Lab 7

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#Rcpp

We will get some experience with speeding up R code using C++ via the `Rcpp` package.

First, clear the workspace and load the `Rcpp` package.

```
#Turn off warnings
options(warn = -1)

pacman::p_load(Rcpp, microbenchmark)
```

Create a variable `n` to be 10 and a vaiable `Nvec` to be 100 initially. Create a random vector via `rnorm` `Nvec` times and load it into a `Nvec` x `n` dimensional matrix.

```
n <- 10
Nvec <- 100
X <- matrix(data = rnorm(Nvec * n), nrow = 100)
head(X)
```

```
##            [,1]       [,2]        [,3]       [,4]       [,5]       [,6]
## [1,]  0.1993440  0.4191974  0.24453453  0.2947189 -1.2865919 -0.6293418
## [2,]  0.5889123 -0.9585081  0.06695021 -0.9488864  0.4753941  0.7284643
## [3,] -0.2902922 -1.1744554 -0.91128519 -0.3253936  0.8848460  0.2454842
## [4,] -0.1477799 -0.4680558 -0.01394135  0.2553497  2.0518457  0.6561717
## [5,]  0.9745939 -0.5232477  1.10382485 -0.8123225  0.5278635  0.2436931
## [6,]  0.9665837 -0.1667978 -0.16772158  0.5024978  1.0130579  0.2751977
##            [,7]        [,8]       [,9]      [,10]
## [1,] -0.2693190 -0.40433542  0.5933246 0.06679633
## [2,] -0.8233167 -0.11038629 -0.3493998 0.16969547
## [3,]  0.2822618  0.04438965 -0.6629287 0.56899007
## [4,]  0.8009164 -0.84898199  2.1109813 0.53841146
## [5,]  0.6253744 -1.27950570 -1.4522970 1.56267665
## [6,]  1.2332056 -0.10607136  0.9667929 0.45796153
```

Write a function `all_angles` that measures the angle between each of the pairs of vectors. You should measure the vector on a scale of 0 to 180 degrees with negative angles coerced to be positive.

```
angle = function(u,v) {

  return(acos(sum(u*v) / sqrt(sum(u^2)*sum(v^2))) * (180/pi))
```

```
}

all_angles = function(X){
  A = matrix(NA, nrow = nrow(X), ncol = nrow(X))

  for(i in 1:(nrow(X)-1)) {

    for(j in (i+1) : nrow(X)) {
      A[i,j] = angle(X[i,], X[j,])
    }

  }

  return(A)
}

head(
all_angles(X)
)
```

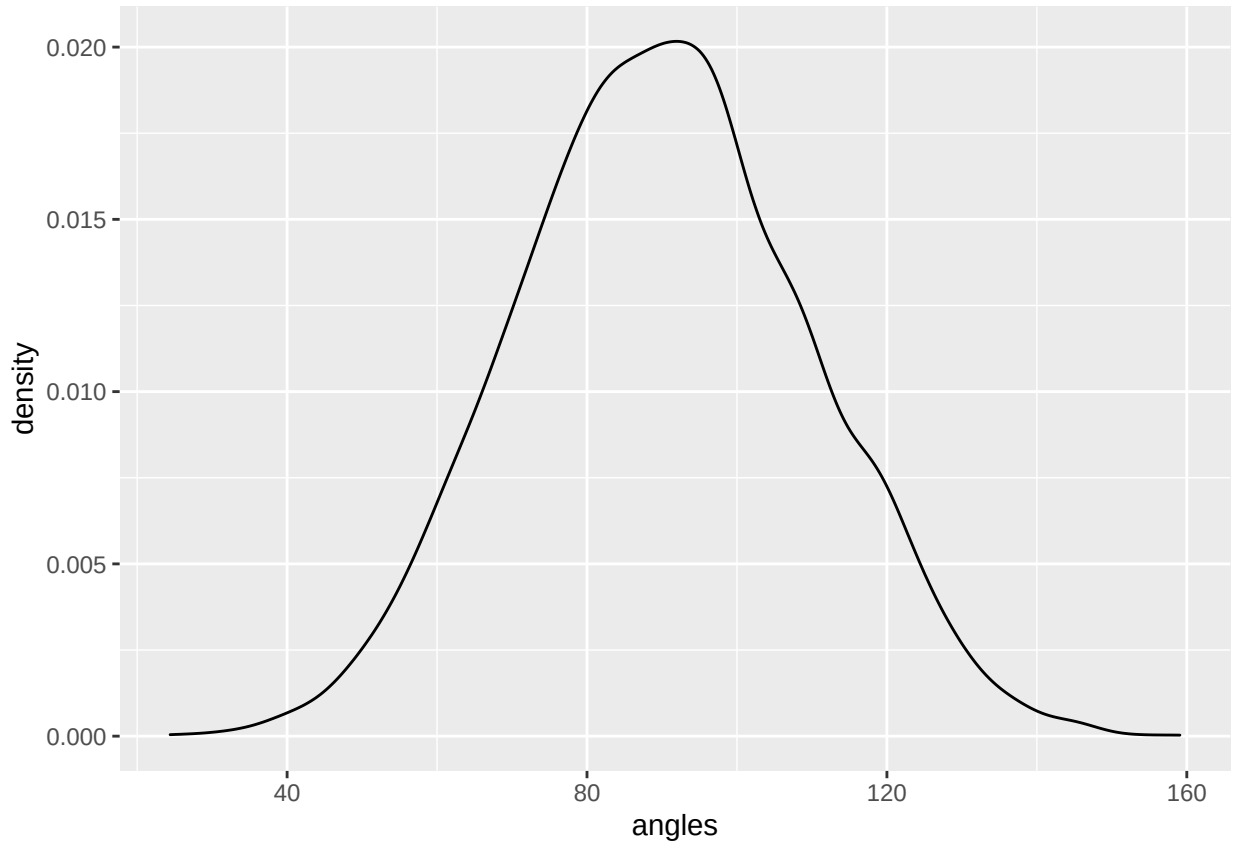
```
##      [,1]     [,2]      [,3]      [,4]      [,5]      [,6]      [,7]      [,8]
## [1,]   NA 117.3727 138.14793 108.09638 103.00968 103.87660 104.38260  80.75897
## [2,]   NA       NA  61.16456  86.80335  63.43701  94.49046  82.37671  66.98440
## [3,]   NA       NA        NA  76.28254  70.95296  79.42299  49.46350  91.38790
## [4,]   NA       NA        NA        NA  87.36522  40.20513  72.22095  88.94095
## [5,]   NA       NA        NA        NA        NA  79.79783  64.20669  74.84913
## [6,]   NA       NA        NA        NA        NA        NA  66.82428 105.74002
##          [,9]     [,10]     [,11]     [,12]    [,13]     [,14]     [,15]
## [1,] 104.23746 102.98322  78.42225 109.07044 84.47408  88.16017  78.96680
## [2,]  62.77047  67.66655  94.19283  88.22478 98.64286 101.52303  78.16107
## [3,]  89.31332  88.01706  98.32845  60.07733 65.90382  84.98568 105.44245
## [4,]  61.48386  81.60990  93.36755  57.14126 95.41331  59.20831 146.55689
## [5,]  84.38019  49.98165 108.47775  64.98475 70.18018  88.04249  73.09220
## [6,]  84.58380  69.57706  94.11386  64.13761 73.15022  67.04294 127.02865
##          [,16]     [,17]     [,18]     [,19]     [,20]     [,21]     [,22]
## [1,] 114.42056 108.30348 143.80922  95.87450 111.89047 107.04703  95.70532
## [2,]  66.14603  73.34674  81.66298  77.31420  86.51980  72.75852  99.15736
## [3,]  90.49729  86.23506  74.11293  98.57781  66.15220  70.44798  97.31586
## [4,] 107.07919 107.08010  73.60954 117.24483 110.38447  74.57874 131.23073
## [5,] 100.58283  63.86211  85.68650 108.47661  91.70636  68.49379 114.67910
## [6,]  98.29650 100.11127  78.83617 113.29007  95.53785  70.43900 112.57451
##          [,23]     [,24]     [,25]     [,26]     [,27]     [,28]     [,29]
## [1,] 116.70375 106.98048  73.61994  78.64592  97.29935  88.44403 110.00368
## [2,]  99.46814  73.03091  74.66905 116.82235  88.61777  85.74160  58.74648
## [3,]  63.74436  84.00844 107.02853 118.61570 101.39536  91.20633  84.45337
## [4,]  69.53286 124.87365 108.29342  69.46553 131.99565 132.87393  95.72673
## [5,]  91.19682  80.35624  81.72779  94.93032 101.14542  85.58663  82.57611
## [6,]  75.51060 105.77450 121.48608  71.19396 126.46476 121.13532 105.24874
##          [,30]     [,31]     [,32]     [,33]     [,34]     [,35]     [,36]
## [1,]  86.25886  70.27196  81.73143  74.29518  71.05443 124.05512  64.67432
## [2,]  98.22406 101.17603 117.90446  80.39514  98.99301  75.35771 108.71320
## [3,] 107.91997 108.65023  89.94992  90.06563 104.39514  66.53665  96.69588
## [4,]  64.34405  77.05303 115.58622 114.74019  99.59651  73.70316  90.74152
```

```
## [5,] 109.90780 117.21215  99.27136  83.61083  82.36091  89.42906 108.42941
## [6,]  74.83453  84.57054 104.00146 106.62643  92.29745  70.19213  74.69395
##          [,37]     [,38]     [,39]     [,40]     [,41]     [,42]     [,43]
## [1,] 122.94413  71.93911 118.21398 138.07393  82.55751 93.51182 103.84195
## [2,]  84.19522  93.39761  90.23633  71.78103  97.03153 71.33256  74.40601
## [3,]  86.53381 120.13396  83.14230  51.25760  99.56160 94.63851  75.05176
## [4,]  90.36831 123.55027  71.22403  93.49146  92.29638 74.05198  85.01329
## [5,]  91.33883 101.51472 100.87765  72.16526 121.93759 66.89267  93.22735
## [6,] 101.55033 129.00960  58.67456  89.27558  83.63565 95.29124  82.06833
##          [,44]     [,45]     [,46]     [,47]     [,48]     [,49]     [,50]
## [1,] 101.22624 120.33974  76.51299 124.19858 84.10120  80.29183  82.58252
## [2,]  82.92184  74.38690 111.70411  91.54380 83.92231  97.77505  86.51633
## [3,]  95.82794  82.78137  99.37472  86.79931 97.48152  99.27206  93.83207
## [4,] 104.60405  86.71921  69.55307  77.66603 90.27324  65.60568 123.60934
## [5,] 113.91827  91.87245 109.36080  85.89897 86.38740 111.41955  99.13590
## [6,] 112.92226  91.32490  76.93976  92.32255 99.62361  59.45349 144.83081
##          [,51]    [,52]     [,53]     [,54]     [,55]     [,56]     [,57]
## [1,]  80.20518  81.3103  89.31380  94.62291  81.61148  79.03124  97.17410
## [2,]  86.73154 121.9341  76.08379 121.67232  74.70797  78.15192  72.80113
## [3,] 116.94310 100.6023  77.51344  90.94371  95.89667  63.34469 109.14174
## [4,]  91.06736 108.1170 111.86229 117.81647  85.85473 100.38279  74.87765
## [5,]  97.67145 136.1512  66.76624 122.03678 101.70181  68.84937  95.63052
## [6,]  80.03601 111.6475 122.63903 110.05956 110.54981  86.89156  70.15202
##          [,58]     [,59]    [,60]     [,61]     [,62]     [,63]     [,64]
## [1,] 112.04353  86.58351 94.41117  75.31691 100.71156 100.71116  65.26402
## [2,]  65.16088  56.55283 75.88125 114.61883  81.47801  87.05750  89.13832
## [3,]  47.63330  83.91927 86.51241 104.50045  72.42962  77.11058 124.29411
## [4,]  88.84231 108.22060 68.60816  98.02846  51.15315  48.23307 113.01922
## [5,]  76.34301  78.48301 75.65888  75.12613 105.89866  74.66126 106.09846
## [6,]  97.49655  94.58762 91.44094 101.00312  62.78479  44.19563 108.75186
##          [,65]     [,66]     [,67]     [,68]     [,69]     [,70]     [,71]
## [1,]  90.27886 112.33010  86.98450  57.32717 103.43206  81.33266  47.91218
## [2,]  85.11713  45.82906  77.19365 103.94530  76.40489  68.49096 117.66669
## [3,]  95.27630  72.89315 102.46974 129.16318  95.30547  97.15542 131.24896
## [4,]  91.88964  92.03234 112.20955  87.69147  97.72193  84.82669  91.61058
## [5,] 146.28812  80.55816  70.77888  86.73584  70.99339  79.02645  83.63866
## [6,] 108.55861 107.48232 102.23902  90.23714  88.26111 104.28624  98.77592
##          [,72]     [,73]     [,74]     [,75]     [,76]     [,77]     [,78]
## [1,]  82.71355  78.04805  83.75285  94.50577 83.67333  84.51925  81.50701
## [2,]  94.78176 106.96334  94.89763 111.32001 92.28112 115.41429 113.34608
## [3,]  81.09322  97.25907 127.69316  93.80239 73.85982  94.77337 105.20645
## [4,]  82.77778  92.73551  90.18877  92.74577 58.76469 103.03206  97.75147
## [5,] 101.71019  82.77630  90.03928 115.43539 88.96529  74.62261  75.25781
## [6,]  89.86186  70.75077  77.26940  80.00998 85.38614  76.22376  90.62504
##          [,79]     [,80]     [,81]     [,82]     [,83]     [,84]     [,85]
## [1,]  85.23133 103.81058  91.24011  91.00455  76.96317  64.62983 101.40026
## [2,] 107.31988  64.26331 119.37050 123.54518  87.61017 119.26976  79.85512
## [3,] 112.89310  91.23029  84.86200  94.57953  80.37770  88.56977  83.72513
## [4,] 117.25833 101.80999  64.07092  84.14564 113.01088  96.75821 105.40647
## [5,] 100.26375  53.28440  82.40311 102.20640  79.09985  75.52244 121.19020
## [6,] 123.90515  83.23733  46.45449  61.14427 120.63202  84.48897 119.19616
##          [,86]    [,87]     [,88]     [,89]    [,90]     [,91]     [,92]
## [1,] 118.17130 81.93892  67.87450 119.19205 57.82388  94.26546  91.89037
## [2,]  79.66670 72.47979  88.33391  73.11755 84.09356  82.37760  69.78570
```

```
## [3,]  75.13340 93.23264 126.67213  65.04988 98.24174  95.31836  81.16707
## [4,]  52.74769 50.48212  68.91447  50.74248 75.79925 102.36487  85.14558
## [5,]  94.86070 74.98510  97.16587  94.01930 73.45768 109.02110 106.56587
## [6,]  68.50034 75.77734  81.55612  61.78464 77.73320 111.39184  89.48598
##          [,93]    [,94]     [,95]     [,96]     [,97]     [,98]     [,99]
## [1,]  73.41732 99.72233  78.03957  98.25486 121.59259  75.54543  90.40516
## [2,]  97.03364 53.13255  99.58436 112.17682 107.94168  65.30061 108.85044
## [3,] 110.11130 69.64348 106.61255 100.23706  88.63626  94.53933 108.81043
## [4,] 113.08019 80.53572  80.55433  98.99775  90.99407 108.65631  63.29470
## [5,]  85.65099 91.04377  64.84402 113.41702 107.87641  77.92461 114.45596
## [6,] 107.83745 79.11174  86.51473  94.57477  83.50549 103.99764  61.10269
##         [,100]
## [1,]  91.63289
## [2,] 108.65848
## [3,] 118.32473
## [4,] 102.45936
## [5,]  83.42427
## [6,]  86.94377
```

