Verification Package: examples using weather forecasts.

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The National Center for Atmospheric Sciences (NCAR) develops and implements weather and climate models. Verification statistics play a key role in this cycle. Functions in the **verification** library contains functions that have been developed in this process.

While the examples in this library focus on atmospheric topics, they are written to be applicable to any situations in which there is a prediction or forecast and an observation of the outcome. The statistics used to verify and study weather and climate forecasts are shared by many fields. Most notably, these include the fields of medicine (where the name misclassification statistics is favored) and signal detection theory. Some useful references are listed below.

The type of predictions and observations determine which methods are appropriate for verification. The following types of predictions are currently supported: binary, categorical, continuous, probabilistic and distributions. The presence or absence of fog is an example of binary data. A forecast for turbulence expressed in terms of low, moderate and extreme is a categorical forecast. The chance of precipitation is an example of a probabilistic forecast. A temperature forecast as a single value is (essentially) a continuous variable. People are finding it increasingly useful to express the uncertainly of a point forecast. In this case, the forecast may be expressed as a distribution.

1 Finley's Tornado

Any discussion of verification must begin in the beginning and for weather, that means John Finley and tornado forecasts. In 1884, John Finley using the telegraph, created yes/no tornado forecasts for 18 regions of the US Finley (1884). Citing the results in Table 1, he explained that his method was 96.6 accurate.

Table 1: Finley Tornado Data

	Forecasts	
Observation	Yes	No
Yes	28	72
No	23	2680

```
Package 'spam' is loaded. Spam version 0.15-2 (2008-09-10).

Type demo( spam) for some demos, help( Spam) for an overview of this package.

 Try help(fields) for an overview of this library

[1] " Assume data entered as c(n11, n01, n10, n00) Obs*Forecast"

The forecasts are binary, the observations are binary.
The contingency table for the forecast
     [,1] [,2]
[1,]   28   72
[2,]   23 2680
```

```
PODy =  0.549
TS   =  0.2276
ETS  =  0.216
FAR  =   0.72
HSS  =  0.3553
PC   =  0.9661
BIAS =  1.961
```

It was quickly pointed out that since tornados are so rare, if one always forecasted no tornado, the percent correct would be 98.2the time. The downside to this that the probability of detecting a tornado (PODy) drops to 0.

```
[1] " Assume data entered as c(n11, n01, n10, n00) Obs*Forecast"

The forecasts are binary, the observations are binary.
The contingency table for the forecast
     [,1] [,2]
[1,]    0    0
[2,]   51 2752

PODy =      0
TS   =      0
ETS  =      0
FAR  =    NaN
HSS  =      0
PC   =  0.9818
BIAS =      0
```

Note: **verify** is an overloaded function whose behavior is dictated by the types of forecasts and observations. By default, **verify** assumes that the forecast is probabilistic and the observation is binary. In the preceding example, since both the forecast and observation are binary, the forecast type needs to be described.

2 Verifying a precipitation forecast

While variables such as temperature, humidity and wind speed are traditionally forecast as a point forecast, precipitation has historically been forecast as a probability. The following example use precipitation forecast made by the Finnish Meteorological Institute Ebert (2006). This data is included as a sample data set in the verification package.

```
If baseline is not included, baseline values  will be calculated from the  sample obs.

The forecasts are probabilistic, the observations are binary.
Sample baseline calculated from observations.
Brier Score (BS)           =  0.1445
Brier Score - Baseline     =  0.1793
Skill Score                =  0.1942
Reliability                =  0.02536
Resolution                 =  0.06017
Uncertainty              =  0.1793
```

Typically, the probability of rain is expressed as one of a finite number of probabilities such as 10%, 20%, etc. Its not typical to see a forecast saying there is a 34.7% chance of rain. For automated forecasts or one's which aren't rounded a continuous range of values between 0 and 1 are possible. The *bins* option addresses

this distinction. If bins = TRUE, forecast are placed into bins and assigned the center values. By default these bins are described by the *threshold* parameter and are (0, 0.1, ..., 0.9, 1). If FALSE, as in the case for precipitation forecasts, each forecast is considered individually. This becomes important when calculating statistics such as the Brier statistic.

```
> plot(A)
```

