

17 Measuring Performance

- Measures for Regression
- Measures for Predicted Classes
- Measures for Class Probabilities
- Lift Curves
- Calibration Curves

17.1 Measures for Regression

The function `postResample` can be used to estimate the root mean squared error (RMSE), simple R^2 , and the mean absolute error (MAE) for numeric outcomes. For example:

```
library(mlbench)

data(BostonHousing)


set.seed(280)

bh_index <- createDataPartition(BostonHousing$medv, p = .75, list
bh_tr <- BostonHousing[ bh_index, ]
bh_te <- BostonHousing[-bh_index, ]


set.seed(7279)

lm_fit <- train(medv ~ . + rm:lstat,
                data = bh_tr,
                method = "lm")

bh_pred <- predict(lm_fit, bh_te)

lm_fit
```



```
## Linear Regression
##
## 381 samples
## 13 predictor
##
## No pre-processing
## Resampling: Bootstrapped (25 reps)
## Summary of sample sizes: 381, 381, 381, 381, 381, 381, ...
## Resampling results:
##
##      RMSE      Rsquared    MAE
## 4.284876 0.7778135 2.955764
##
## Tuning parameter 'intercept' was held constant at a value of Tl
```



```
postResample(pred = bh_pred, obs = bh_te$medv)
```

```
##      RMSE  Rsquared    MAE
## 4.4412987 0.7781877 3.0926842
```

A note about how R^2 is calculated by `caret` : it takes the straightforward approach of computing the correlation between the observed and predicted values (i.e. R) and squaring the value. When the model is poor, this can lead to differences between this estimator and the more widely known estimate derived from linear regression

models. Mostly notably, the correlation approach will not generate negative values of R^2 (which are theoretically invalid). A comparison of these and other estimators can be found in Kvalseth 1985.

17.2 Measures for Predicted Classes

Before proceeding, let's make up some test set data:

```
set.seed(144)
true_class <- factor(sample(paste0("Class", 1:2),
                             size = 1000,
                             prob = c(.2, .8), replace = TRUE))
true_class <- sort(true_class)
class1_probs <- rbeta(sum(true_class == "Class1"), 4, 1)
class2_probs <- rbeta(sum(true_class == "Class2"), 1, 2.5)
test_set <- data.frame(obs = true_class,
                      Class1 = c(class1_probs, class2_probs))
test_set$Class2 <- 1 - test_set$Class1
test_set$pred <- factor(ifelse(test_set$Class1 >= .5, "Class1", "(
```