Plot the density of these angles.

```
pacman::p_load(ggplot2)

ggplot(data.frame(angles = c(all_angles(X)) )) +
  aes(x = angles) +
  geom_density()
```



Write an Rcpp function `all_angles_cpp` that does the same thing. Use an IDE if you want, but write it below in-line.

```
cppFunction('
  NumericMatrix all_angles_cpp(NumericMatrix X) {
    int n = X.nrow();
    int p = X.ncol();
    NumericMatrix A(n, n);
    std::fill(A.begin(), A.end(), NA_REAL);
    for (int i_1 = 0; i_1 < (n - 1); i_1++){
      //Rcout << "computing for row #: " << (i_1 + 1) << "\\n";
      for (int i_2 = i_1 + 1; i_2 < n; i_2++){
        double sum_sqd_u = 0;
        double sum_sqd_v = 0;
        double sum_u_v = 0;

        for (int j = 0; j < p; j++){

          //sqd_diff += pow(X(i_1, j) - X(i_2, j), 2); //by default the cmath library in std is loaded

          sum_sqd_u += pow(X(i_1, j), 2);
          sum_sqd_v += pow(X(i_2, j), 2);
          sum_u_v += X(i_1, j) * X(i_2, j);


        }
        A(i_1, i_2) = acos(sum_u_v / sqrt(sum_sqd_u * sum_sqd_v)) * (180 / M_PI); //by default the cmath
      }
    }
    return A;
  }
')

head(all_angles_cpp(X))
```

```
##      [,1]     [,2]      [,3]      [,4]      [,5]      [,6]      [,7]      [,8]
## [1,]   NA 117.3727 138.14793 108.09638 103.00968 103.87660 104.38260  80.75897
## [2,]   NA       NA  61.16456  86.80335  63.43701  94.49046  82.37671  66.98440
## [3,]   NA       NA        NA  76.28254  70.95296  79.42299  49.46350  91.38790
## [4,]   NA       NA        NA        NA  87.36522  40.20513  72.22095  88.94095
## [5,]   NA       NA        NA        NA        NA  79.79783  64.20669  74.84913
## [6,]   NA       NA        NA        NA        NA        NA  66.82428 105.74002
##          [,9]     [,10]     [,11]     [,12]    [,13]     [,14]     [,15]
## [1,] 104.23746 102.98322  78.42225 109.07044 84.47408  88.16017  78.96680
## [2,]  62.77047  67.66655  94.19283  88.22478 98.64286 101.52303  78.16107
## [3,]  89.31332  88.01706  98.32845  60.07733 65.90382  84.98568 105.44245
## [4,]  61.48386  81.60990  93.36755  57.14126 95.41331  59.20831 146.55689
## [5,]  84.38019  49.98165 108.47775  64.98475 70.18018  88.04249  73.09220
## [6,]  84.58380  69.57706  94.11386  64.13761 73.15022  67.04294 127.02865
##         [,16]     [,17]     [,18]     [,19]     [,20]     [,21]     [,22]
## [1,] 114.42056 108.30348 143.80922  95.87450 111.89047 107.04703  95.70532
## [2,]  66.14603  73.34674  81.66298  77.31420  86.51980  72.75852  99.15736
## [3,]  90.49729  86.23506  74.11293  98.57781  66.15220  70.44798  97.31586
## [4,] 107.07919 107.08010  73.60954 117.24483 110.38447  74.57874 131.23073
```

```
## [5,] 100.58283  63.86211  85.68650 108.47661  91.70636  68.49379 114.67910
## [6,]  98.29650 100.11127  78.83617 113.29007  95.53785  70.43900 112.57451
##          [,23]     [,24]     [,25]     [,26]     [,27]     [,28]     [,29]
## [1,] 116.70375 106.98048  73.61994  78.64592  97.29935  88.44403 110.00368
## [2,]  99.46814  73.03091  74.66905 116.82235  88.61777  85.74160  58.74648
## [3,]  63.74436  84.00844 107.02853 118.61570 101.39536  91.20633  84.45337
## [4,]  69.53286 124.87365 108.29342  69.46553 131.99565 132.87393  95.72673
## [5,]  91.19682  80.35624  81.72779  94.93032 101.14542  85.58663  82.57611
## [6,]  75.51060 105.77450 121.48608  71.19396 126.46476 121.13532 105.24874
##          [,30]     [,31]     [,32]     [,33]     [,34]     [,35]     [,36]
## [1,]  86.25886  70.27196  81.73143  74.29518  71.05443 124.05512  64.67432
## [2,]  98.22406 101.17603 117.90446  80.39514  98.99301  75.35771 108.71320
## [3,] 107.91997 108.65023  89.94992  90.06563 104.39514  66.53665  96.69588
## [4,]  64.34405  77.05303 115.58622 114.74019  99.59651  73.70316  90.74152
## [5,] 109.90780 117.21215  99.27136  83.61083  82.36091  89.42906 108.42941
## [6,]  74.83453  84.57054 104.00146 106.62643  92.29745  70.19213  74.69395
##          [,37]     [,38]     [,39]     [,40]     [,41]    [,42]     [,43]
## [1,] 122.94413  71.93911 118.21398 138.07393  82.55751 93.51182 103.84195
## [2,]  84.19522  93.39761  90.23633  71.78103  97.03153 71.33256  74.40601
## [3,]  86.53381 120.13396  83.14230  51.25760  99.56160 94.63851  75.05176
## [4,]  90.36831 123.55027  71.22403  93.49146  92.29638 74.05198  85.01329
## [5,]  91.33883 101.51472 100.87765  72.16526 121.93759 66.89267  93.22735
## [6,] 101.55033 129.00960  58.67456  89.27558  83.63565 95.29124  82.06833
##          [,44]     [,45]     [,46]     [,47]    [,48]     [,49]     [,50]
## [1,] 101.22624 120.33974  76.51299 124.19858 84.10120  80.29183  82.58252
## [2,]  82.92184  74.38690 111.70411  91.54380 83.92231  97.77505  86.51633
## [3,]  95.82794  82.78137  99.37472  86.79931 97.48152  99.27206  93.83207
## [4,] 104.60405  86.71921  69.55307  77.66603 90.27324  65.60568 123.60934
## [5,] 113.91827  91.87245 109.36080  85.89897 86.38740 111.41955  99.13590
## [6,] 112.92226  91.32490  76.93976  92.32255 99.62361  59.45349 144.83081
##          [,51]    [,52]     [,53]     [,54]     [,55]     [,56]     [,57]
## [1,]  80.20518  81.3103  89.31380  94.62291  81.61148  79.03124  97.17410
## [2,]  86.73154 121.9341  76.08379 121.67232  74.70797  78.15192  72.80113
## [3,] 116.94310 100.6023  77.51344  90.94371  95.89667  63.34469 109.14174
## [4,]  91.06736 108.1170 111.86229 117.81647  85.85473 100.38279  74.87765
## [5,]  97.67145 136.1512  66.76624 122.03678 101.70181  68.84937  95.63052
## [6,]  80.03601 111.6475 122.63903 110.05956 110.54981  86.89156  70.15202
##          [,58]     [,59]    [,60]     [,61]     [,62]     [,63]     [,64]
## [1,] 112.04353  86.58351 94.41117  75.31691 100.71156 100.71116  65.26402
## [2,]  65.16088  56.55283 75.88125 114.61883  81.47801  87.05750  89.13832
## [3,]  47.63330  83.91927 86.51241 104.50045  72.42962  77.11058 124.29411
## [4,]  88.84231 108.22060 68.60816  98.02846  51.15315  48.23307 113.01922
## [5,]  76.34301  78.48301 75.65888  75.12613 105.89866  74.66126 106.09846
## [6,]  97.49655  94.58762 91.44094 101.00312  62.78479  44.19563 108.75186
##          [,65]     [,66]     [,67]     [,68]     [,69]     [,70]     [,71]
## [1,]  90.27886 112.33010  86.98450  57.32717 103.43206  81.33266  47.91218
## [2,]  85.11713  45.82906  77.19365 103.94530  76.40489  68.49096 117.66669
## [3,]  95.27630  72.89315 102.46974 129.16318  95.30547  97.15542 131.24896
## [4,]  91.88964  92.03234 112.20955  87.69147  97.72193  84.82669  91.61058
## [5,] 146.28812  80.55816  70.77888  86.73584  70.99339  79.02645  83.63866
## [6,] 108.55861 107.48232 102.23902  90.23714  88.26111 104.28624  98.77592
##          [,72]     [,73]     [,74]     [,75]    [,76]     [,77]     [,78]
## [1,]  82.71355  78.04805  83.75285  94.50577 83.67333  84.51925  81.50701
## [2,]  94.78176 106.96334  94.89763 111.32001 92.28112 115.41429 113.34608
```

```
## [3,]  81.09322  97.25907 127.69316  93.80239 73.85982  94.77337 105.20645
## [4,]  82.77778  92.73551  90.18877  92.74577 58.76469 103.03206  97.75147
## [5,] 101.71019  82.77630  90.03928 115.43539 88.96529  74.62261  75.25781
## [6,]  89.86186  70.75077  77.26940  80.00998 85.38614  76.22376  90.62504
##          [,79]     [,80]     [,81]     [,82]     [,83]     [,84]     [,85]
## [1,]  85.23133 103.81058  91.24011  91.00455  76.96317  64.62983 101.40026
## [2,] 107.31988  64.26331 119.37050 123.54518  87.61017 119.26976  79.85512
## [3,] 112.89310  91.23029  84.86200  94.57953  80.37770  88.56977  83.72513
## [4,] 117.25833 101.80999  64.07092  84.14564 113.01088  96.75821 105.40647
## [5,] 100.26375  53.28440  82.40311 102.20640  79.09985  75.52244 121.19020
## [6,] 123.90515  83.23733  46.45449  61.14427 120.63202  84.48897 119.19616
##          [,86]    [,87]     [,88]     [,89]    [,90]     [,91]     [,92]
## [1,] 118.17130 81.93892  67.87450 119.19205 57.82388  94.26546  91.89037
## [2,]  79.66670 72.47979  88.33391  73.11755 84.09356  82.37760  69.78570
## [3,]  75.13340 93.23264 126.67213  65.04988 98.24174  95.31836  81.16707
## [4,]  52.74769 50.48212  68.91447  50.74248 75.79925 102.36487  85.14558
## [5,]  94.86070 74.98510  97.16587  94.01930 73.45768 109.02110 106.56587
## [6,]  68.50034 75.77734  81.55612  61.78464 77.73320 111.39184  89.48598
##          [,93]    [,94]     [,95]     [,96]     [,97]     [,98]     [,99]
## [1,]  73.41732 99.72233  78.03957  98.25486 121.59259  75.54543  90.40516
## [2,]  97.03364 53.13255  99.58436 112.17682 107.94168  65.30061 108.85044
## [3,] 110.11130 69.64348 106.61255 100.23706  88.63626  94.53933 108.81043
## [4,] 113.08019 80.53572  80.55433  98.99775  90.99407 108.65631  63.29470
## [5,]  85.65099 91.04377  64.84402 113.41702 107.87641  77.92461 114.45596
## [6,] 107.83745 79.11174  86.51473  94.57477  83.50549 103.99764  61.10269
##         [,100]
## [1,]  91.63289
## [2,] 108.65848
## [3,] 118.32473
## [4,] 102.45936
## [5,]  83.42427
## [6,]  86.94377
```