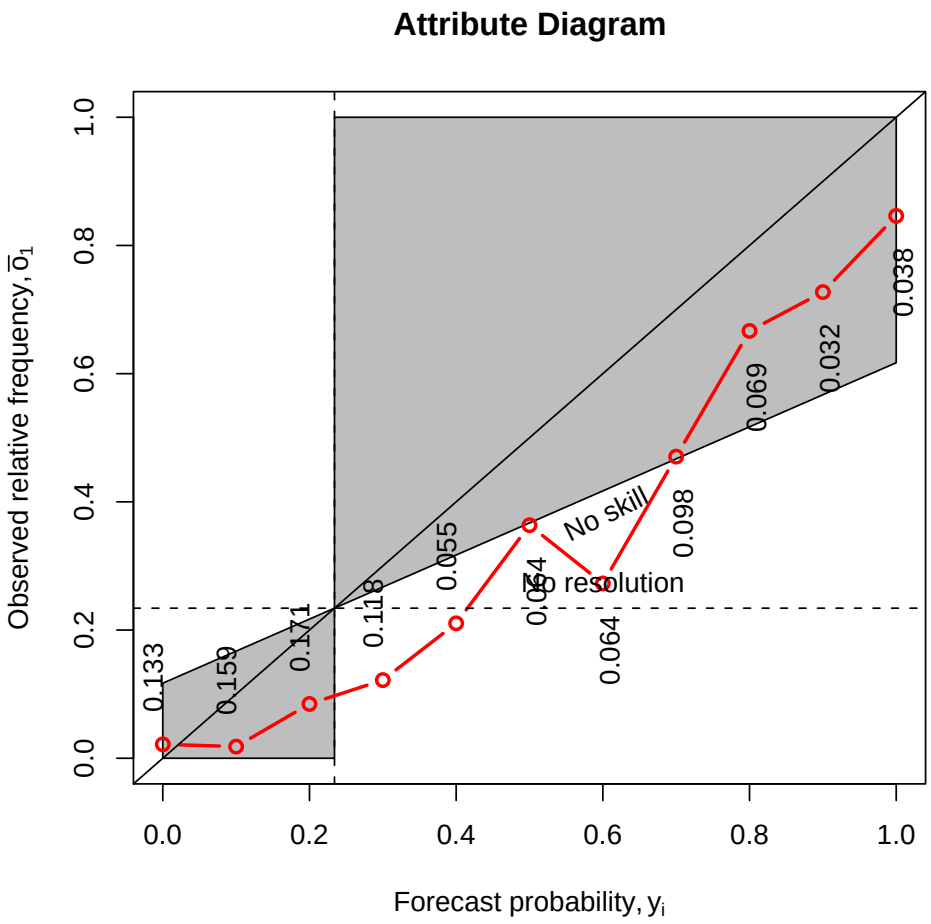

Figure 1: Attribute Diagram for light precipitation forecast

While the attribute diagram (Figure 1) is the default diagram for a probabilistic forecast, there are other very useful diagrams. The receiver operating characteristics (ROC) plot is also commonly used. A ROC plot displays the relation between false alarms and hits (successfully forecasted events) across a range of thresholds. Figure 2 shows a ROC plot for the probability of precipitation forecast. Since one wants a high ratio of hits to false alarms, the better the forecast, the further into the upper left hand corner the plot extends. This plot displays two lines. The black, un-smooth line is the empirical ROC plot. At each threshold, points are plotted. The smoother line is the result of fitted a binormal distribution to the points. For a perfect forecast, the area under the ROC curve would equal 1. In this example, the area under the curve is shown in the legend box. First the area under empirical curve is shown followed by the area under the bi-normal curve.

```
> mod24 <- verify(d$obs_norain, d$p24_norain, bins = FALSE)

If baseline is not included, baseline values  will be calculated from the  sample obs.

> mod48 <- verify(d$obs_norain, d$p48_norain, bins = FALSE)

If baseline is not included, baseline values  will be calculated from the  sample obs.

> roc.plot(mod24, plot.thres = NULL)
> lines.roc(mod48, col = 2, lwd = 2)
> leg.txt <- c("24 hour forecast", "48 hour forecast")
> legend(0.6, 0.4, leg.txt, col = c(1, 2), lwd = 2)
```