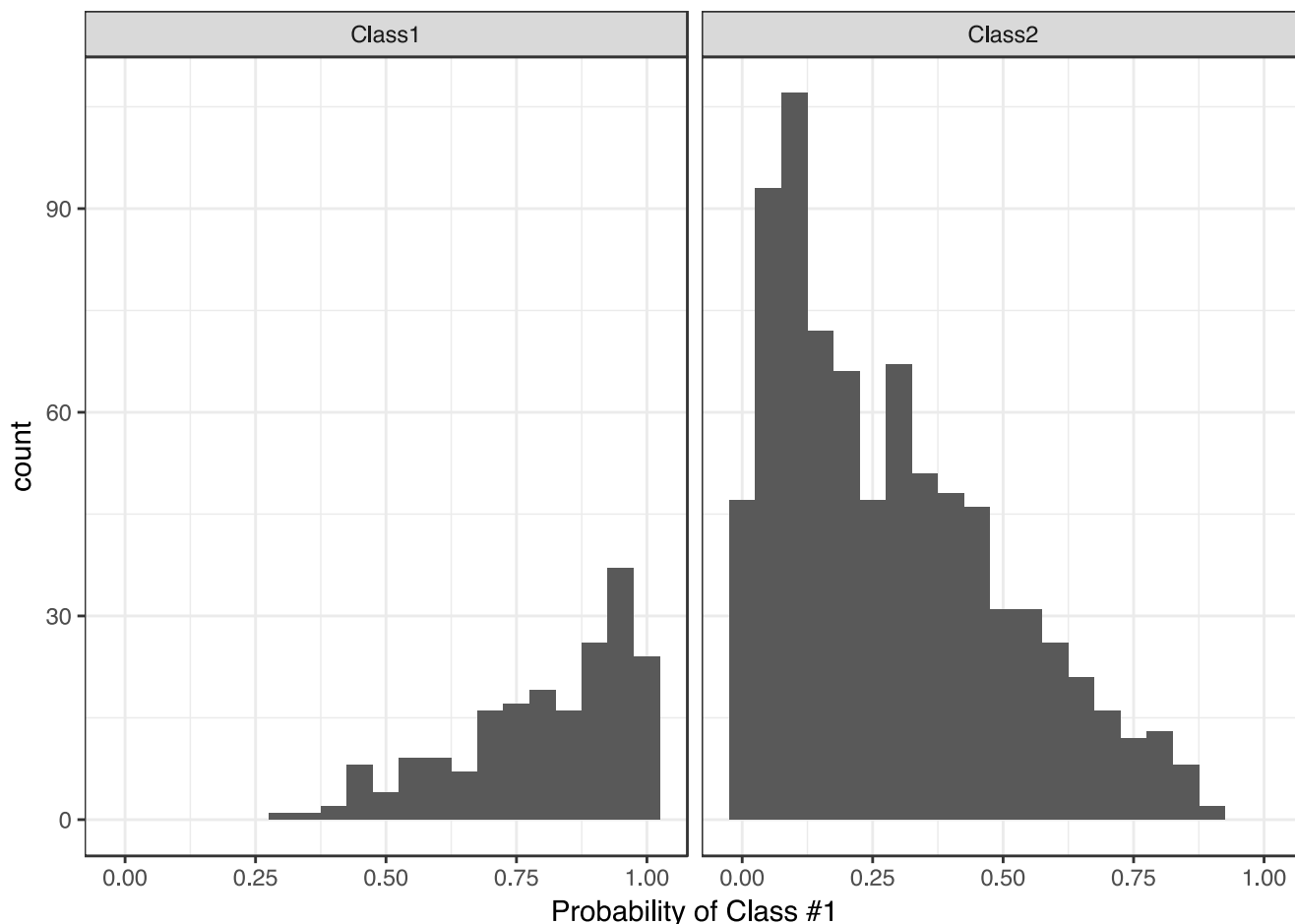
第一列为true_class, colname=obs, 第二列class1和2对应的probs, colname=Class1

增加一列为colname= class2

We would expect that this model will do well on these data:

```
rbeta(n, shape1, shape2, ncp = 0)
n      number of observations. If length(n) > 1, the length is taken to be the number required.
shape1, shape2 non-negative parameters of the Beta distribution
```

```
ggplot(test_set, aes(x = Class1)) +  
  geom_histogram(binwidth = .05) +  
  facet_wrap(~obs) +  
  xlab("Probability of Class #1")
```



Generating the predicted classes based on the typical 50% cutoff for the probabilities, we can compute the *confusion matrix*, which shows a cross-tabulation of the observed and predicted classes. The `confusionMatrix` function can be used to generate these results:

```
confusionMatrix(data = test_set$pred, reference = test_set$obs)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Class1 Class2
##      Class1      183      141
##      Class2       13      663
##
##           Accuracy : 0.846
##           95% CI : (0.8221, 0.8678)
##      No Information Rate : 0.804
##      P-Value [Acc > NIR] : 0.0003424
##
##           Kappa : 0.6081
##  McNemar's Test P-Value : < 2.2e-16
##
##           Sensitivity : 0.9337
##           Specificity : 0.8246
##      Pos Pred Value : 0.5648
##      Neg Pred Value : 0.9808
##           Prevalence : 0.1960
##      Detection Rate : 0.1830
##  Detection Prevalence : 0.3240
##      Balanced Accuracy : 0.8792
##
##      'Positive' Class : Class1
##
```

For two classes, this function assumes that the class corresponding to an event is the *first* class level (but this can be changed using the `positive` argument).