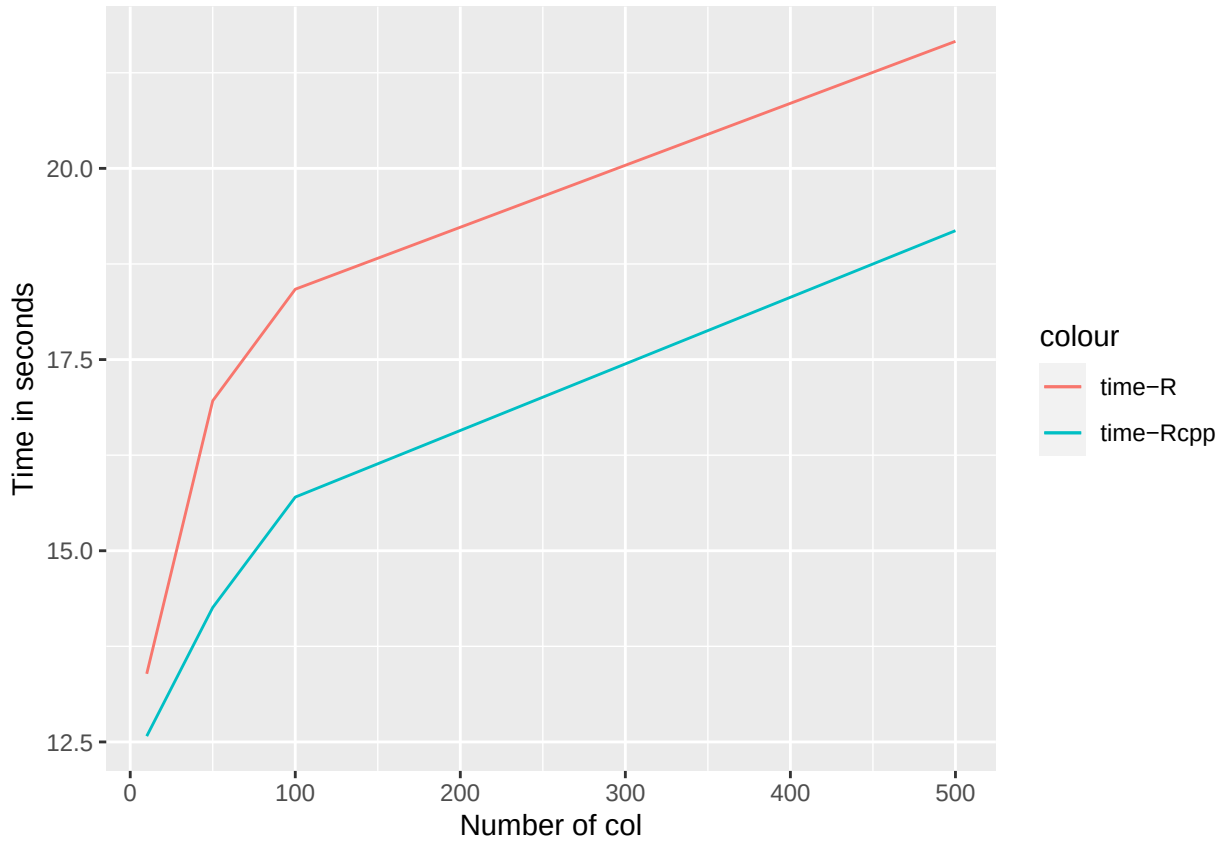
Test the time difference between these functions for `n = 1000` and `Nvec = 100, 500, 1000, 5000` using the package `microbenchmark`. Store the results in a matrix with rows representing `Nvec` and two columns for base R and Rcpp.

```
Nvec = c(10, 50, 100, 500)

n <- 1000
time_for_R <- c()
time_for_cpp <- c()

for (i in 1:length(Nvec)) {
  X <- c()

  for (j in 1:n) {
    X <- cbind(X, rnorm(Nvec[i]))
  }

  time_for_R <- c(
    time_for_R,
    mean(microbenchmark(
      angles_r = all_angles(X),
```

```
      times = 3,
      unit = "s"
    )$time)
  )

  time_for_cpp <- c(
    time_for_cpp,
    mean(microbenchmark(angles_cpp = all_angles_cpp(X),
      times = 3,
      unit = "s"
    )$time)
  )

}
```

Plot the divergence of performance (in log seconds) over n using a line geometry. Use two different colors for the R and CPP functions. Make sure there's a color legend on your plot. We wil see later how to create "long" matrices that make such plots easier.

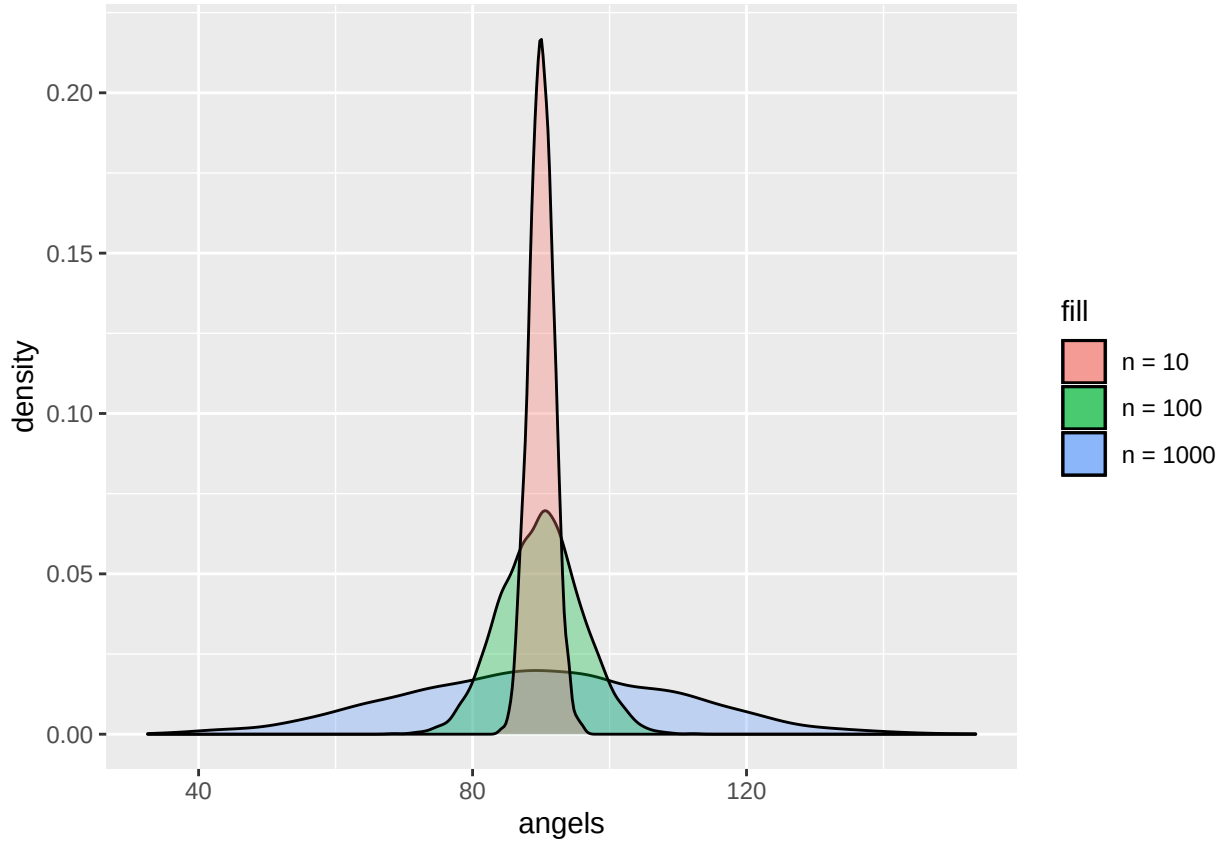
```
ggplot() +
  geom_line(aes(x = Nvec, y = log(time_for_R), col = "time-R")) +

  geom_line(aes(x = Nvec, y = log(time_for_cpp), col = "time-Rcpp")) +

  xlab("Number of col") +

  ylab("Time in seconds")
```



Let `Nvec = 10000` and vary `n` to be 10, 100, 1000. Plot the density of angles for all three values of `n` on one plot using color to signify `n`. Make sure you have a color legend. This is not easy.

```
Nvec = 100
X <- c()
for (i in 1:10) {
  X <- cbind(X, rnorm(Nvec))
}
a1 <- all_angles(X)

X <- c()
for (i in 1:100) {
  X <- cbind(X, rnorm(Nvec))
}
a2 <- all_angles(X)

X <- c()
for (i in 1:1000) {
  X <- cbind(X, rnorm(Nvec))
}
a3 <- all_angles(X)

ggplot() +
  geom_density(aes(x = a1, fill = "red"), alpha = .33) +
  geom_density(aes(x = a2, fill = "green"), alpha = .33) +
  geom_density(aes(x = a3, fill = "blue"), alpha = .33) +
```

```
  scale_fill_discrete(labels = c("n = 10", "n = 100", "n = 1000")) +
  xlab("angels")
```



Write an R function `nth_fibonnaci` that finds the nth Fibonnaci number via recursion but allows you to specify the starting number. For instance, if the sequency started at 1, you get the familiar 1, 1, 2, 3, 5, etc. But if it started at 0.01, you would get 0.01, 0.01, 0.02, 0.03, 0.05, etc.

```
nth_fibonacci <- function(n, start) {

  if (n == 1 | n == 2)
    return(start)
  else
    return(nth_fibonacci(n-1, start) + nth_fibonacci(n-2, start))

}
```

Write an Rcpp function `nth_fibonnacci_cpp` that does the same thing. Use an IDE if ou want, but write it below in-line.

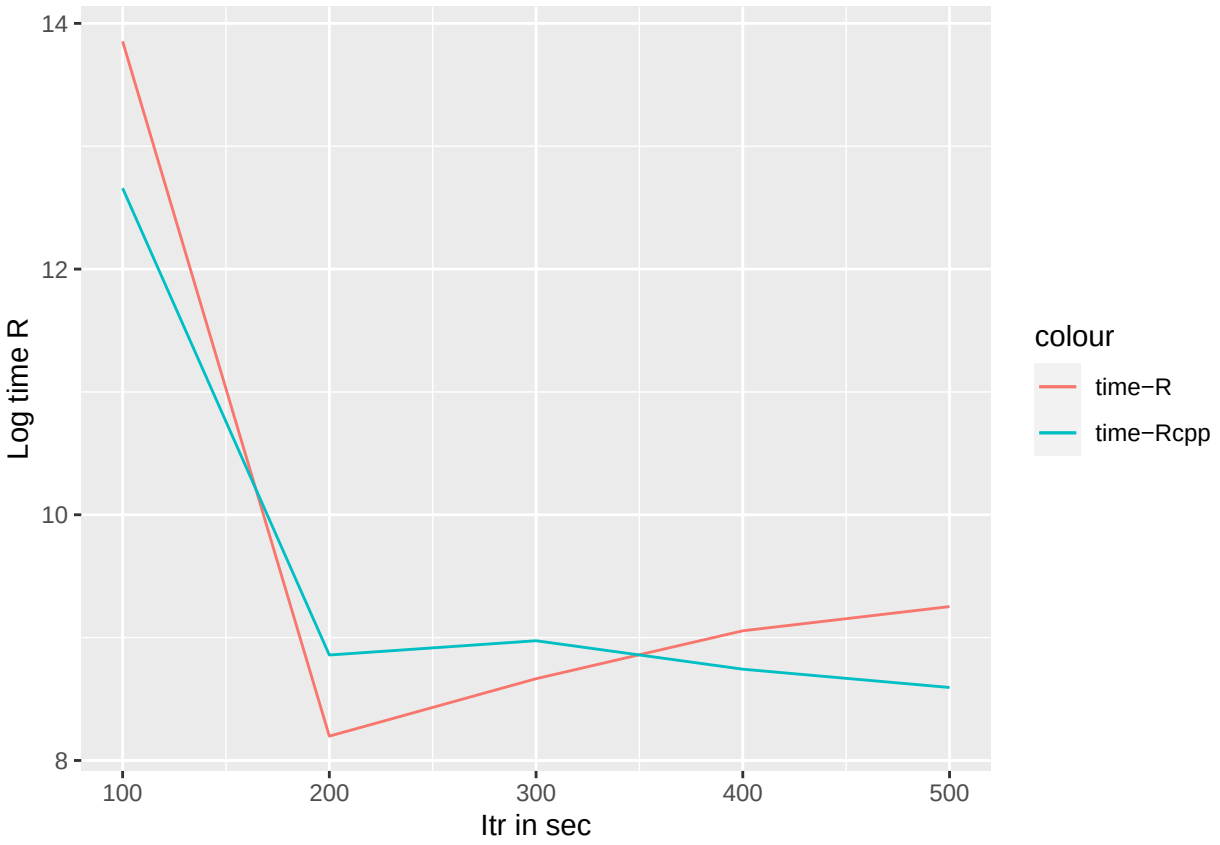
```
cppFunction("
  double nth_fibonnaci_cpp(int n, double start) {
     if (n - 1 <= 1)
        return start;
     return nth_fibonnaci_cpp(n-1, start) + nth_fibonnaci_cpp(n-2, start);
  }
")
```