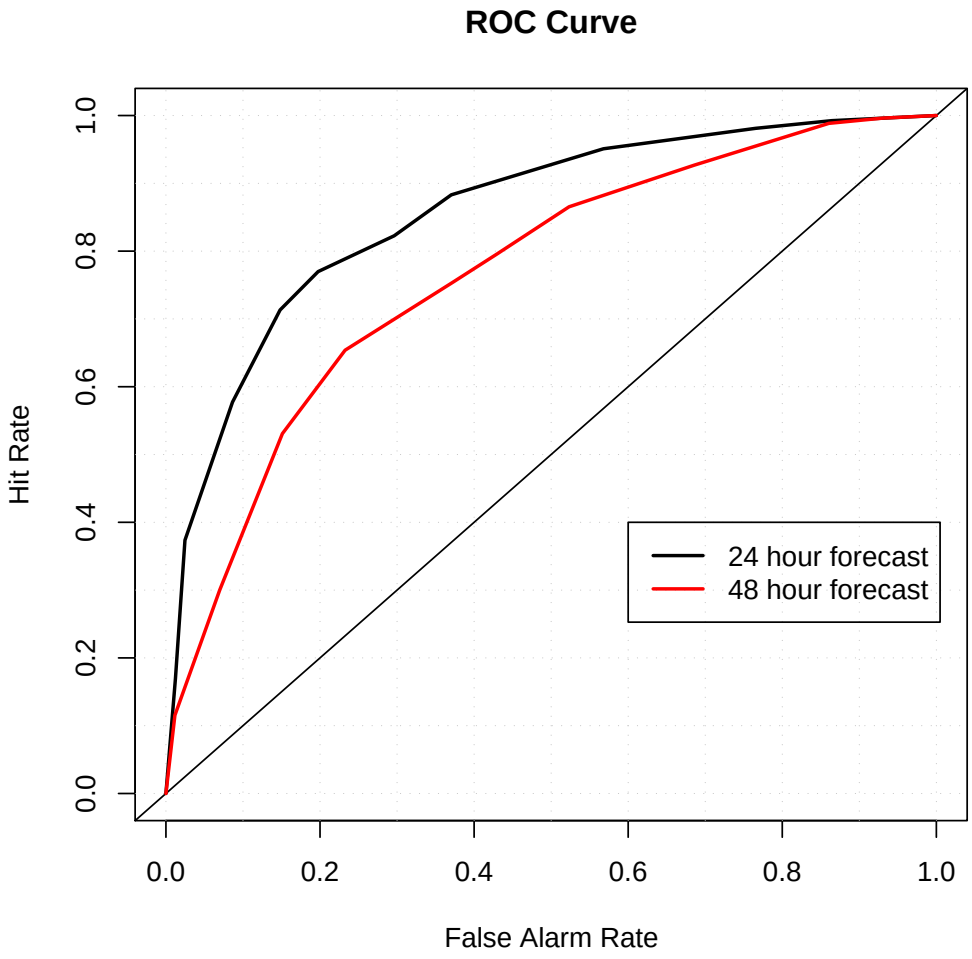

Figure 2: Receiver operating characteristic curve for chance of rain forecast at 24 and 48 hour lead times.

Unfortunately, estimating and expressing the uncertainty in these curves is seldom done. The verification packages offers a couple options for this. The data can be bootstrapped, to estimate the variance at the set thresholds (Figure 3).

```
> B <- roc.plot(A, CI = TRUE, n.boot = 100)
```

