Presentation of new R functions for forecast verification

Stefan Siegert, (s.siegert@exeter.ac.uk)

please go to **https://github.com/sieste/ic3-workshop** and download all files into a new directory

This workshop

- **https://github.com/sieste/ic3-workshop**
- hands-on session
- presentation of some new R functions
- interpretation of the output

Overview of available verification packages in R

- `verification`
  - developed at NCAR
  - methods: Brier, CRPS, ROC, reliability diagram, rank histogram
- `s2dverification`
  - currently developed at IC3
  - methods: ACC, RMSSS, plotting!

New contributions

- ensemble verification
- uncertainty estimates
- comparative verification
- . . . **work in progress**

```r
source("R/toydata.r")
```

```
## Loading required package: boot
```

```r
source("R/rankhist.r")
source("R/rel-diag.r")
source("R/ensemble-scores.r")
```

Gaussian toy data

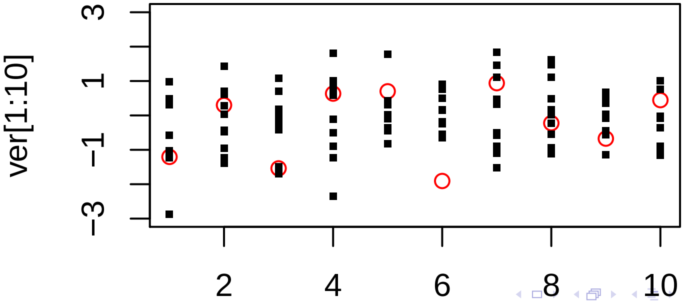
- Gaussian ensemble data with mean `mu.ens` and stdev `sd.ens`
- Gaussian verification with mean `mu.ver` and stdev `sd.ver`
- number of samples `N`
- number of ensemble members `K`

```
K <- 10
toydata <- GenerateToyData(mu.ens=0, sd.ens=1,
                           mu.ver=0, sd.ver=1,
                           K=K, N=100)
objects(toydata)
```

```
## [1] "ens" "ver"
```

Gaussian toy data

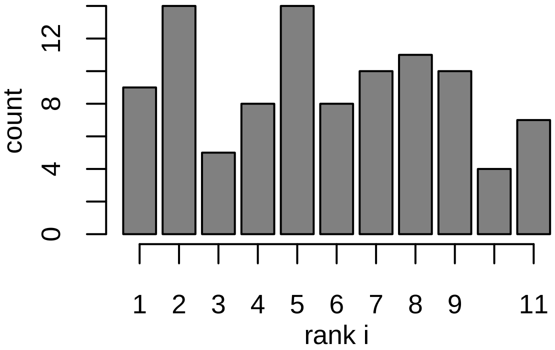
```
with(toydata, {
  plot(1:10, ver[1:10], col="red", ylim=c(-3,3))
  matplot(1:10, ens[1:10, ], pch=15, cex=.5,
          col="black", add=TRUE)
})
```



Rank histogram

- r_i: rank of the verification in the ordered ensemble
- e.g. ver=1.5, ens=$\{$1,2,3$\}$: rank $= 2$
- histogram over the observed ranks

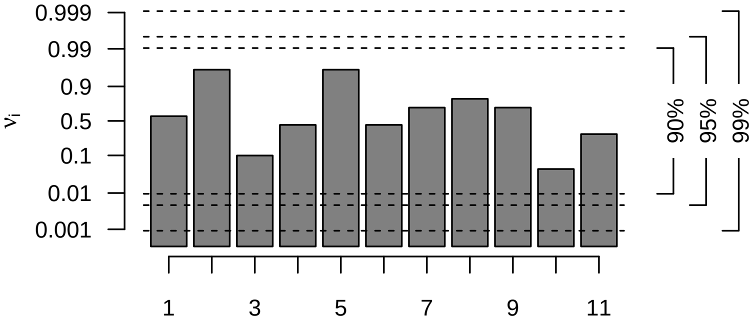
```
source("R/rankhist.r")
rh <- with(toydata, rankhist(ens, ver))
PlotRankhist(rh, mode="raw")
```



Rank histogram on probability paper

- H_0: the individual rank counts are $\sim Binomial(N, \frac{1}{K+1})$
- plot the cumulative likelihood of the observed rank counts under H_0

```
PlotRankhist(rh, mode="prob.paper")
```