Note that there are a number of statistics shown here. The “no-information rate” is the largest proportion of the observed classes (there were more class 2 data than class 1 in this test set). A hypothesis test is also computed to evaluate whether the overall accuracy rate is greater than the rate of the largest class. Also, the prevalence of the “positive event” is computed from the data (unless passed in as an argument), the detection rate (the rate of true events also predicted to be events) and the detection prevalence (the prevalence of predicted events).

If the prevalence of the event is different than those seen in the test set, the `prevalence` option can be used to adjust this.

Suppose a 2x2 table:

Predicted	Reference	
	Event	No Event
Event	A	B
No Event	C	D

The formulas used here are:

$$Sensitivity = \frac{A}{A + C}$$

$$Specificity = \frac{D}{B + D}$$

$$Prevalence = \frac{A + C}{A + B + C + D}$$

$$PPV = \frac{sensitivity \times prevalence}{((sensitivity \times prevalence) + ((1 - specificity) \times (1 - prevalence)))}$$

$$NPV = \frac{specificity \times (1 - prevalence)}{((1 - sensitivity) \times prevalence) + ((specificity) \times (1 - prevalence))}$$

$$Detection Rate = \frac{A}{A + B + C + D}$$

$$Detection Prevalence = \frac{A + B}{A + B + C + D}$$

$$Balanced Accuracy = (sensitivity + specificity) / 2$$

$$Precision = \frac{A}{A + B}$$

$$Recall = \frac{A}{A + C}$$

$$F1 = \frac{(1 + \beta^2) \times precision \times recall}{(\beta^2 \times precision) + recall}$$

When there are three or more classes, `confusionMatrix` will show the confusion matrix and a set of “one-versus-all” results. For example, in a three class problem, the sensitivity of the first class is calculated against all the samples in the second and third classes (and so on).

The `confusionMatrix` matrix frames the errors in terms of sensitivity and specificity. In the case of information retrieval, the precision and recall might be more appropriate. In this case, the option `mode` can be used to get those statistics:


```
confusionMatrix(data = test_set$pred, reference = test_set$obs, m
```



```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction Class1 Class2
##      Class1      183      141
##      Class2       13      663
##
##           Accuracy : 0.846
##           95% CI : (0.8221, 0.8678)
##      No Information Rate : 0.804
##      P-Value [Acc > NIR] : 0.0003424
##
##           Kappa : 0.6081
##  McNemar's Test P-Value : < 2.2e-16
##
##           Precision : 0.5648
##           Recall : 0.9337
##           F1 : 0.7038
##           Prevalence : 0.1960
##      Detection Rate : 0.1830
##      Detection Prevalence : 0.3240
##      Balanced Accuracy : 0.8792
##
##      'Positive' Class : Class1
##
```

Again, the `positive` argument can be used to control which factor level is associated with a “found” or “important” document or sample.

There are individual functions called `sensitivity` , `specificity` , `posPredValue` , `negPredValue` , `precision` , `recall` , and `F_meas` .

Also, a resampled estimate of the training set can also be obtained using `confusionMatrix.train` . For each resampling iteration, a confusion matrix is created from the hold-out samples and these values can be aggregated to diagnose issues with the model fit.

These values are the percentages that hold-out samples landed in the confusion matrix during resampling. There are several methods for normalizing these values. See `?confusionMatrix.train` for details.

The default performance function used by `train` is `postResample` , which generates the accuracy and Kappa statistics:

```
postResample(pred = test_set$pred, obs = test_set$obs)
```

```
## Accuracy      Kappa
```

```
## 0.8460000 0.6081345
```

As shown below, another function called `twoClassSummary` can be used to get the sensitivity and specificity using the default probability cutoff. Another function, `multiClassSummary` , can do similar calculations when there are three or more classes but both require class probabilities for each class.

