, y)
 user system elapsed
# 5.922 0.452
                                            ~ 6 seconds of execution (~87x faster)
                 6.383
```

runstats R package

Provides methods for fast computation of running sample statistics for a time-series.

Implemented running sample statistics:

- mean, standard deviation, and variance over a fixed-length window of time-series,
- **correlation**, **covariance**, and **Euclidean distance** (L2 norm) between short-time pattern and time-series.

CRAN index: https://cran.r-project.org/web/packages/runstats/index.html

runstats R package - a comparator example

Dane Van Domelen (personal website)

- Former post doc in JHU Biostat
- Biostatistician at Karyopharm Therapeutics Inc
- Authored a bunch of interesting R packages
- R package <u>dvmisc</u>: Convenience Functions,
 Moving Window Statistics, and Graphics
 - includes sliding_cor, sliding_cov functions implemented in rcpp; very fast!



- accelerometry
- crowdopt
- dvmisc
- nhanesaccel
- nhanesdata
- pooling
- tab
- stocks

Note:

- Implementation of convolution via convolution theorem + FFT is a general way that can be used to speed-up convolution in mostly any language (i.e. Python)
- Nearest future plans for runstats update: search for fastest
 FFT implementation I can plug to use in R (perhaps rcpp?)