Rank histogram significance tests

- Pearson χ^2-test
- Jolliffe-Primo χ^2-decomposition

```
rh.tests <- rankhist.tests(rh)
print(rh.tests)
```

```
##                pearson.chi2 jp.slope jp.convex
## test.statistic      11.3200   1.0890    0.7601
## p.value              0.3331   0.2967    0.3833
```

Fair Brier Score for binary ensemble forecasts

- j ... verification, $1 =$ yes, $0 =$ no
- i ... number of ensemble members that predict the event
- $Br(i, j) = (j - \frac{i}{K})^2 - \frac{i(K-i)}{K^2(K-1)}$

```
source("R/ensemble-scores.r")
tau <- 1 # exceedance threshold
with(toydata, mean(fairbrier(ens, ver, tau)))
```

```
## [1] 0.1024
```

Fair continuously ranked probability score for ensemble forecasts

- fair Brier Score integrated over all possible thresholds
- $crps(e, y) = \langle |y - e_i| \rangle - \frac{1}{2K(K-1)} \langle |e_i - e_j| \rangle$

```
source("R/ensemble-scores.r")
fcrps <- with(toydata, faircrps(ens, ver))
mean(fcrps)
```

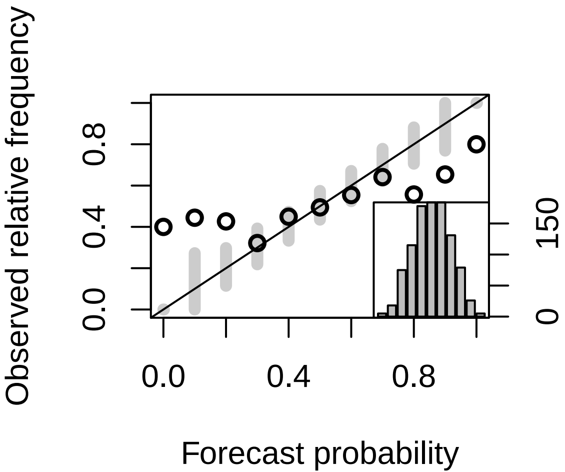
```
## [1] 0.5043
```

“Unfair” reliability diagram

```
N <- 1000
mu <- runif(N)
toydata <- GenerateToyData(N=N, mu.ens=mu, mu.ver=mu)
tau <- .5
i <- with(toydata, rowSums(ens > tau))
j <- with(toydata, 1 * (ver > tau))
```

Reliability diagram

```
source("R/rel-diag.r")
rd <- rel.diag(probs=i/K, ver=j, nbins=11, plot=TRUE)
```



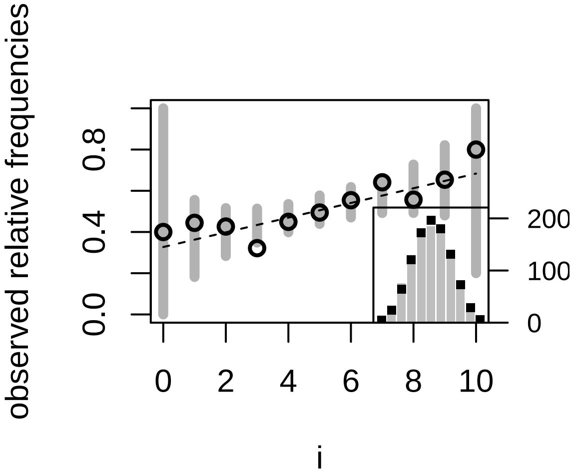
Reliability diagram

```r
print(rd)
```

```
##    p.avgs cond.probs cbar.lo cbar.hi
## 1     0.0     0.4000  0.0000  0.0000
## 2     0.1     0.4444  0.0000  0.2727
## 3     0.2     0.4267  0.1147  0.2973
## 4     0.3     0.3217  0.2188  0.3922
## 5     0.4     0.4494  0.3332  0.4727
## 6     0.5     0.4946  0.4350  0.5741
## 7     0.6     0.5543  0.5247  0.6706
## 8     0.7     0.6412  0.6229  0.7778
## 9     0.8     0.5570  0.7059  0.8816
## 10    0.9     0.6538  0.7692  1.0000
## 11    1.0     0.8000  1.0000  1.0000
```