Time the difference in these functions for n = 100, 200, ..., 1500 while starting the sequence at the smallest possible floating point value in R. Store the results in a matrix.

```
n <- 1000
Nvec <- c(100, 200, 300, 400, 500)

time_for_R <- c()

time_for_cpp <- c()

for (i in 1:length(Nvec)){
  X <- c()

  for (j in 1:n) {
    X <- cbind(X, rnorm(Nvec[i]))
  }

  time_for_R <- c(time_for_R, mean(microbenchmark(fib_r = nth_fibonacci(i, .Machine$double.min), times =

  time_for_cpp <- c(time_for_cpp, mean(microbenchmark(fib_cpp = nth_fibonnaci_cpp(i, .Machine$double.mi
}
```

Plot the divergence of performance (in log seconds) over n using a line geometry. Use two different colors for the R and CPP functions. Make sure there's a color legend on your plot.

```
ggplot() +
  geom_line(aes(x = Nvec, y = log(time_for_R), col = "time-R")) +
  geom_line(aes(x = Nvec, y = log(time_for_cpp), col = "time-Rcpp")) +
  xlab("Itr in sec") +
  ylab("Log time R")
```



Data Wrangling / Munging / Carpentry

Throughout this assignment you can use either the `tidyverse` package suite or `data.table` to answer but not base R. You can mix `data.table` with `magrittr` piping if you wish but don't go back and forth between `tbl_df`'s and `data.table` objects.

```
pacman::p_load(tidyverse, magrittr, data.table)
```

Load the `storms` dataset from the `dplyr` package and investigate it using `str` and `summary` and `head`. Which two columns should be converted to type factor? Do so below.

```
data(storms)
```

Reorder the columns so name is first, status is second, category is third and the rest are the same.

```
storms %>%
  select(name, status, category, everything())
```

```
## # A tibble: 10,010 x 13
##    name  status      category  year month   day  hour   lat  long  wind pressure
##    <chr> <chr>       <ord>    <dbl> <dbl> <int> <dbl> <dbl> <dbl> <int>    <int>
##  1 Amy   tropical d~ -1        1975     6    27     0  27.5 -79      25     1013
##  2 Amy   tropical d~ -1        1975     6    27     6  28.5 -79      25     1013
```

```
##  3 Amy   tropical d~ -1        1975     6    27    12  29.5 -79      25     1013
##  4 Amy   tropical d~ -1        1975     6    27    18  30.5 -79      25     1013
##  5 Amy   tropical d~ -1        1975     6    28     0  31.5 -78.8    25     1012
##  6 Amy   tropical d~ -1        1975     6    28     6  32.4 -78.7    25     1012
##  7 Amy   tropical d~ -1        1975     6    28    12  33.3 -78      25     1011
##  8 Amy   tropical d~ -1        1975     6    28    18  34   -77      30     1006
##  9 Amy   tropical s~ 0         1975     6    29     0  34.4 -75.8    35     1004
## 10 Amy   tropical s~ 0         1975     6    29     6  34   -74.8    40     1002
## # ... with 10,000 more rows, and 2 more variables: ts_diameter <dbl>,
## #   hu_diameter <dbl>
```

Find a subset of the data of storms only in the 1970's.

```
storms %>%
  filter(year >= 1970 & year <= 1979)
```

```
## # A tibble: 546 x 13
##    name   year month   day  hour   lat  long status      category  wind pressure
##    <chr> <dbl> <dbl> <int> <dbl> <dbl> <dbl> <chr>       <ord>    <int>    <int>
##  1 Amy    1975     6    27     0  27.5 -79   tropical d~ -1          25     1013
##  2 Amy    1975     6    27     6  28.5 -79   tropical d~ -1          25     1013
##  3 Amy    1975     6    27    12  29.5 -79   tropical d~ -1          25     1013
##  4 Amy    1975     6    27    18  30.5 -79   tropical d~ -1          25     1013
##  5 Amy    1975     6    28     0  31.5 -78.8 tropical d~ -1          25     1012
##  6 Amy    1975     6    28     6  32.4 -78.7 tropical d~ -1          25     1012
##  7 Amy    1975     6    28    12  33.3 -78   tropical d~ -1          25     1011
##  8 Amy    1975     6    28    18  34   -77   tropical d~ -1          30     1006
##  9 Amy    1975     6    29     0  34.4 -75.8 tropical s~ 0           35     1004
## 10 Amy    1975     6    29     6  34   -74.8 tropical s~ 0           40     1002
## # ... with 536 more rows, and 2 more variables: ts_diameter <dbl>,
## #   hu_diameter <dbl>
```

Find a subset of the data of storm observations only with category 4 and above and wind speed 100MPH and above.

```
storms %>%
  filter(category >= 4 & wind >= 100)
```

```
## # A tibble: 416 x 13
##    name   year month   day  hour   lat  long status    category  wind pressure
##    <chr> <dbl> <dbl> <int> <dbl> <dbl> <dbl> <chr>     <ord>    <int>    <int>
##  1 Anita  1977     9     2     0  24.6 -96.2 hurricane 5          140      931
##  2 Anita  1977     9     2     6  24.2 -97.1 hurricane 5          150      926
##  3 Anita  1977     9     2    12  23.7 -98   hurricane 4          120      940
##  4 David  1979     8    28     0  12.2 -52.9 hurricane 4          115      947
##  5 David  1979     8    28     6  12.5 -54.4 hurricane 4          125      941
##  6 David  1979     8    28    12  12.8 -55.7 hurricane 4          130      938
##  7 David  1979     8    28    18  13.2 -56.9 hurricane 4          125      941
##  8 David  1979     8    29     0  13.7 -58   hurricane 4          120      944
##  9 David  1979     8    29     6  14.2 -59.2 hurricane 4          120      942
## 10 David  1979     8    29    12  14.8 -60.3 hurricane 4          125      938
## # ... with 406 more rows, and 2 more variables: ts_diameter <dbl>,
## #   hu_diameter <dbl>
```

Create a new feature `wind_speed_per_unit_pressure`.

```
storms %>%
  mutate(wind_speed_per_unit_pressure = wind / pressure)
```

```
## # A tibble: 10,010 x 14
##    name   year month   day  hour   lat  long status      category  wind pressure
##    <chr> <dbl> <dbl> <int> <dbl> <dbl> <dbl> <chr>       <ord>    <int>    <int>
##  1 Amy    1975     6    27     0  27.5 -79   tropical d~ -1          25     1013
##  2 Amy    1975     6    27     6  28.5 -79   tropical d~ -1          25     1013
##  3 Amy    1975     6    27    12  29.5 -79   tropical d~ -1          25     1013
##  4 Amy    1975     6    27    18  30.5 -79   tropical d~ -1          25     1013
##  5 Amy    1975     6    28     0  31.5 -78.8 tropical d~ -1          25     1012
##  6 Amy    1975     6    28     6  32.4 -78.7 tropical d~ -1          25     1012
##  7 Amy    1975     6    28    12  33.3 -78   tropical d~ -1          25     1011
##  8 Amy    1975     6    28    18  34   -77   tropical d~ -1          30     1006
##  9 Amy    1975     6    29     0  34.4 -75.8 tropical s~ 0           35     1004
## 10 Amy    1975     6    29     6  34   -74.8 tropical s~ 0           40     1002
## # ... with 10,000 more rows, and 3 more variables: ts_diameter <dbl>,
## #   hu_diameter <dbl>, wind_speed_per_unit_pressure <dbl>
```

Create a new feature: `average_diameter` which averages the two diameter metrics. If one is missing, then use the value of the one that is present. If both are missing, leave missing.

```
storms%>%
  rowwise() %>%
  arrange(desc(year)) %>%
  mutate(average_diameter = mean(c(ts_diameter, hu_diameter), na.rm = TRUE))
```

```
## # A tibble: 10,010 x 14
## # Rowwise:
##    name   year month   day  hour   lat  long status      category  wind pressure
##    <chr> <dbl> <dbl> <int> <dbl> <dbl> <dbl> <chr>       <ord>    <int>    <int>
##  1 Ana    2015     5     9     6  32.2 -77.5 tropical s~ 0           50      998
##  2 Ana    2015     5     9    12  32.5 -77.8 tropical s~ 0           50     1001
##  3 Ana    2015     5     9    18  32.7 -78   tropical s~ 0           45     1001
##  4 Ana    2015     5    10     0  33.1 -78.3 tropical s~ 0           45     1001
##  5 Ana    2015     5    10     6  33.5 -78.6 tropical s~ 0           40     1002
##  6 Ana    2015     5    10    10  33.8 -78.8 tropical s~ 0           40     1002
##  7 Ana    2015     5    10    12  33.9 -78.8 tropical s~ 0           35     1002
##  8 Ana    2015     5    10    18  34.3 -78.7 tropical d~ -1          30     1006
##  9 Ana    2015     5    11     0  34.7 -78.5 tropical d~ -1          30     1009
## 10 Ana    2015     5    11     6  35.5 -78   tropical d~ -1          30     1010
## # ... with 10,000 more rows, and 3 more variables: ts_diameter <dbl>,
## #   hu_diameter <dbl>, average_diameter <dbl>
```

For each storm, summarize the maximum wind speed. "Summarize" means create a new dataframe with only the summary metrics you care about.

```
storms %>%
  group_by(name) %>%
  summarise(max_wind_speed = max(wind, na.rm = TRUE))
```

```
## # A tibble: 198 x 2
##    name     max_wind_speed
##  * <chr>             <int>
##  1 AL011993             30
##  2 AL012000             25
##  3 AL021992             30
##  4 AL021994             30
##  5 AL021999             30
##  6 AL022000             30
##  7 AL022001             25
##  8 AL022003             30
##  9 AL022006             45
## 10 AL031987             40
## # ... with 188 more rows
```

Order your dataset by maximum wind speed storm but within the rows of storm show the observations in time order from early to late.

```
storms %>%
 group_by(name) %>%
  mutate(max_wind_storm = max(wind, na.rm = TRUE)) %>%
  select(name, max_wind_storm, everything()) %>%
  arrange(max_wind_storm, year, day, hour)
```

```
## # A tibble: 10,010 x 14
## # Groups:   name [198]
##    name   max_wind_storm  year month   day  hour   lat  long status     category
##    <chr>           <int> <dbl> <dbl> <int> <dbl> <dbl> <dbl> <chr>      <ord>
##  1 AL101~             25  1991    10    24    12  13.4 -42.3 tropical ~ -1
##  2 AL101~             25  1991    10    24    18  13.7 -43.6 tropical ~ -1
##  3 AL101~             25  1991    10    25     0  13.8 -44.9 tropical ~ -1
##  4 AL101~             25  1991    10    25     6  14   -46.4 tropical ~ -1
##  5 AL101~             25  1991    10    25    12  14.1 -47.7 tropical ~ -1
##  6 AL012~             25  2000     6     7    18  21   -93   tropical ~ -1
##  7 AL012~             25  2000     6     8     0  20.9 -92.8 tropical ~ -1
##  8 AL012~             25  2000     6     8     6  20.7 -93.1 tropical ~ -1
##  9 AL012~             25  2000     6     8    12  20.8 -93.5 tropical ~ -1
## 10 AL022~             25  2001     7    11    18  10.9 -42.1 tropical ~ -1
## # ... with 10,000 more rows, and 4 more variables: wind <int>, pressure <int>,
## #   ts_diameter <dbl>, hu_diameter <dbl>
```

Find the strongest storm by wind speed per year.

```
storms %>%
  group_by(year) %>%
  arrange(desc(wind)) %>%
  slice(1) %>% #Take the first row
  select(name, year)
```

```
## # A tibble: 41 x 2
## # Groups:   year [41]
##    name      year
```

```
##    <chr>    <dbl>
##  1 Caroline  1975
##  2 Belle     1976
##  3 Anita     1977
##  4 Cora      1978
##  5 David     1979
##  6 Ivan      1980
##  7 Harvey    1981
##  8 Debby     1982
##  9 Alicia    1983
## 10 Diana     1984
## # ... with 31 more rows
```

For each named storm, find its maximum category, wind speed, pressure and diameters. Do not allow the max to be NA (unless all the measurements for that storm were NA).