17.3 Measures for Class Probabilities

For data with two classes, there are specialized functions for measuring model performance. First, the `twoClassSummary` function computes the area under the ROC curve and the specificity and sensitivity under the 50% cutoff. Note that:

- this function uses the first class level to define the “event” of interest. To change this, use the `lev` option to the function
- there must be columns in the data for each of the class probabilities (named the same as the outcome’s class levels)

```
twoClassSummary(test_set, lev = levels(test_set$obs))
```

```
##           ROC           Sens           Spec
## 0.9560044 0.9336735 0.8246269
```

A similar function can be used to get the analogous precision-recall values and the area under the precision-recall curve:

```
prSummary(test_set, lev = levels(test_set$obs))
```

```
##           AUC Precision           Recall           F
## 0.8582695 0.5648148 0.9336735 0.7038462
```

This function requires that the `MLmetrics` package is installed.

For multi-class problems, there are additional functions that can be used to calculate performance. One, `mnLogLoss` computes the negative of the multinomial log-likelihood (smaller is better) based on the class probabilities. This can be used to optimize tuning parameters but can lead to results that are inconsistent with other measures (e.g. accuracy or the area under the ROC curve), especially when the other measures are near their best possible values. The function has similar arguments to the other functions described above. Here is the two-class data from above:

```
mnLogLoss(test_set, lev = levels(test_set$obs))
```

```
## logLoss
```

```
## 0.370626
```

Additionally, the function `multiClassSummary` computes a number of relevant metrics:

- the overall accuracy and Kappa statistics using the predicted classes
- the negative of the multinomial log loss (if class probabilities are available)
- averages of the “one versus all” statistics such as sensitivity, specificity, the area under the ROC curve, etc.