Fair reliability diagram

```
frd <- fair.rel.diag(i=i, j=j, K=K, plot=TRUE, plot.refin=TRUE)
```



Fair reliability diagram

```
print(frd)
```

```
##      i cond.probs H0.line cbar.lo cbar.hi
## 1    0     0.4000  0.3271  0.0000  1.0000
## 2    1     0.4444  0.3627  0.1818  0.5557
## 3    2     0.4267  0.3984  0.2833  0.5161
## 4    3     0.3217  0.4340  0.3486  0.5136
## 5    4     0.4494  0.4696  0.3986  0.5360
## 6    5     0.4946  0.5053  0.4391  0.5773
## 7    6     0.5543  0.5409  0.4702  0.6183
## 8    7     0.6412  0.5765  0.4917  0.6593
## 9    8     0.5570  0.6122  0.4921  0.7273
## 10   9     0.6538  0.6478  0.4800  0.8214
## 11  10     0.8000  0.6834  0.2000  1.0000
```

Comparative ensemble verification

- We want to address the question: Is the forecast `ens` better than a reference forecast `ens.ref` at predicting the same verification `ver`?
- Our hindcast dataset now has 3 members

Comparison of two imperfect ensemble forecasts

- ens and ver as before
- additionally: ens.ref, a benchmark ensemble, to which the performance of ens is compared

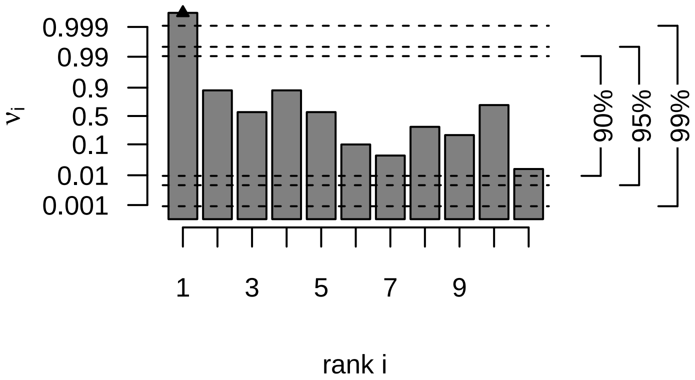
```
K <- 10
toydata2 <- GenerateToyData(mu.ver=0, sd.ver=1,
                            mu.ref=0.4, sd.ref=1,
                            mu.ens=0.15, sd.ens=1,
                            K=K, K.ref=K, N=100)
objects(toydata2)
```

```
## [1] "ens"     "ens.ref" "ver"
```

Good statistical tests should find that both ensembles are unreliable (biased), and that ens is more reliable than ens.ref.

Rank histogram analysis of `ens.ref`

```
rh.ref <- with(toydata2, rankhist(ens.ref, ver))
PlotRankhist(rh.ref, mode="prob.paper")
```



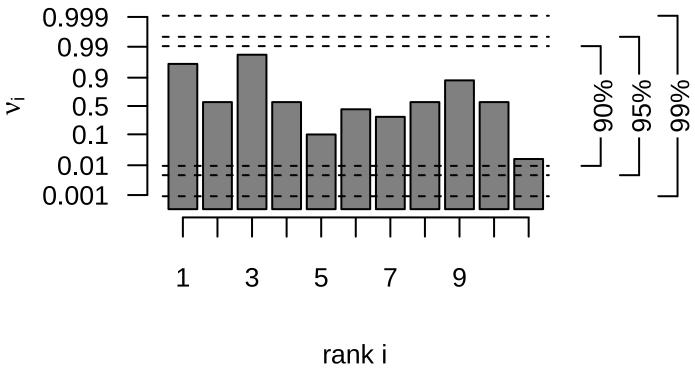
Rank histogram analysis of ens.ref

```
rh.tests.ref <- rankhist.tests(rh.ref)
print(rh.tests.ref)
```

```
##                  pearson.chi2  jp.slope jp.convex
## test.statistic     3.354e+01 1.742e+01    6.5482
## p.value            2.209e-04 2.990e-05    0.0105
```