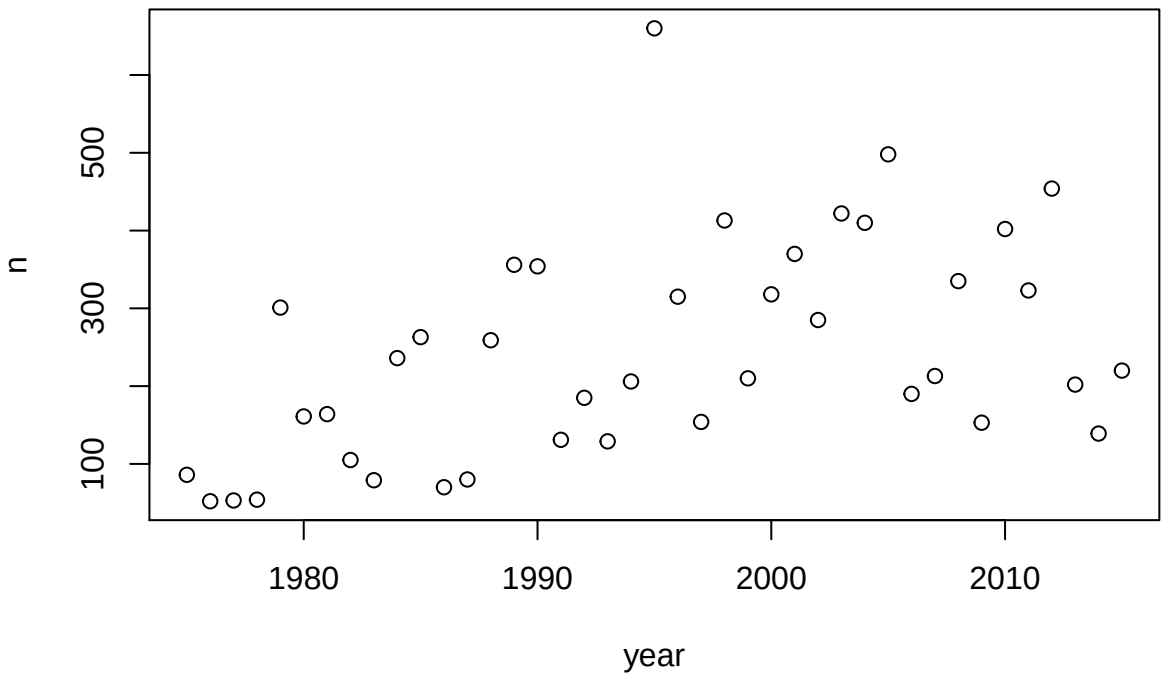
```
storms %>%
  group_by(name) %>%
  mutate(max_wind_speed = max(wind, na.rm = TRUE)) %>%
  mutate(max_pressure = max(pressure, na.rm = TRUE)) %>%
  mutate(max_hu_diameter = max(hu_diameter, na.rm = TRUE)) %>%
  mutate(max_ts_diameter = max(ts_diameter, na.rm = TRUE)) %>%
  select(max_pressure, max_wind_speed,  max_ts_diameter,max_hu_diameter) %>%
  ungroup() %>%
  distinct
```

```
## Adding missing grouping variables: `name`
```

```
## # A tibble: 198 x 5
##    name     max_pressure max_wind_speed max_ts_diameter max_hu_diameter
##    <chr>           <int>          <int>           <dbl>           <dbl>
##  1 Amy              1013             60            -Inf            -Inf
##  2 Caroline         1014            100            -Inf            -Inf
##  3 Doris            1005             95            -Inf            -Inf
##  4 Belle            1012            105            -Inf            -Inf
##  5 Gloria           1009            125            -Inf            -Inf
##  6 Anita            1012            150            -Inf            -Inf
##  7 Clara            1015             65            -Inf            -Inf
##  8 Evelyn           1010             70            -Inf            -Inf
##  9 Amelia           1010             45            -Inf            -Inf
## 10 Bess             1012             45            -Inf            -Inf
## # ... with 188 more rows
```

For each year in the dataset, tally the number of storms. "Tally" is a fancy word for "count the number of". Plot the number of storms by year. Any pattern?

```
#data(storms)

storms %>%
  group_by(year) %>%
  tally() %>%
  plot
```



For each year in the dataset, tally the storms by category.

```
storms %>%
  group_by(year,category) %>%
  summarise(tally = n())
```

```
## `summarise()` has grouped output by 'year'. You can override using the `.groups` argument.
```

```
## # A tibble: 233 x 3
## # Groups:   year [41]
##     year category tally
##    <dbl> <ord>    <int>
##  1  1975 -1          30
##  2  1975 0           33
##  3  1975 1           12
##  4  1975 2            9
##  5  1975 3            2
##  6  1976 -1          10
##  7  1976 0           20
##  8  1976 1           10
##  9  1976 2            9
## 10  1976 3            3
## # ... with 223 more rows
```

For each year in the dataset, find the maximum wind speed per status level.

```
storms %>%
  group_by(year, status) %>%
  summarise(max_wind_speed = max(wind))
```

```
## `summarise()` has grouped output by 'year'. You can override using the `.groups` argument.
```

```
## # A tibble: 123 x 3
## # Groups:   year [41]
##     year status              max_wind_speed
##    <dbl> <chr>                        <int>
##  1  1975 hurricane                      100
##  2  1975 tropical depression             30
##  3  1975 tropical storm                  60
##  4  1976 hurricane                      105
##  5  1976 tropical depression             30
##  6  1976 tropical storm                  60
##  7  1977 hurricane                      150
##  8  1977 tropical depression             30
##  9  1977 tropical storm                  60
## 10  1978 hurricane                       80
## # ... with 113 more rows
```

For each storm, summarize its average location in latitude / longitude coordinates.

```
storms %>%
  group_by(name) %>%
  summarize(average_latitude = mean(lat), avrage_longitude = mean(long))
```

```
## # A tibble: 198 x 3
##    name     average_latitude avrage_longitude
##  * <chr>               <dbl>            <dbl>
##  1 AL011993             24.7             -78.0
##  2 AL012000             20.8             -93.1
##  3 AL021992             26.7             -84.5
##  4 AL021994             33.6             -79.7
##  5 AL021999             20.4             -96.4
##  6 AL022000              9.9             -28.5
##  7 AL022001             11.9             -45.3
##  8 AL022003              9.62            -43.4
##  9 AL022006             41.3             -63.5
## 10 AL031987             30.8             -88.7
## # ... with 188 more rows
```

For each storm, summarize its duration in number of hours (to the nearest 6hr increment).

```
storms %>%
  group_by(name) %>%
  mutate(duration = (n()-1)*6) %>%
  summarise(neareast_6hr_increment = (round((n()-1)*6/6) * 6)) %>%
  distinct
```

```
## # A tibble: 198 x 2
##    name     neareast_6hr_increment
##    <chr>                     <dbl>
##  1 AL011993                     42
##  2 AL012000                     18
##  3 AL021992                     24
##  4 AL021994                     30
##  5 AL021999                     18
##  6 AL022000                     66
##  7 AL022001                     24
##  8 AL022003                     18
##  9 AL022006                     24
## 10 AL031987                    186
## # ... with 188 more rows
```

For storm in a category, create a variable `storm_number` that enumerates the storms 1, 2, … (in date order).

```
storms %>%
  group_by(name) %>%
  mutate(storm_number = dense_rank(paste(year, month, day)))
```

```
## # A tibble: 10,010 x 14
## # Groups:   name [198]
##    name   year month   day  hour   lat  long status      category  wind pressure
##    <chr> <dbl> <dbl> <int> <dbl> <dbl> <dbl> <chr>       <ord>    <int>    <int>
##  1 Amy    1975     6    27     0  27.5 -79   tropical d~ -1          25     1013
##  2 Amy    1975     6    27     6  28.5 -79   tropical d~ -1          25     1013
##  3 Amy    1975     6    27    12  29.5 -79   tropical d~ -1          25     1013
##  4 Amy    1975     6    27    18  30.5 -79   tropical d~ -1          25     1013
##  5 Amy    1975     6    28     0  31.5 -78.8 tropical d~ -1          25     1012
##  6 Amy    1975     6    28     6  32.4 -78.7 tropical d~ -1          25     1012
##  7 Amy    1975     6    28    12  33.3 -78   tropical d~ -1          25     1011
##  8 Amy    1975     6    28    18  34   -77   tropical d~ -1          30     1006
##  9 Amy    1975     6    29     0  34.4 -75.8 tropical s~ 0           35     1004
## 10 Amy    1975     6    29     6  34   -74.8 tropical s~ 0           40     1002
## # ... with 10,000 more rows, and 3 more variables: ts_diameter <dbl>,
## #   hu_diameter <dbl>, storm_number <int>
```

Convert year, month, day, hour into the variable `timestamp` using the `lubridate` package. Although the new package `clock` just came out, `lubridate` still seems to be standard. Next year I'll probably switch the class to be using `clock`.

```
pacman::p_load(lubridate)

storms %>%
  mutate(timestamp = make_datetime(year, month, day, hour)) %>%
  select(timestamp, everything())
```

```
## # A tibble: 10,010 x 14
##    timestamp           name   year month   day  hour   lat  long status category
##    <dttm>              <chr> <dbl> <dbl> <int> <dbl> <dbl> <dbl> <chr>  <ord>
##  1 1975-06-27 00:00:00 Amy    1975     6    27     0  27.5 -79   tropi~ -1
```

```
##  2 1975-06-27 06:00:00 Amy    1975     6    27     6  28.5 -79   tropi~ -1
##  3 1975-06-27 12:00:00 Amy    1975     6    27    12  29.5 -79   tropi~ -1
##  4 1975-06-27 18:00:00 Amy    1975     6    27    18  30.5 -79   tropi~ -1
##  5 1975-06-28 00:00:00 Amy    1975     6    28     0  31.5 -78.8 tropi~ -1
##  6 1975-06-28 06:00:00 Amy    1975     6    28     6  32.4 -78.7 tropi~ -1
##  7 1975-06-28 12:00:00 Amy    1975     6    28    12  33.3 -78   tropi~ -1
##  8 1975-06-28 18:00:00 Amy    1975     6    28    18  34   -77   tropi~ -1
##  9 1975-06-29 00:00:00 Amy    1975     6    29     0  34.4 -75.8 tropi~ 0
## 10 1975-06-29 06:00:00 Amy    1975     6    29     6  34   -74.8 tropi~ 0
## # ... with 10,000 more rows, and 4 more variables: wind <int>, pressure <int>,
## #   ts_diameter <dbl>, hu_diameter <dbl>
```

Using the `lubridate` package, create new variables `day_of_week` which is a factor with levels "Sunday", "Monday", ... "Saturday" and `week_of_year` which is integer 1, 2, ..., 52.

```
storms %>%
  mutate(timestamp = make_datetime(year, month, day),
    day_of_the_week = wday(ymd(timestamp), label = TRUE, abbr = FALSE),
    week_of_year = week(ymd(timestamp))
  )
```

```
## # A tibble: 10,010 x 16
##    name   year month   day  hour   lat  long status      category  wind pressure
##    <chr> <dbl> <dbl> <int> <dbl> <dbl> <dbl> <chr>       <ord>    <int>    <int>
##  1 Amy    1975     6    27     0  27.5 -79   tropical d~ -1          25     1013
##  2 Amy    1975     6    27     6  28.5 -79   tropical d~ -1          25     1013
##  3 Amy    1975     6    27    12  29.5 -79   tropical d~ -1          25     1013
##  4 Amy    1975     6    27    18  30.5 -79   tropical d~ -1          25     1013
##  5 Amy    1975     6    28     0  31.5 -78.8 tropical d~ -1          25     1012
##  6 Amy    1975     6    28     6  32.4 -78.7 tropical d~ -1          25     1012
##  7 Amy    1975     6    28    12  33.3 -78   tropical d~ -1          25     1011
##  8 Amy    1975     6    28    18  34   -77   tropical d~ -1          30     1006
##  9 Amy    1975     6    29     0  34.4 -75.8 tropical s~ 0           35     1004
## 10 Amy    1975     6    29     6  34   -74.8 tropical s~ 0           40     1002
## # ... with 10,000 more rows, and 5 more variables: ts_diameter <dbl>,
## #   hu_diameter <dbl>, timestamp <dttm>, day_of_the_week <ord>,
## #   week_of_year <dbl>
```

For each storm, summarize the day in which is started in the following format "Friday, June 27, 1975".

```
storms %>%
  group_by(name) %>%
  arrange(day, hour) %>%
  slice(1) %>%
  mutate(timestamp = make_datetime(year, month, day),
    day_of_week = wday(ymd(timestamp), label = TRUE, abbr = FALSE)
  ) %>%
  summarize(
    start_date = paste(day_of_week,
                       paste(
                         month(
                           month,
                           label = TRUE,
```

```
                          abbr = FALSE),
                        day),
    year,
    sep = ", ")
  )
```

```
## # A tibble: 198 x 2
##    name     start_date
##    <chr>    <chr>
##  1 AL011993 Tuesday, June 1, 1993
##  2 AL012000 Wednesday, June 7, 2000
##  3 AL021992 Thursday, June 25, 1992
##  4 AL021994 Wednesday, July 20, 1994
##  5 AL021999 Friday, July 2, 1999
##  6 AL022000 Friday, June 23, 2000
##  7 AL022001 Wednesday, July 11, 2001
##  8 AL022003 Wednesday, June 11, 2003
##  9 AL022006 Monday, July 17, 2006
## 10 AL031987 Sunday, August 9, 1987
## # ... with 188 more rows
```