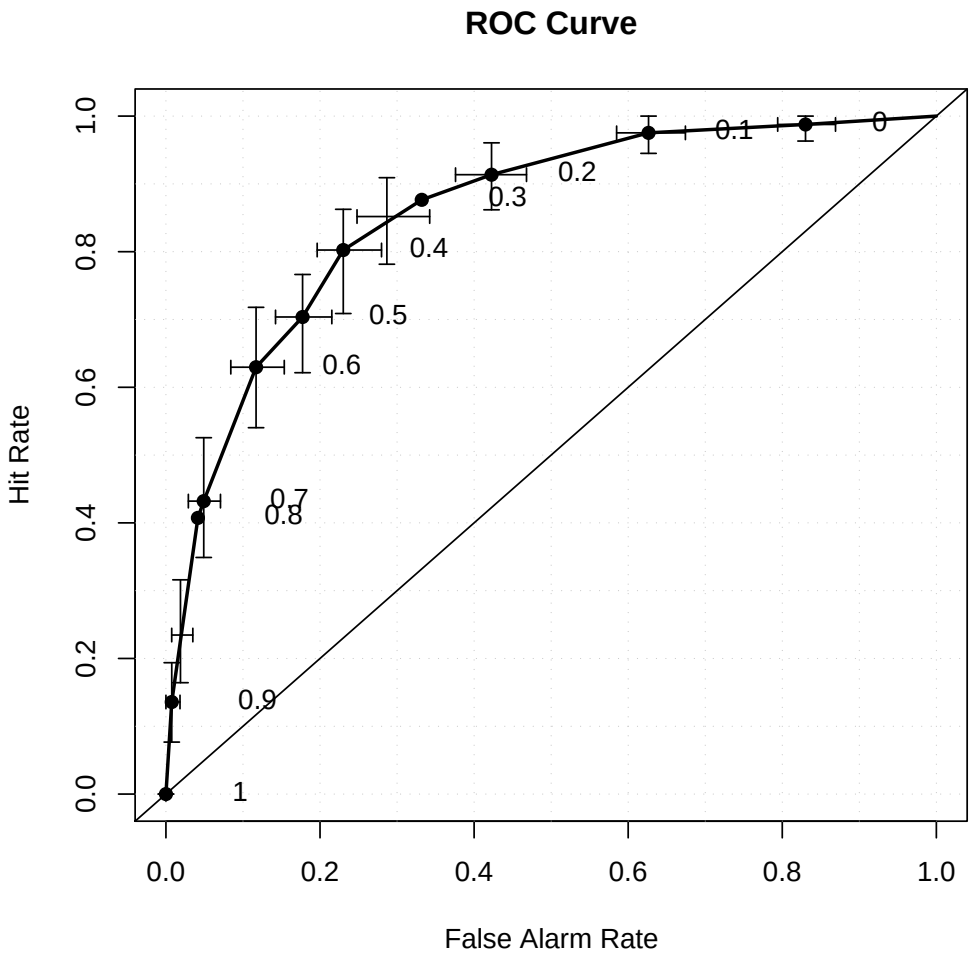

Figure 3: ROC curve with bootstrapped confidence intervals.

3 Value Diagrams

The utility of a forecast varies based upon the needs and concerns of an individual user. Value diagrams can be used to determine over what range of cost-lost (cl) ratios a forecast will provide value. The cost-lost ratio is the ratio of the cost of preparing for an event that doesn't occur over the losses that will occur if one is not prepared. Small values indicate that the costs to prepare are small in relation to the losses. The peaks of this graph occurs at the baseline average of an event. Figure 4 is an illustration of a value diagram for the Finnish precipitation data.

```
> value(d$obs_rain, d$p24_rain, main = "Rain-No Rain Forecast",
+     cl = seq(0.01, 0.99, 0.05), all = TRUE)
```