Rank histogram analysis of ens

```
rh <- with(toydata2, rankhist(ens, ver))
PlotRankhist(rh, mode="prob.paper")
```



Rank histogram analysis of ens

```
rh.tests <- rankhist.tests(rh)
print(rh.tests)
```

```
##                  pearson.chi2 jp.slope jp.convex
## test.statistic        13.9600  3.84400    0.2051
## p.value                0.1748  0.04992    0.6506
```

Comparison of rank histograms: AnalyzeRankhistDifference

```
rh.comp <- with(toydata2,
           AnalyzeRankhistDifference(ens, ens.ref,
                                     ver, n.boot=100))
```

`rh.comp` is a matrix that summarizes the rank histogram comparison:

```
print(t(as.matrix(rh.comp)))
```

```
##            pearson.chi2 jp.slope jp.convex
## score.diff       19.580   13.580     6.343
## p.value           0.060    0.010     0.150
## Q0.01           -38.150   -1.894   -15.417
## Q0.05           -15.191   -1.055    -5.049
## Q0.1             -3.388    3.681    -1.023
## Q0.9             59.906   22.357    31.172
## Q0.95            81.686   24.675    39.391
## Q0.99           116.853   31.923    52.397
```

Similar for the specific scores for slope and convexity:

- p-values:

```
print(t(rh.comp[2:3, 1:2]))
```

```
##            jp.slope jp.convex
## score.diff    13.58     6.343
## p.value        0.01     0.150
```

- bootstrap quantiles:

```
print(rh.comp[2:3, 3:8])
```

```
##             Q0.01  Q0.05   Q0.1  Q0.9 Q0.95 Q0.99
## jp.slope   -1.894 -1.055  3.681 22.36 24.67 31.92
## jp.convex -15.417 -5.049 -1.023 31.17 39.39 52.40
```

Comparison of fair Brier Scores

```
K <- 10
toydata3 <- GenerateToyData(mu.ver=0, sd.ver=1,
                            mu.ens=0, sd.ens=1,
                            mu.ref=0, sd.ref=2,
                            K=K, K.ref=K, N=100)
```

Analysis of fair Brier score difference

```
fbr.comp <- with(toydata3,
  AnalyzeFairBrierDifference(ens, ens.ref, ver,
                             tau=.5, n.boot=100))
print(as.matrix(fbr.comp))
```

```
##                      [,1]
## fair.brier.diff   0.01956
## p.value           0.20000
## Q0.01            -0.03849
## Q0.05            -0.02274
## Q0.1             -0.01193
## Q0.9              0.05360
## Q0.95             0.05712
## Q0.99             0.06434
```

Comparison of fair crps

```
fcrps.comp <- with(toydata3,
  AnalyzeFairCrpsDifference(ens=ens, ens.ref=ens.ref,
                            ver=ver, n.boot=100))
print(as.matrix(fcrps.comp))
```

```
##                     [,1]
## fair.crps.diff 0.12023
## p.value        0.00000
## Q0.01          0.04691
## Q0.05          0.05940
## Q0.1           0.06810
## Q0.9           0.18077
## Q0.95          0.19096
## Q0.99          0.20236
```

Some actual data

- tropical sea surface temperature data
- 51 years
- 10 lead times (10 years)
- 8 different ensembles
- up to 10 members each

```
load("R/SST-raw.Rdata")
print(dim(SST.trop))
```

```
## [1] 51 10  8 10
```

```
print(dim(SST.trop.obs))
```

```
## [1] 51 10
```

Some actual data

- the available models

```
matrix(dimnames(SST.trop)[[3]], ncol=2)
```

```
##       [,1]        [,2]
## [1,] "gfdl"       "hadcm3_ff"
## [2,] "cancm4"     "ec_earth_ff"
## [3,] "miroc5"     "ec_earth_an"
## [4,] "hadcm3_an"  "bcc"
```