Create a new factor variable `decile_windspeed` by binning wind speed into 10 bins.

```
x = (1:10) / 10

storms <- storms %>%
  mutate(decile_windspeed = cut(wind, quantile(wind, x), labels =FALSE))

storms
```

```
## # A tibble: 10,010 x 14
##    name   year month   day  hour   lat  long status      category  wind pressure
##    <chr> <dbl> <dbl> <int> <dbl> <dbl> <dbl> <chr>       <ord>    <int>    <int>
##  1 Amy    1975     6    27     0  27.5 -79   tropical d~ -1          25     1013
##  2 Amy    1975     6    27     6  28.5 -79   tropical d~ -1          25     1013
##  3 Amy    1975     6    27    12  29.5 -79   tropical d~ -1          25     1013
##  4 Amy    1975     6    27    18  30.5 -79   tropical d~ -1          25     1013
##  5 Amy    1975     6    28     0  31.5 -78.8 tropical d~ -1          25     1012
##  6 Amy    1975     6    28     6  32.4 -78.7 tropical d~ -1          25     1012
##  7 Amy    1975     6    28    12  33.3 -78   tropical d~ -1          25     1011
##  8 Amy    1975     6    28    18  34   -77   tropical d~ -1          30     1006
##  9 Amy    1975     6    29     0  34.4 -75.8 tropical s~ 0           35     1004
## 10 Amy    1975     6    29     6  34   -74.8 tropical s~ 0           40     1002
## # ... with 10,000 more rows, and 3 more variables: ts_diameter <dbl>,
## #   hu_diameter <dbl>, decile_windspeed <int>
```

Create a new data frame `serious_storms` which are category 3 and above hurricanes.

```
serious_storms <- storms %>%
  filter(category >= 3)

serious_storms
```

```
## # A tibble: 779 x 14
##    name      year month   day  hour   lat  long status   category  wind pressure
##    <chr>    <dbl> <dbl> <int> <dbl> <dbl> <dbl> <chr>    <ord>    <int>    <int>
##  1 Caroline  1975     8    31     0  24   -97   hurrica~ 3          100      973
##  2 Caroline  1975     8    31     6  24.1 -97.5 hurrica~ 3          100      963
##  3 Belle     1976     8     8    18  29.5 -75.3 hurrica~ 3          100      958
##  4 Belle     1976     8     9     0  30.9 -75.3 hurrica~ 3          105      957
##  5 Belle     1976     8     9     6  32.5 -75.2 hurrica~ 3          105      959
##  6 Anita     1977     9     1    18  25.2 -95.5 hurrica~ 3          110      945
##  7 Anita     1977     9     2     0  24.6 -96.2 hurrica~ 5          140      931
##  8 Anita     1977     9     2     6  24.2 -97.1 hurrica~ 5          150      926
##  9 Anita     1977     9     2    12  23.7 -98   hurrica~ 4          120      940
## 10 David     1979     8    28     0  12.2 -52.9 hurrica~ 4          115      947
## # ... with 769 more rows, and 3 more variables: ts_diameter <dbl>,
## #   hu_diameter <dbl>, decile_windspeed <int>
```

In `serious_storms`, merge the variables lat and long together into `lat_long` with values `lat / long` as a string.

```
serious_storms %>%
  unite(lat_long, lat, long, sep=" / ")
```

```
## # A tibble: 779 x 13
##    name      year month   day  hour lat_long    status   category  wind pressure
##    <chr>    <dbl> <dbl> <int> <dbl> <chr>       <chr>    <ord>    <int>    <int>
##  1 Caroline  1975     8    31     0 24 / -97    hurrica~ 3          100      973
##  2 Caroline  1975     8    31     6 24.1 / -97~ hurrica~ 3          100      963
##  3 Belle     1976     8     8    18 29.5 / -75~ hurrica~ 3          100      958
##  4 Belle     1976     8     9     0 30.9 / -75~ hurrica~ 3          105      957
##  5 Belle     1976     8     9     6 32.5 / -75~ hurrica~ 3          105      959
##  6 Anita     1977     9     1    18 25.2 / -95~ hurrica~ 3          110      945
##  7 Anita     1977     9     2     0 24.6 / -96~ hurrica~ 5          140      931
##  8 Anita     1977     9     2     6 24.2 / -97~ hurrica~ 5          150      926
##  9 Anita     1977     9     2    12 23.7 / -98  hurrica~ 4          120      940
## 10 David     1979     8    28     0 12.2 / -52~ hurrica~ 4          115      947
## # ... with 769 more rows, and 3 more variables: ts_diameter <dbl>,
## #   hu_diameter <dbl>, decile_windspeed <int>
```

Let's return now to the original storms data frame. For each category, find the average wind speed, pressure and diameters (do not count the NA's in your averaging).

```
storms %>%
  group_by(category) %>%
  summarize(
    avg_wind_speed = mean(wind, na.rm = TRUE),
    avg_pressure = mean(pressure, na.rm = TRUE),
    avg_ts_diameter = mean(ts_diameter, na.rm = TRUE),
    avg_hu_diameter = mean(hu_diameter, na.rm = TRUE)
  )
```

```
## # A tibble: 7 x 5
##   category avg_wind_speed avg_pressure avg_ts_diameter avg_hu_diameter
```

```
## * <ord>             <dbl>        <dbl>           <dbl>           <dbl>
## 1 -1                27.3        1008.              0              0
## 2 0                 45.8         999.            160.             0
## 3 1                 70.9         982.            278.            57.3
## 4 2                 89.4         967.            282.            78.8
## 5 3                105.          954.            307.            91.4
## 6 4                122.          940.            315.           102.
## 7 5                145.          916.            317.           120.
```

For each named storm, find its maximum category, wind speed, pressure and diameters (do not allow the max to be NA) and the number of readings (i.e. observations).

```
storms <- storms %>%
  filter(!is.na(ts_diameter), !is.na(hu_diameter)) %>%
  group_by(name) %>%
  mutate(
    max_category = max(category),
    max_wind = max(wind),
    max_pressure = max(pressure),
    max_ts_diameter = max(ts_diameter),
    max_hu_diameter = max(hu_diameter)
  ) %>%
  ungroup()

storms
```

```
## # A tibble: 3,482 x 19
##    name   year month   day  hour   lat  long status      category  wind pressure
##    <chr> <dbl> <dbl> <int> <dbl> <dbl> <dbl> <chr>       <ord>    <int>    <int>
##  1 Alex   2004     7    31    18  30.3 -78.3 tropical d~ -1          25     1010
##  2 Alex   2004     8     1     0  31   -78.8 tropical d~ -1          25     1009
##  3 Alex   2004     8     1     6  31.5 -79   tropical d~ -1          25     1009
##  4 Alex   2004     8     1    12  31.6 -79.1 tropical d~ -1          30     1009
##  5 Alex   2004     8     1    18  31.6 -79.2 tropical s~ 0           35     1009
##  6 Alex   2004     8     2     0  31.5 -79.3 tropical s~ 0           35     1007
##  7 Alex   2004     8     2     6  31.4 -79.4 tropical s~ 0           40     1005
##  8 Alex   2004     8     2    12  31.3 -79   tropical s~ 0           50      992
##  9 Alex   2004     8     2    18  31.8 -78.7 tropical s~ 0           50      993
## 10 Alex   2004     8     3     0  32.4 -78.2 tropical s~ 0           60      987
## # ... with 3,472 more rows, and 8 more variables: ts_diameter <dbl>,
## #   hu_diameter <dbl>, decile_windspeed <int>, max_category <ord>,
## #   max_wind <int>, max_pressure <int>, max_ts_diameter <dbl>,
## #   max_hu_diameter <dbl>
```

Calculate the distance from each storm observation to Miami in a new variable `distance_to_miami`. This is very challenging. You will need a function that computes distances from two sets of latitude / longitude coordinates.

```
MIAMI_LAT_LONG_COORDS = c(25.7617, -80.1918)

distance_to_miami <- function(lat1, long1, lat2, long2) {

  #Conversion for angles
```

```
  lat1 = lat1 * 180/pi

  lat2 = lat2 * 180/pi

  long1 = long1 * 180/pi

  long2 = long2 * 180/pi


  #https://en.wikipedia.org/wiki/Haversine_formula
  a = sin(lat2 - lat1 / 2)^2 + (cos(lat2) * cos(lat1)) * sin(long2 - long1 / 2) ^ 2
  b = 2 * atan2(sqrt(a), sqrt(1 - a))

  distance = 6373.0 * b

  return(distance)
}

storms <- storms %>%
  mutate(distance_to_miami = distance_to_miami(lat, long, MIAMI_LAT_LONG_COORDS[1], MIAMI_LAT_LONG_COORD

storms
```

```
## # A tibble: 3,482 x 20
##    name   year month   day  hour   lat  long status      category  wind pressure
##    <chr> <dbl> <dbl> <int> <dbl> <dbl> <dbl> <chr>       <ord>    <int>    <int>
##  1 Alex   2004     7    31    18  30.3 -78.3 tropical d~ -1          25     1010
##  2 Alex   2004     8     1     0  31   -78.8 tropical d~ -1          25     1009
##  3 Alex   2004     8     1     6  31.5 -79   tropical d~ -1          25     1009
##  4 Alex   2004     8     1    12  31.6 -79.1 tropical d~ -1          30     1009
##  5 Alex   2004     8     1    18  31.6 -79.2 tropical s~ 0           35     1009
##  6 Alex   2004     8     2     0  31.5 -79.3 tropical s~ 0           35     1007
##  7 Alex   2004     8     2     6  31.4 -79.4 tropical s~ 0           40     1005
##  8 Alex   2004     8     2    12  31.3 -79   tropical s~ 0           50      992
##  9 Alex   2004     8     2    18  31.8 -78.7 tropical s~ 0           50      993
## 10 Alex   2004     8     3     0  32.4 -78.2 tropical s~ 0           60      987
## # ... with 3,472 more rows, and 9 more variables: ts_diameter <dbl>,
## #   hu_diameter <dbl>, decile_windspeed <int>, max_category <ord>,
## #   max_wind <int>, max_pressure <int>, max_ts_diameter <dbl>,
## #   max_hu_diameter <dbl>, distance_to_miami <dbl>
```

For each storm observation, use the function from the previous question to calculate the distance it moved since the previous observation.

```
storms <- storms %>%
  group_by(name) %>%
  mutate(dist_from_prev = ifelse(name != lag(name), 0, distance_to_miami(lat, long, lag(lat), lag(long)
  mutate(dist_from_prev = ifelse(is.na(dist_from_prev), 0, dist_from_prev))

storms
```

```
## # A tibble: 3,482 x 21
## # Groups:   name [114]
```

```
##    name   year month   day  hour   lat  long status      category  wind pressure
##    <chr> <dbl> <dbl> <int> <dbl> <dbl> <dbl> <chr>       <ord>    <int>    <int>
##  1 Alex   2004     7    31    18  30.3 -78.3 tropical d~ -1          25     1010
##  2 Alex   2004     8     1     0  31   -78.8 tropical d~ -1          25     1009
##  3 Alex   2004     8     1     6  31.5 -79   tropical d~ -1          25     1009
##  4 Alex   2004     8     1    12  31.6 -79.1 tropical d~ -1          30     1009
##  5 Alex   2004     8     1    18  31.6 -79.2 tropical s~ 0           35     1009
##  6 Alex   2004     8     2     0  31.5 -79.3 tropical s~ 0           35     1007
##  7 Alex   2004     8     2     6  31.4 -79.4 tropical s~ 0           40     1005
##  8 Alex   2004     8     2    12  31.3 -79   tropical s~ 0           50      992
##  9 Alex   2004     8     2    18  31.8 -78.7 tropical s~ 0           50      993
## 10 Alex   2004     8     3     0  32.4 -78.2 tropical s~ 0           60      987
## # ... with 3,472 more rows, and 10 more variables: ts_diameter <dbl>,
## #   hu_diameter <dbl>, decile_windspeed <int>, max_category <ord>,
## #   max_wind <int>, max_pressure <int>, max_ts_diameter <dbl>,
## #   max_hu_diameter <dbl>, distance_to_miami <dbl>, dist_from_prev <dbl>
```

For each storm, find the total distance it moved over its observations and its total displacement. "Distance" is a scalar quantity that refers to "how much ground an object has covered" during its motion. "Displacement" is a vector quantity that refers to "how far out of place an object is"; it is the object's overall change in position.

```
storms %>%
  group_by(name) %>%
  summarize(
    Distance = sum(dist_from_prev),
    Displacement = paste(round(last(lat) - first(lat), 2), round(last(long) - first(long), 2), sep = " ,
  )
```

```
## # A tibble: 114 x 3
##    name     Distance Displacement
##  * <chr>       <dbl> <chr>
##  1 AL022006   24361. 4.6 / 6.3
##  2 AL102004   36454. 4.7 / 5.4
##  3 Al202011   29375. 1.7 / 2.1
##  4 Alberto   216936. 11.5 / 8.9
##  5 Alex      389785. -7.1 / -23.6
##  6 Ana       220407. 22.6 / -48.4
##  7 Andrea     30050. 8.4 / 6.4
##  8 Arthur    204244. 24.8 / 19.9
##  9 Barry     168924. -2.7 / -11.2
## 10 Beryl     182274. 1.4 / -5.6
## # ... with 104 more rows
```