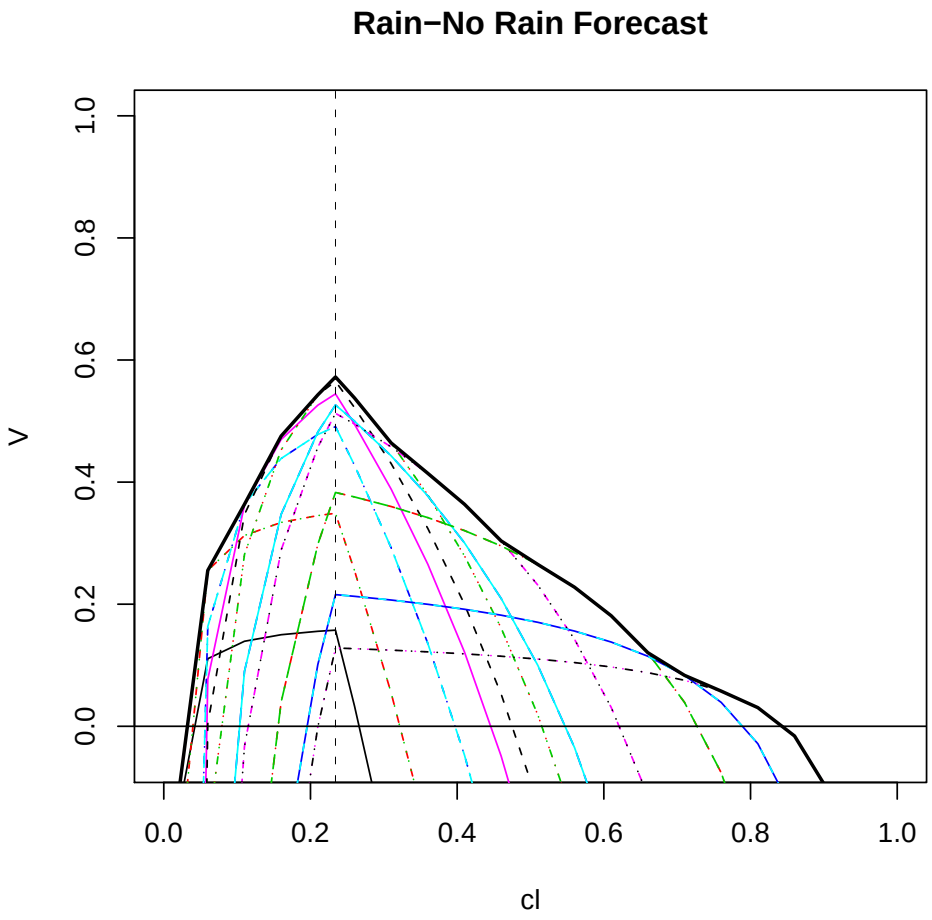

Figure 4: Value diagram of light precipitation forecast.

4 Discrimination Plot

A discrimination plot illustrates the the distributions of forecasts grouped by different types of distributions. Ideally, one would see a distinct histograms (Figure 5) .

```
> discrimination.plot(disc.dat$group.id, disc.dat$frcst, main = "Sample Plot")
```

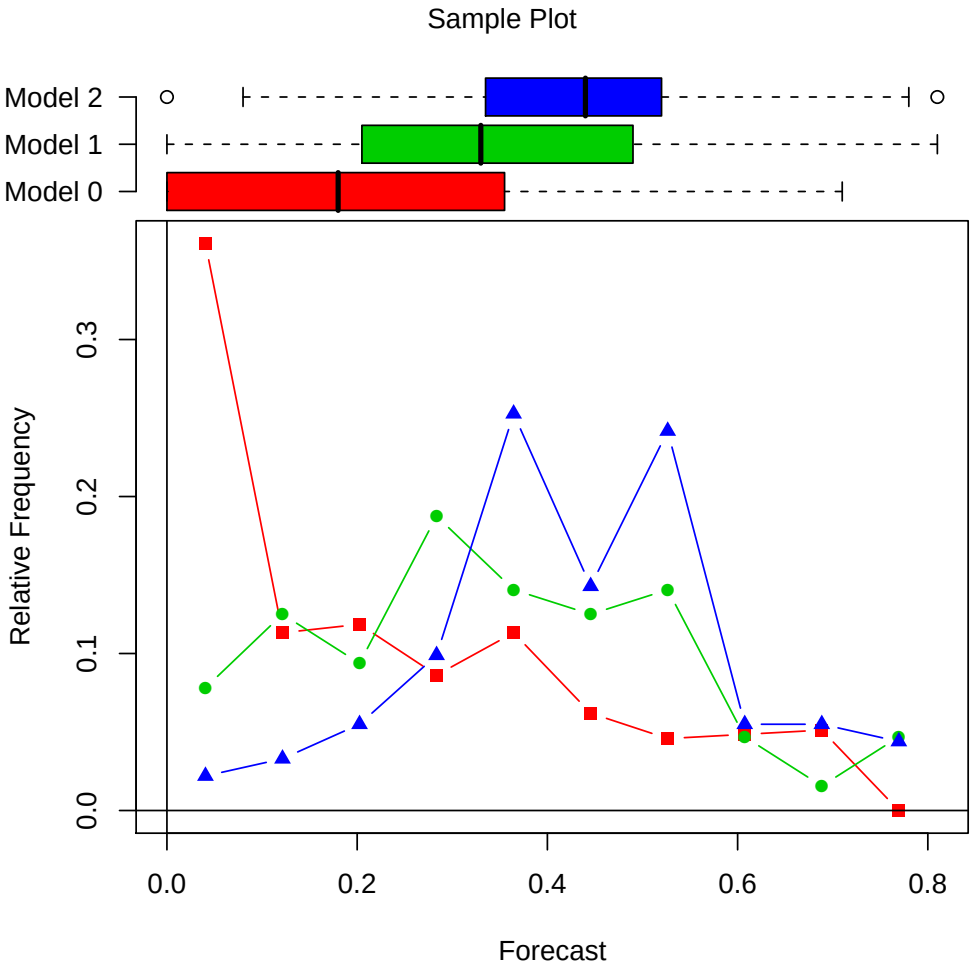

Figure 5: Discrimination plot using aviation forecast.