A specific analysis

- set parameters

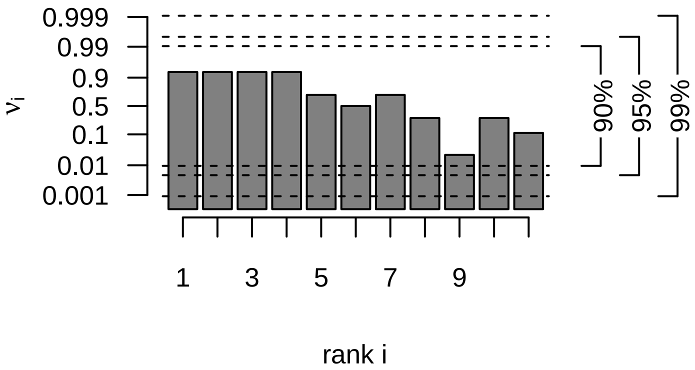
```
lead <- 7
model <- "hadcm3_ff"
model.ref <- "hadcm3_an"
dates <- 1:40
members <- 1:10
members.ref <- 1:10
```

- get data:

```
ens <- SST.trop[dates, lead, model, members]
ens.ref <- SST.trop[dates, lead, model.ref, members.ref]
ver <- SST.trop.obs[dates, lead]
```

Rank histogram of ens.ref

```
rh.ref <- rankhist(ens.ref,ver)
PlotRankhist(rh.ref, mode="prob.paper")
```



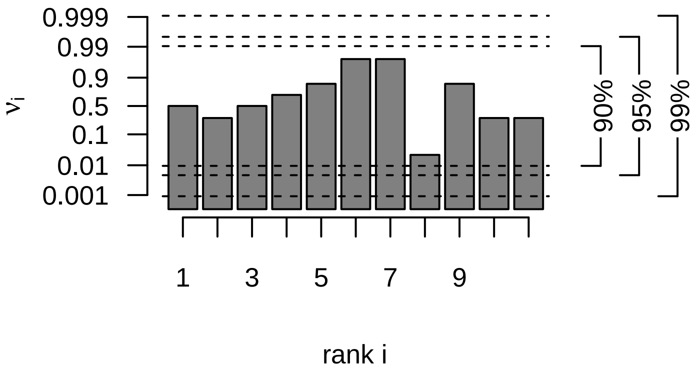
Rank histogram of ens.ref

```
rankhist.tests(rh.ref)
```

```
##                pearson.chi2  jp.slope jp.convex
## test.statistic      13.3500 1.122e+01  0.002885
## p.value              0.2048 8.081e-04  0.957167
```

Rank histogram of ens

```r
rh <- rankhist(ens,ver)
PlotRankhist(rh, mode="prob.paper")
```



Rank histogram of ens

```
rankhist.tests(rh)
```

```
##                  pearson.chi2 jp.slope jp.convex
## test.statistic        13.3500   0.0625    3.9490
## p.value                0.2048   0.8026    0.0469
```

Rank histogram comparison

```
rh.comp <- AnalyzeRankhistDifference(ens, ens.ref,
                                     ver, n.boot=100)
print(t(as.matrix(rh.comp)))
```

```
##            pearson.chi2 jp.slope jp.convex
## score.diff        0.000  11.1600    -3.946
## p.value           0.490   0.0000     0.840
## Q0.01           -26.554  -0.6922   -13.215
## Q0.05           -18.727   0.8324    -6.823
## Q0.1             -6.655   3.6180    -4.015
## Q0.9             28.655  18.4220     4.903
## Q0.95            32.532  20.4600     7.525
## Q0.99            50.072  26.1248    14.706
```

Brier Score comparison

```
br.comp <- AnalyzeFairBrierDifference(ens, ens.ref, ver,
                                       tau=mean(ver),
                                       n.boot=100)
print(as.matrix(br.comp))
```

```
##                       [,1]
## fair.brier.diff -3.383e-18
## p.value          5.100e-01
## Q0.01           -8.678e-02
## Q0.05           -6.133e-02
## Q0.1            -4.478e-02
## Q0.9             4.006e-02
## Q0.95            5.353e-02
## Q0.99            6.488e-02
```

Crps comparison

```
crps.comp <- AnalyzeFairCrpsDifference(ens, ens.ref,
                                       ver, n.boot=100)
print(as.matrix(crps.comp))
```

```
##                    [,1]
## fair.crps.diff 0.013999
## p.value        0.010000
## Q0.01          0.002906
## Q0.05          0.005512
## Q0.1           0.006312
## Q0.9           0.020968
## Q0.95          0.023224
## Q0.99          0.026772
```