For each storm observation, calculate the average speed the storm moved in location.

```
storms <- storms %>%
  mutate(speed = dist_from_prev / 6)

storms
```

```
## # A tibble: 3,482 x 22
## # Groups:   name [114]
```

```
##    name   year month   day  hour   lat  long status      category  wind pressure
##    <chr> <dbl> <dbl> <int> <dbl> <dbl> <dbl> <chr>       <ord>    <int>    <int>
##  1 Alex   2004     7    31    18  30.3 -78.3 tropical d~ -1          25     1010
##  2 Alex   2004     8     1     0  31   -78.8 tropical d~ -1          25     1009
##  3 Alex   2004     8     1     6  31.5 -79   tropical d~ -1          25     1009
##  4 Alex   2004     8     1    12  31.6 -79.1 tropical d~ -1          30     1009
##  5 Alex   2004     8     1    18  31.6 -79.2 tropical s~ 0           35     1009
##  6 Alex   2004     8     2     0  31.5 -79.3 tropical s~ 0           35     1007
##  7 Alex   2004     8     2     6  31.4 -79.4 tropical s~ 0           40     1005
##  8 Alex   2004     8     2    12  31.3 -79   tropical s~ 0           50      992
##  9 Alex   2004     8     2    18  31.8 -78.7 tropical s~ 0           50      993
## 10 Alex   2004     8     3     0  32.4 -78.2 tropical s~ 0           60      987
## # ... with 3,472 more rows, and 11 more variables: ts_diameter <dbl>,
## #   hu_diameter <dbl>, decile_windspeed <int>, max_category <ord>,
## #   max_wind <int>, max_pressure <int>, max_ts_diameter <dbl>,
## #   max_hu_diameter <dbl>, distance_to_miami <dbl>, dist_from_prev <dbl>,
## #   speed <dbl>
```

For each storm, calculate its average ground speed (how fast its eye is moving which is different from windspeed around the eye).

```
storms %>%
  group_by(name) %>%
  summarize(avg_ground_speed = mean(speed))
```

```
## # A tibble: 114 x 2
##    name     avg_ground_speed
##  * <chr>               <dbl>
##  1 AL022006             812.
##  2 AL102004             759.
##  3 Al202011             612.
##  4 Alberto             1205.
##  5 Alex                1249.
##  6 Ana                 1361.
##  7 Andrea               556.
##  8 Arthur              1174.
##  9 Barry               1224.
## 10 Beryl               1125.
## # ... with 104 more rows
```

Is there a relationship between average ground speed and maximum category attained? Use a dataframe summary (not a regression).

```
ret <- storms %>%
  group_by(name) %>%
  summarize(avg_ground_speed = mean(speed),
    maximum_category = as.numeric(max(category))
  )

#Depict relationship
cor(ret[,2], ret[,3])
```

```
##                   maximum_category
## avg_ground_speed         0.2531993
```

Now we want to transition to building real design matrices for prediction. This is more in tune with what happens in the real world. Large data dump and you convert it into X and y how you see fit.

Suppose we wish to predict the following: given the first three readings of a storm, can you predict its maximum wind speed? Identify the `y` and identify which features you need $x_1, ...x_p$ and build that matrix with `dplyr` functions. This is not easy, but it is what it's all about. Feel free to "featurize" as creatively as you would like. You aren't going to overfit if you only build a few features relative to the total 198 storms.

```
storms2 <- storms %>%
  group_by(name) %>%
  summarize(
    y = max(wind),
    max_category = max(category),
    pressure = max(pressure),
    speed = max(speed),
    total_distance_traveled = sum(dist_from_prev),
    status = last(status)
  ) %>%
  select(-name) %>%
  ungroup()

head(storms2)
```

```
## # A tibble: 6 x 6
##       y max_category pressure speed total_distance_traveled status
##   <int> <ord>           <int> <dbl>                   <dbl> <chr>
## 1    45 0                1008 2210.                  24361. tropical storm
## 2    30 -1               1013 2907.                  36454. tropical depression
## 3    40 0                1011 1728.                  29375. tropical storm
## 4    60 0                1008 2603.                 216936. tropical storm
## 5   105 3                1010 3184.                 389785. tropical depression
## 6    50 0                1012 2672.                 220407. tropical depression
```

Fit your model. Validate it.

```
n = nrow(storms2)
K = 5 # 1/5 split
test_indices = sample(1 : n, 1 / K * n)
train_indices = setdiff(1:n, test_indices)
X = select(storms2, -y)
y = storms2$y

#Testing and training
X_test = X[test_indices,]
y_test = y[test_indices]
X_train = X[train_indices,]
y_train = y[train_indices]
model = lm(y_train ~ ., data.frame(X_train))

#In sample metrics
is_Rsq = summary(model)$r.squared
is_RMSE = sqrt(mean((model$residuals)^2))

#Out sample metrics
```

```
y_hat_oos = predict(model, data.frame(X_test))
oos_residuals = y_test - y_hat_oos
oos_Rsq = 1 - sum(oos_residuals^2) / sum((y_test - mean(y_test))^2)
oos_RMSE = sqrt(mean((oos_residuals)^2))

#Put validations in table
validations = data.frame(
  Metric = c("IS R^2:", "In SSE:", "OOS R^2:", "OOS SE:"),
  Value = c(is_Rsq, is_RMSE, oos_Rsq, oos_RMSE)
)

validations
```

```
##     Metric     Value
## 1  IS R^2: 0.9755183
## 2  In SSE: 4.9048232
## 3 OOS R^2: 0.9599224
## 4  OOS SE: 7.7903678
```

Assess your level of success at this endeavor.

We see from the sample metrics that the model can pridict the maximum speed of a storm with having a margin of up to 7. This model achieved a high out of sample R^2 when limited to using only 5 features. These metrics state that this will be a good model.

The Forward Stepwise Procedure for Probability Estimation Models

Set a seed and load the `adult` dataset and remove missingness and randomize the order.

```
set.seed(1)
pacman::p_load_gh("coatless/ucidata")
data(adult)
adult = na.omit(adult)
adult = adult[sample(1 : nrow(adult)), ]
```

Copy from the previous lab all cleanups you did to this dataset.

```
#Copied from prev lab
adult$fnlwgt = NULL
adult$marital_status = as.character(adult$marital_status)
adult$marital_status = ifelse(adult$marital_status == "Married-AF-spouse" | adult$marital_status == "Ma
adult$marital_status = as.factor(adult$marital_status)
adult$education = as.character(adult$education)
adult$education = ifelse(adult$education == "1st-4th" | adult$education == "Preschool", "<=4th", adult$
adult$education = as.factor(adult$education)
adult$education = NULL
tab = sort(table(adult$native_country))
adult$native_country = as.character(adult$native_country)
adult$native_country= ifelse(adult$native_country %in% names(tab[tab<50]), "Other", adult$native_countr
adult$native_country= as.factor(adult$native_country)
```

```
adult$worktype = paste(adult$occupation, adult$workclass, sep = ":")
tab_worktype = sort(table(adult$worktype))
adult$occupation = NULL
adult$workclass = NULL
adult$worktype = as.character(adult$worktype)
adult$worktype = ifelse(adult$worktype %in% names(tab_worktype[tab_worktype<100]), "Other", adult$workty
adult$worktype = as.factor(adult$worktype)
adult$status = paste(as.character(adult$relationship), as.character(adult$marital_status), sep = ":")
adult$status = as.character(adult$status)
tab_status = sort(table(adult$status))
adult$relationship = NULL
adult$marital_status = NULL
adult$status = as.factor(adult$status)
```

We will be doing model selection. We will split the dataset into 3 distinct subsets. Set the size of our splits here. For simplicitiy, all three splits will be identically sized. We are making it small so the stepwise algorithm can compute quickly. If you have a faster machine, feel free to increase this.

```
Nsplitsize = 1000
```

Now create the following variables: `Xtrain`, `ytrain`, `Xselect`, `yselect`, `Xtest`, `ytest` with `Nsplitsize` observations. Binarize the y values.

```
Xtrain = adult[1 : Nsplitsize, ]
Xtrain$income = NULL
ytrain = ifelse(adult[1 : Nsplitsize, "income"] == ">50K", 1, 0)
Xselect = adult[(Nsplitsize + 1) : (2 * Nsplitsize), ]
Xselect$income = NULL
yselect = ifelse(adult[(Nsplitsize + 1) : (2 * Nsplitsize), "income"] ==">50K", 1, 0)
Xtest = adult[(2 * Nsplitsize + 1) : (3 * Nsplitsize), ]
Xtest$income = NULL
ytest = ifelse(adult[(2 * Nsplitsize + 1) : (3 * Nsplitsize), "income"] == ">50K", 1, 0)
```

Fit a vanilla logistic regression on the training set.

```
logistic_mod = glm(ytrain ~ ., Xtrain, family = binomial(link = logit))
```

and report the log scoring rule, the Brier scoring rule.

```
p_hat_train = predict(logistic_mod, Xtrain, type = 'response')

#Scores log & Brier
mean(ytrain * log(p_hat_train) + (1 - ytrain) * log(1 - p_hat_train))
```

```
## [1] -0.2671121
```

```
mean(-(ytrain - p_hat_train) ^ 2)
```

```
## [1] -0.08715781
```

We will be doing model selection using a basis of linear features consisting of all first-order interactions of the 14 raw features (this will include square terms as squares are interactions with oneself).

Create a model matrix from the training data containing all these features. Make sure it has an intercept column too (the one vector is usually an important feature). Cast it as a data frame so we can use it more easily for modeling later on. We're going to need those model matrices (as data frames) for both the select and test sets. So make them here too (copy-paste). Make sure their dimensions are sensible.

```
Xmm_train = data.frame(model.matrix( ~ . , Xtrain))

Xmm_select = data.frame(model.matrix( ~ . , Xselect))

Xmm_test = data.frame(model.matrix( ~ . , Xtest))

dim(Xmm_train)
```

```
## [1] 1000   93
```

```
dim(Xmm_select)
```

```
## [1] 1000   93
```

```
dim(Xmm_test)
```

```
## [1] 1000   93
```

Write code that will fit a model stepwise. You can refer to the chunk in the practice lecture. Use the negative Brier score to do the selection. The negative of the Brier score is always positive and lower means better making this metric kind of like s_e so the picture will be the same as the canonical U-shape for oos performance.

Run the code and hit "stop" when you begin to the see the Brier score degrade appreciably oos. Be patient as it will wobble.

```
#Turn off warnings
options(warn = -1)

pacman::p_load(Matrix)
p_plus_one = ncol(Xmm_train)

#Grow list with iterations
predictor_by_iteration = c()
in_sample_brier_by_iteration = c()
oos_brier_by_iteration = c()

i = 1
repeat {

  all_briers = array(NA, p_plus_one)

  for (j_try in 1 : p_plus_one) {
```

```
    if (j_try %in% predictor_by_iteration) {

      next

    }

    sub = Xmm_train[, c(predictor_by_iteration, j_try), drop = FALSE]

    logistic_mod = (glm(ytrain ~ ., sub, family = "binomial"))

    phat_t = (predict(logistic_mod, sub, type = 'response'))

    all_briers[j_try] = -mean(-(ytrain - phat_t)^2)
  }

  j_star = which.max(all_briers)

  predictor_by_iteration = c(predictor_by_iteration, j_star)

  in_sample_brier_by_iteration = c(in_sample_brier_by_iteration, all_briers[j_star])


  sub = Xmm_train[, predictor_by_iteration, drop = FALSE]

  logistic_mod = (glm(ytrain ~ ., sub, family = "binomial"))

  phat_t = (predict(logistic_mod, sub, type = 'response'))

  all_briers[j_try] = -mean( - (ytrain - phat_t) ^ 2)

  phat_s = (predict(logistic_mod, Xmm_select[, predictor_by_iteration, drop = FALSE], type = 'response'

  oos_brier = -mean(-(yselect - phat_s)^2)

  oos_brier_by_iteration = c(oos_brier_by_iteration, oos_brier)

  cat(
    "i =", i,
    "is_brier =", all_briers[j_star],
    "oos_brier =", oos_brier,
    "predictor =", colnames(Xmm_train)[j_star],
    "\n"
  )

  i = i + 1

  if (i > Nsplitsize || i > p_plus_one){
    break
  }
}
```