17.4 Lift Curves

The `lift` function can be used to evaluate probabilities thresholds that can capture a certain percentage of hits. The function requires a set of sample probability predictions (not from the training set) and the true class labels. For example, we can simulate two-class samples using the `twoClassSim` function and fit a set of models to the training set:

```
set.seed(2)

lift_training <- twoClassSim(1000)
lift_testing  <- twoClassSim(1000)

ctrl <- trainControl(method = "cv", classProbs = TRUE,
                     summaryFunction = twoClassSummary)

set.seed(1045)
fda_lift <- train(Class ~ ., data = lift_training,
                  method = "fda", metric = "ROC",
                  tuneLength = 20,
                  trControl = ctrl)

set.seed(1045)
lda_lift <- train(Class ~ ., data = lift_training,
                  method = "lda", metric = "ROC",
                  trControl = ctrl)

library(C50)

set.seed(1045)
c5_lift <- train(Class ~ ., data = lift_training,
                 method = "C5.0", metric = "ROC",
                 tuneLength = 10,
                 trControl = ctrl,
                 control = C5.0Control(earlyStopping = FALSE))

## Generate the test set results

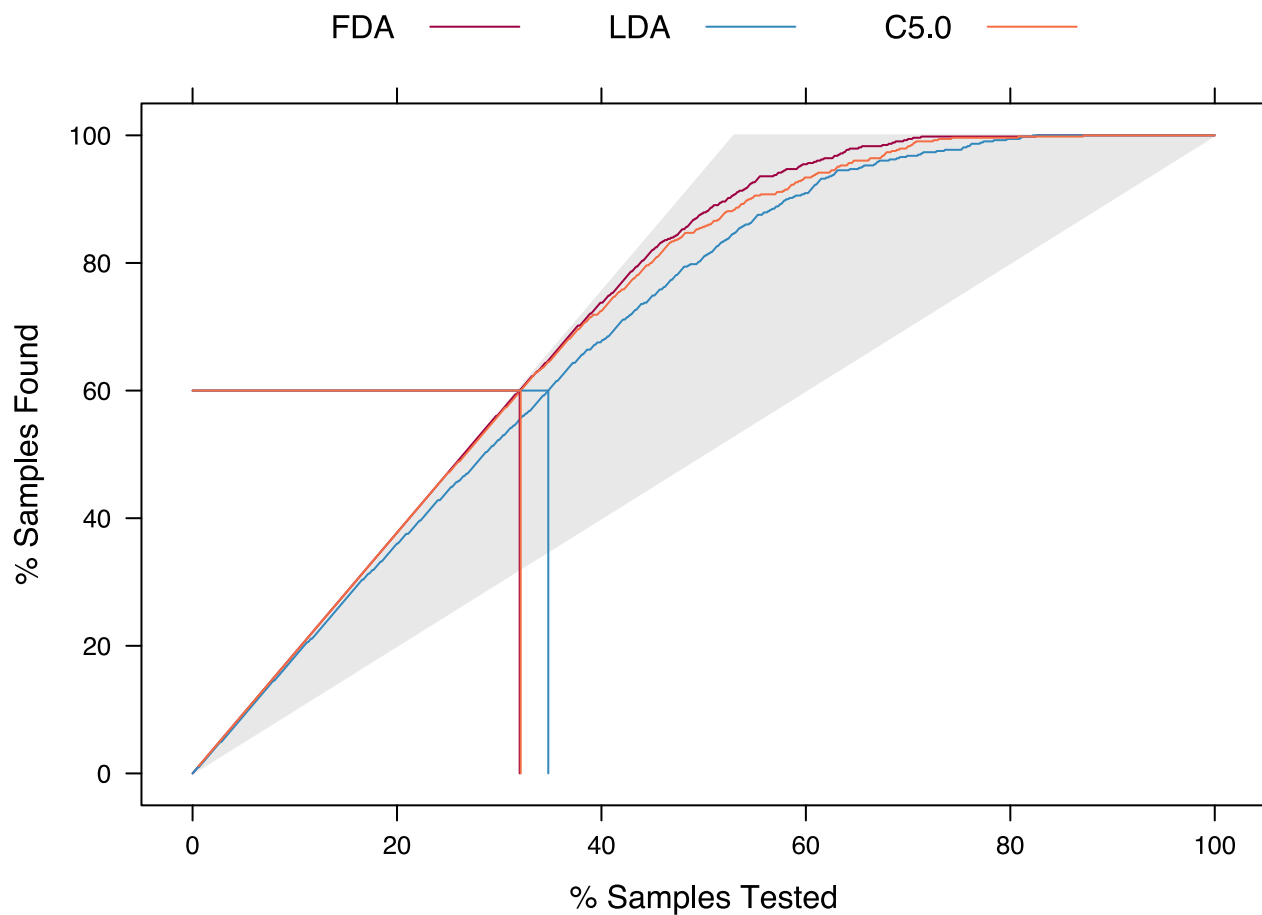
lift_results <- data.frame(Class = lift_testing$Class)
```

```
lift_results$FDA <- predict(fda_lift, lift_testing, type = "prob")
lift_results$LDA <- predict(lda_lift, lift_testing, type = "prob")
lift_results$C5.0 <- predict(c5_lift, lift_testing, type = "prob")
head(lift_results)
```

```
##      Class      FDA      LDA      C5.0
## 1 Class1 0.99240772 0.8838205 0.8445830
## 2 Class1 0.99252389 0.7572450 0.8882418
## 3 Class1 0.81693932 0.8883830 0.5732098
## 4 Class2 0.06018117 0.0140480 0.1690251
## 5 Class1 0.76891734 0.9320695 0.4824400
## 6 Class2 0.12191475 0.0524154 0.3310495
```