5 Reliability Diagram

Related to the attribute diagram is the reliability diagram. A reliability diagram can be used to compare multiple forecasts. Figure 6 is an example using data from Wilks (1995).

```
> y.i <- c(0, 0.05, seq(0.1, 1, 0.1))
> obar.i <- c(0.006, 0.019, 0.059, 0.15, 0.277, 0.377, 0.511, 0.587,
+     0.723, 0.779, 0.934, 0.933)
> prob.y <- c(0.4112, 0.0671, 0.1833, 0.0986, 0.0616, 0.0366, 0.0303,
+     0.0275, 0.245, 0.022, 0.017, 0.203)
> obar <- 0.162
> reliability.plot(y.i, obar.i, prob.y, titl = " Wilks Data", legend.names = c("Model A"))
```

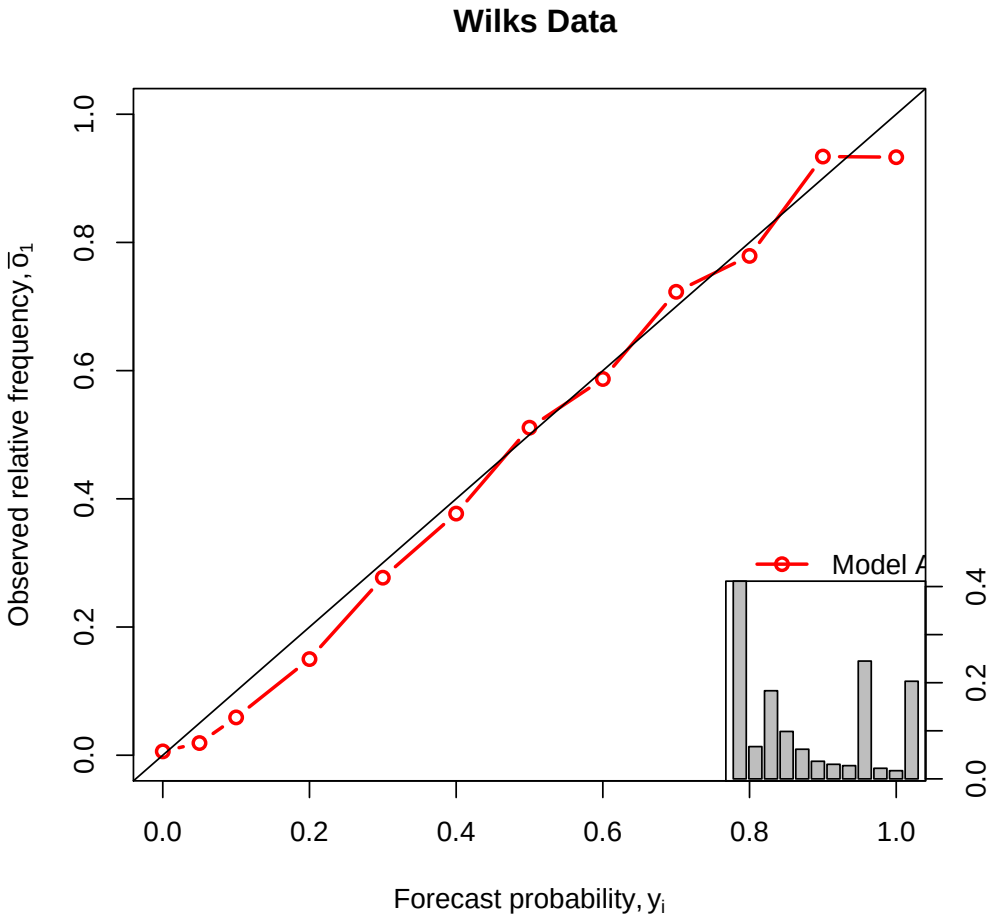

Figure 6: Reliability diagram of Wilks example.

References

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