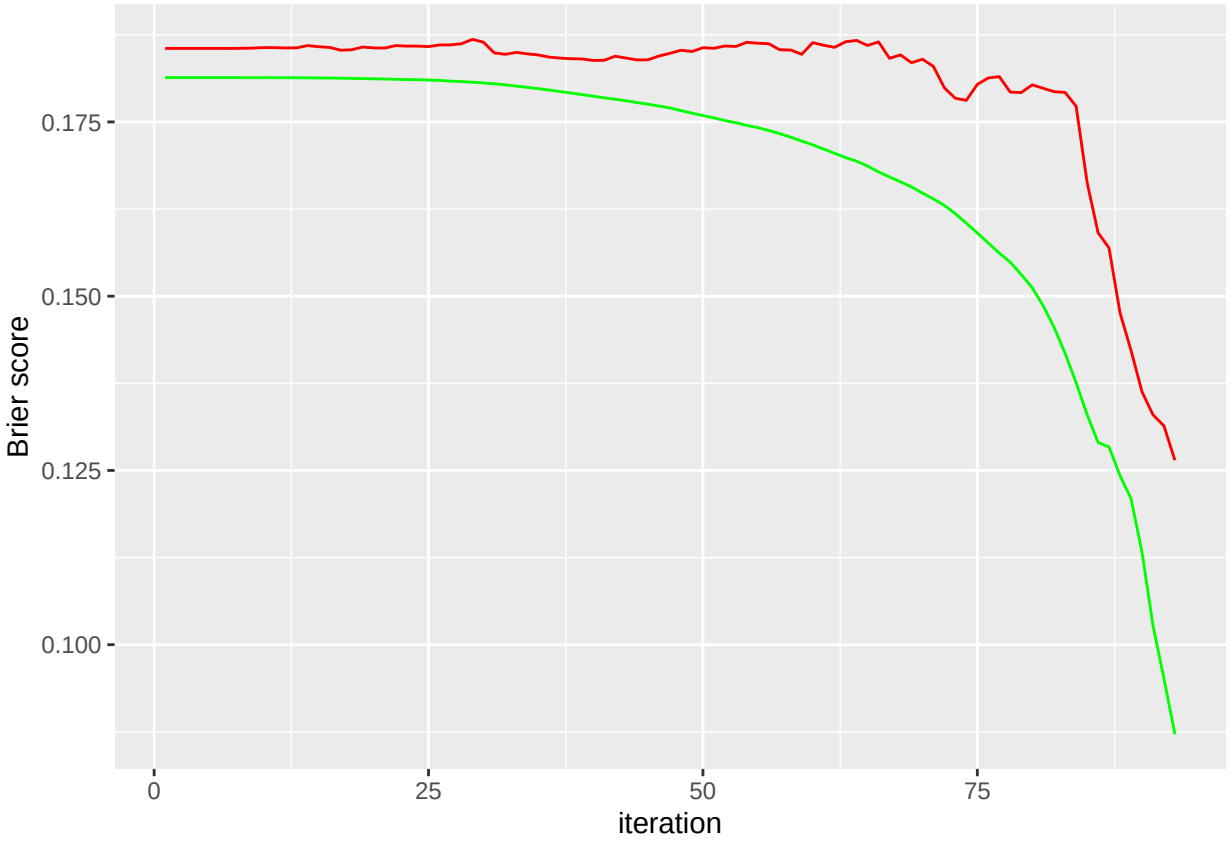
```
## i = 1 is_brier = 0.181356 oos_brier = 0.185548 predictor = X.Intercept.
## i = 2 is_brier = 0.181356 oos_brier = 0.185548 predictor = native_countryPoland
```

```
## i = 3 is_brier = 0.181356 oos_brier = 0.185548 predictor = statusNot.in.family.Married
## i = 4 is_brier = 0.181356 oos_brier = 0.185548 predictor = statusOther.relative.Separated
## i = 5 is_brier = 0.181356 oos_brier = 0.185548 predictor = statusOther.relative.Widowed
## i = 6 is_brier = 0.181356 oos_brier = 0.185548 predictor = statusOwn.child.Widowed
## i = 7 is_brier = 0.1813554 oos_brier = 0.1855417 predictor = worktypeTransport.moving.Self.emp.not.in
## i = 8 is_brier = 0.1813548 oos_brier = 0.1855661 predictor = statusUnmarried.Married.spouse.absent
## i = 9 is_brier = 0.1813542 oos_brier = 0.1855927 predictor = worktypeSales.Self.emp.not.inc
## i = 10 is_brier = 0.181353 oos_brier = 0.1856649 predictor = statusUnmarried.Widowed
## i = 11 is_brier = 0.1813499 oos_brier = 0.1856563 predictor = worktypeCraft.repair.Private
## i = 12 is_brier = 0.1813447 oos_brier = 0.1856134 predictor = native_countryIndia
## i = 13 is_brier = 0.1813373 oos_brier = 0.1856355 predictor = native_countryPuerto.Rico
## i = 14 is_brier = 0.1813246 oos_brier = 0.1859607 predictor = worktypeFarming.fishing.Private
## i = 15 is_brier = 0.1813123 oos_brier = 0.1857883 predictor = worktypeFarming.fishing.Self.emp.not.in
## i = 16 is_brier = 0.1812982 oos_brier = 0.1856838 predictor = statusNot.in.family.Separated
## i = 17 is_brier = 0.1812717 oos_brier = 0.1852927 predictor = worktypeProf.specialty.Federal.gov
## i = 18 is_brier = 0.1812449 oos_brier = 0.1853558 predictor = native_countryGuatemala
## i = 19 is_brier = 0.181218 oos_brier = 0.1857469 predictor = worktypeCraft.repair.Local.gov
## i = 20 is_brier = 0.1811902 oos_brier = 0.1856173 predictor = raceOther
## i = 21 is_brier = 0.1811586 oos_brier = 0.1855962 predictor = worktypeExec.managerial.State.gov
## i = 22 is_brier = 0.1811215 oos_brier = 0.1859505 predictor = worktypeAdm.clerical.Local.gov
## i = 23 is_brier = 0.1810644 oos_brier = 0.185881 predictor = native_countryDominican.Republic
## i = 24 is_brier = 0.1810644 oos_brier = 0.185881 predictor = statusOwn.child.Married.spouse.absent
## i = 25 is_brier = 0.1810073 oos_brier = 0.1858114 predictor = native_countryVietnam
## i = 26 is_brier = 0.1809499 oos_brier = 0.1860419 predictor = statusOwn.child.Married
## i = 27 is_brier = 0.1808553 oos_brier = 0.1860526 predictor = native_countryOther
## i = 28 is_brier = 0.1807887 oos_brier = 0.1862179 predictor = native_countryUnited.States
## i = 29 is_brier = 0.180699 oos_brier = 0.1868485 predictor = worktypeTech.support.Private
## i = 30 is_brier = 0.1805934 oos_brier = 0.1864382 predictor = worktypeOther.service.Local.gov
## i = 31 is_brier = 0.1804642 oos_brier = 0.1848996 predictor = worktypeExec.managerial.Self.emp.inc
## i = 32 is_brier = 0.1803137 oos_brier = 0.1846994 predictor = native_countryJapan
## i = 33 is_brier = 0.1801419 oos_brier = 0.1849772 predictor = worktypeProtective.serv.State.gov
## i = 34 is_brier = 0.1799592 oos_brier = 0.1847671 predictor = statusOther.relative.Divorced
## i = 35 is_brier = 0.179768 oos_brier = 0.1846089 predictor = worktypeProtective.serv.Private
## i = 36 is_brier = 0.1795723 oos_brier = 0.1842935 predictor = worktypeProf.specialty.Local.gov
## i = 37 is_brier = 0.179356 oos_brier = 0.1841564 predictor = native_countryChina
## i = 38 is_brier = 0.1791469 oos_brier = 0.1840683 predictor = native_countryColumbia
## i = 39 is_brier = 0.1789191 oos_brier = 0.1840311 predictor = worktypeOther.service.State.gov
## i = 40 is_brier = 0.1786884 oos_brier = 0.1838212 predictor = statusOwn.child.Divorced
## i = 41 is_brier = 0.1784501 oos_brier = 0.1838435 predictor = native_countryEl.Salvador
## i = 42 is_brier = 0.1782627 oos_brier = 0.1844303 predictor = statusOther.relative.Married.spouse.abs
## i = 43 is_brier = 0.1780273 oos_brier = 0.1841625 predictor = worktypeTransport.moving.Local.gov
## i = 44 is_brier = 0.1777802 oos_brier = 0.1838986 predictor = worktypeCraft.repair.Self.emp.not.inc
## i = 45 is_brier = 0.1775394 oos_brier = 0.1839145 predictor = worktypeSales.Self.emp.inc
## i = 46 is_brier = 0.1772784 oos_brier = 0.184464 predictor = worktypeAdm.clerical.State.gov
## i = 47 is_brier = 0.1770012 oos_brier = 0.1848479 predictor = native_countryEngland
## i = 48 is_brier = 0.1766289 oos_brier = 0.1852858 predictor = native_countryItaly
## i = 49 is_brier = 0.1762576 oos_brier = 0.1850986 predictor = worktypeTransport.moving.Private
## i = 50 is_brier = 0.1759073 oos_brier = 0.185645 predictor = statusOther.relative.Married
## i = 51 is_brier = 0.1755777 oos_brier = 0.1855656 predictor = worktypePriv.house.serv.Private
## i = 52 is_brier = 0.1752024 oos_brier = 0.1858937 predictor = worktypeOther
## i = 53 is_brier = 0.1748781 oos_brier = 0.1858285 predictor = native_countryGermany
## i = 54 is_brier = 0.1744952 oos_brier = 0.1864225 predictor = native_countryCuba
## i = 55 is_brier = 0.1741871 oos_brier = 0.186287 predictor = statusOwn.child.Separated
## i = 56 is_brier = 0.1737656 oos_brier = 0.1862193 predictor = native_countrySouth
```

```
## i = 57 is_brier = 0.1733164 oos_brier = 0.1853527 predictor = worktypeOther.service.Self.emp.not.inc
## i = 58 is_brier = 0.1728051 oos_brier = 0.1853208 predictor = worktypeProf.specialty.Self.emp.inc
## i = 59 is_brier = 0.1722497 oos_brier = 0.1846987 predictor = worktypeSales.Private
## i = 60 is_brier = 0.1717164 oos_brier = 0.1863781 predictor = worktypeProtective.serv.Local.gov
## i = 61 is_brier = 0.1711044 oos_brier = 0.1860013 predictor = statusNot.in.family.Widowed
## i = 62 is_brier = 0.1705002 oos_brier = 0.1857051 predictor = worktypeExec.managerial.Self.emp.not.i
## i = 63 is_brier = 0.1698833 oos_brier = 0.1865027 predictor = native_countryJamaica
## i = 64 is_brier = 0.1693691 oos_brier = 0.1866908 predictor = raceWhite
## i = 65 is_brier = 0.1686613 oos_brier = 0.1859704 predictor = statusUnmarried.Separated
## i = 66 is_brier = 0.1678313 oos_brier = 0.1864843 predictor = raceBlack
## i = 67 is_brier = 0.1671104 oos_brier = 0.1841216 predictor = worktypeMachine.op.inspct.Private
## i = 68 is_brier = 0.1664096 oos_brier = 0.1846154 predictor = raceAsian.Pac.Islander
## i = 69 is_brier = 0.165671 oos_brier = 0.1834925 predictor = worktypeProf.specialty.Self.emp.not.inc
## i = 70 is_brier = 0.164799 oos_brier = 0.1839977 predictor = native_countryPhilippines
## i = 71 is_brier = 0.1639532 oos_brier = 0.1829634 predictor = statusOther.relative.Never.married
## i = 72 is_brier = 0.1630177 oos_brier = 0.1798843 predictor = worktypeProf.specialty.Private
## i = 73 is_brier = 0.161836 oos_brier = 0.178388 predictor = worktypeHandlers.cleaners.Private
## i = 74 is_brier = 0.1604635 oos_brier = 0.1780931 predictor = worktypeExec.managerial.Local.gov
## i = 75 is_brier = 0.1590754 oos_brier = 0.1803847 predictor = native_countryMexico
## i = 76 is_brier = 0.1576239 oos_brier = 0.18131 predictor = statusNot.in.family.Married.spouse.absen
## i = 77 is_brier = 0.1561724 oos_brier = 0.1814974 predictor = worktypeExec.managerial.Federal.gov
## i = 78 is_brier = 0.154877 oos_brier = 0.1792748 predictor = worktypeAdm.clerical.Private
## i = 79 is_brier = 0.1530984 oos_brier = 0.1792153 predictor = worktypeProf.specialty.State.gov
## i = 80 is_brier = 0.1512046 oos_brier = 0.1803241 predictor = statusUnmarried.Divorced
## i = 81 is_brier = 0.1486265 oos_brier = 0.1798221 predictor = statusUnmarried.Never.married
## i = 82 is_brier = 0.1455114 oos_brier = 0.1793399 predictor = statusWife.Married
## i = 83 is_brier = 0.141789 oos_brier = 0.179233 predictor = statusNot.in.family.Divorced
## i = 84 is_brier = 0.1375809 oos_brier = 0.1772499 predictor = capital_loss
## i = 85 is_brier = 0.1330105 oos_brier = 0.1663411 predictor = hours_per_week
## i = 86 is_brier = 0.1290151 oos_brier = 0.1591097 predictor = worktypeExec.managerial.Private
## i = 87 is_brier = 0.1283621 oos_brier = 0.1569123 predictor = worktypeOther.service.Private
## i = 88 is_brier = 0.1242607 oos_brier = 0.1476126 predictor = education_num
## i = 89 is_brier = 0.1209538 oos_brier = 0.1422338 predictor = statusOwn.child.Never.married
## i = 90 is_brier = 0.1133092 oos_brier = 0.1362918 predictor = sexMale
## i = 91 is_brier = 0.1027663 oos_brier = 0.1329848 predictor = statusNot.in.family.Never.married
## i = 92 is_brier = 0.09516563 oos_brier = 0.1313902 predictor = age
## i = 93 is_brier = 0.08715781 oos_brier = 0.1264595 predictor = capital_gain
```

Plot the in-sample and oos (select set) Brier score by p. Does this look like what's expected?

```
simulation_results = data.frame(

  iteration = 1 : length(in_sample_brier_by_iteration),

  in_sample_brier_by_iteration = in_sample_brier_by_iteration,

  oos_brier_by_iteration = oos_brier_by_iteration

)

ggplot(simulation_results) +
  geom_line(aes(x = iteration, y = in_sample_brier_by_iteration), color = "green") +
  geom_line(aes(x = iteration, y = oos_brier_by_iteration), color = "red") +
  ylab("Brier score")
```


Brier score
0.175
0.150
0.125
0.100
0
25
50
75
iteration