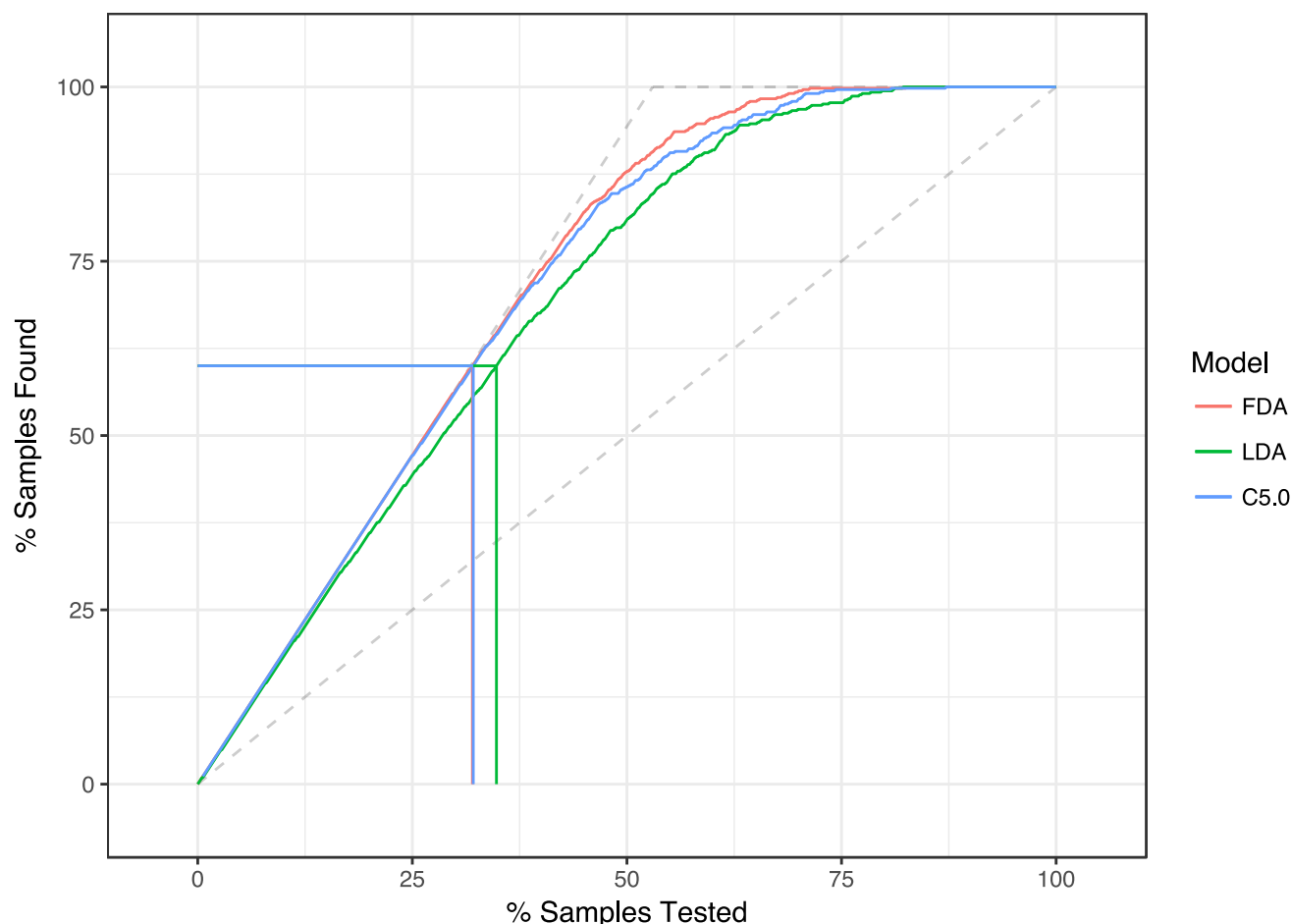
The `lift` function does the calculations and the corresponding `plot` function is used to plot the lift curve (although some call this the *gain curve*). The `value` argument creates reference lines:

```
trellis.par.set(caretTheme())
lift_obj <- lift(Class ~ FDA + LDA + C5.0, data = lift_results)
plot(lift_obj, values = 60, auto.key = list(columns = 3,
                                             lines = TRUE,
                                             points = FALSE))
```

There is also a `ggplot` method for `lift` objects:

```
ggplot(lift_obj, values = 60)
```



From this we can see that, to find 60 percent of the hits, a little more than 30 percent of the data can be sampled (when ordered by the probability predictions). The LDA model does somewhat worse than the other two models.

17.5 Calibration Curves

Calibration curves can be used to characterize how consistent the predicted class probabilities are with the observed event rates.

Other functions in the `gbm` package, the `rms` package (and others) can also produce calibration curves. The format for the function is very similar to the lift function:

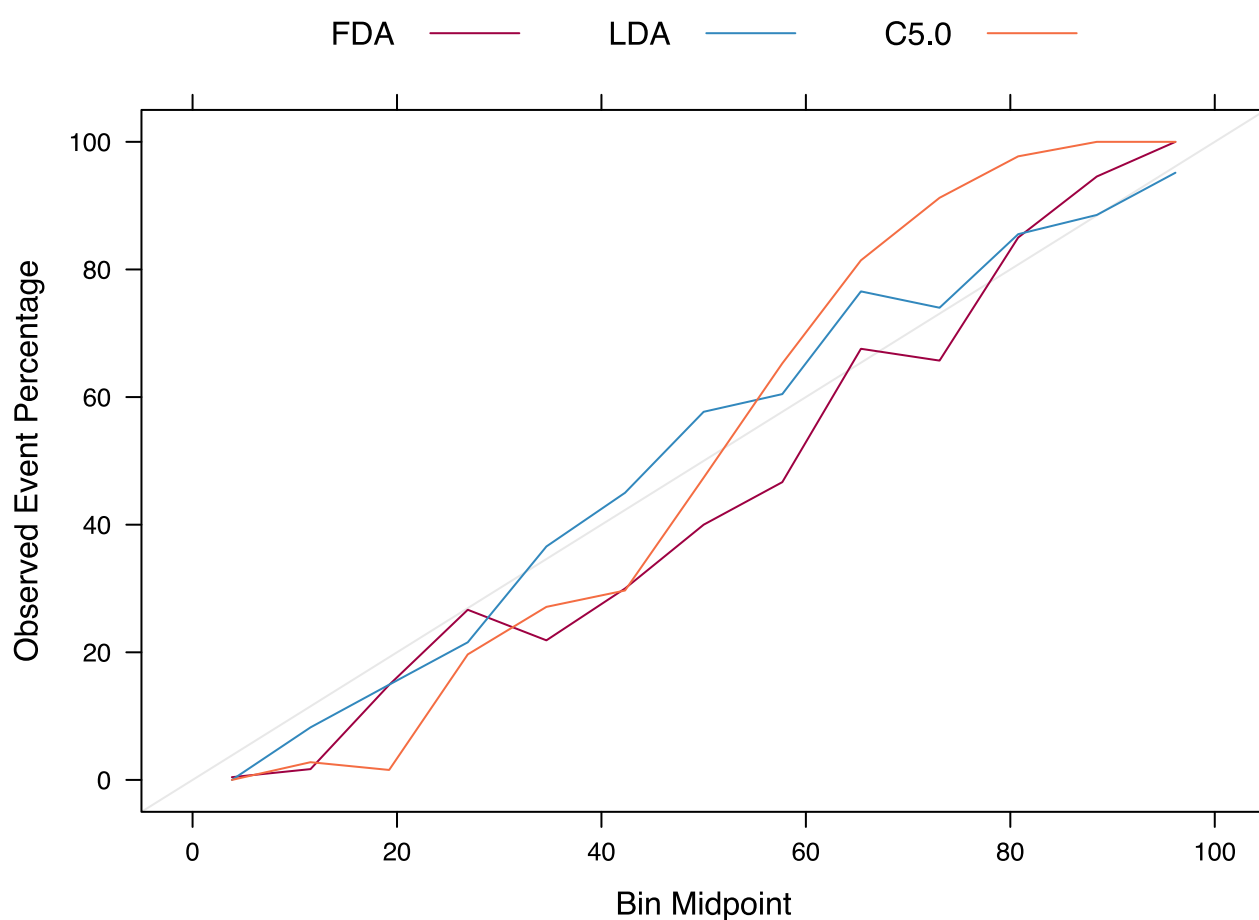
```

trellis.par.set(caretTheme())

cal_obj <- calibration(Class ~ FDA + LDA + C5.0,
                      data = lift_results,
                      cuts = 13)

plot(cal_obj, type = "l", auto.key = list(columns = 3,
                                           lines = TRUE,
                                           points = FALSE))

```



There is also a `ggplot` method that shows the confidence intervals for the proportions inside of the subsets:

```
ggplot(cal_obj)
```

