Logistic Regression

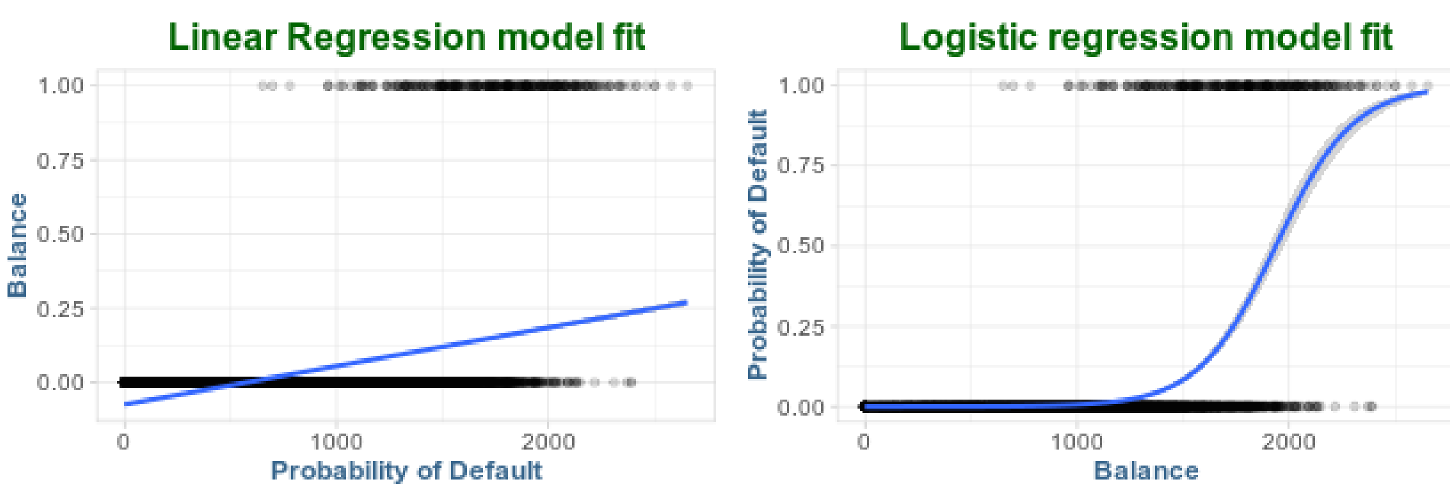
Data Set

```
attrition <- attrition %>% mutate_if(is.ordered, factor, order = F)
attrition.h2o <- as.h2o(attrition)
```

Overview

Linear Regression vs Logistic Regression

```
p1 <- ISLR::Default %>%
   mutate(prob = ifelse(default == "Yes", 1, 0)) %>%
   ggplot(aes(balance, prob)) +
   geom_point(alpha = .15) +
   geom_smooth(method = "lm") +
   ggtitle("Linear Regression model fit") +
   ylab("Balance") + xlab("Probability of Default")

p2 <- ISLR::Default %>%
   mutate(prob = ifelse(default == "Yes", 1, 0)) %>%
   ggplot(aes(balance, prob)) +
   geom_point(alpha = .15) +
   geom_smooth(method = "glm", method.args = list(family = "binomial")) +
   ggtitle("Logistic regression model fit") +
   xlab("Balance") + ylab("Probability of Default")

gridExtra::grid.arrange(p1, p2, nrow = 1)
```



Create training (70%) and test (30%) tests.

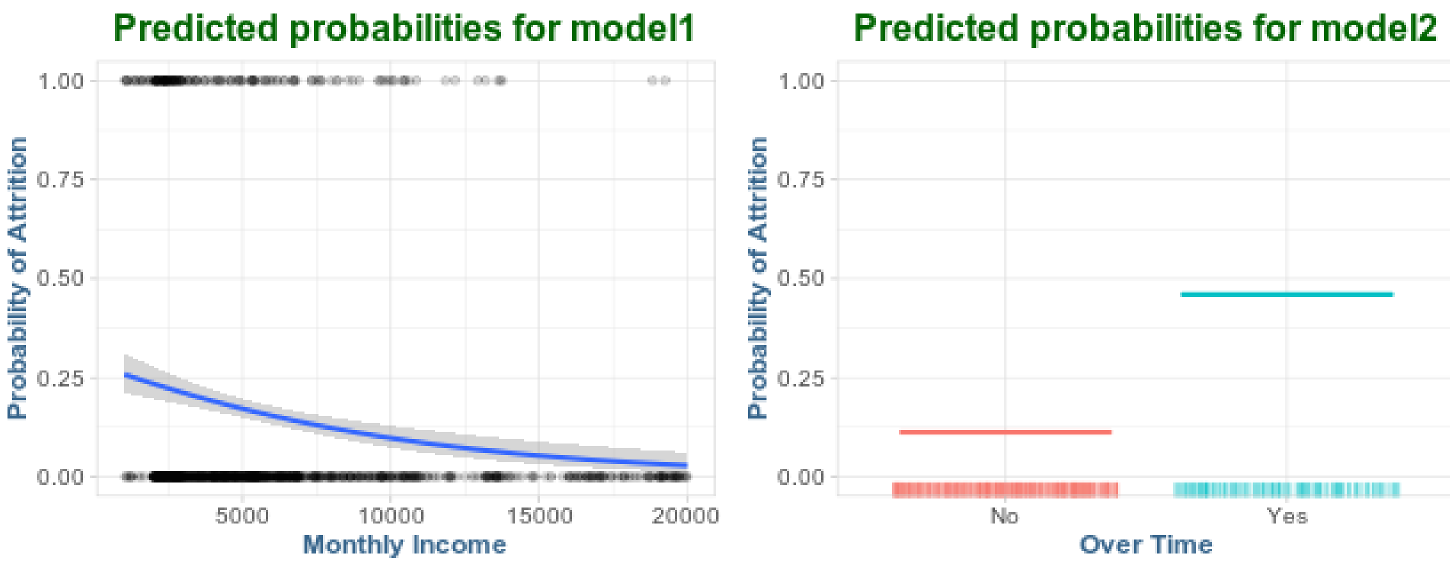
```r
set.seed(123)

churn_split <- initial_split(attrition,
                             prop = 0.7, strata = "Attrition")

churn_train <- training(churn_split)
churn_test <- testing(churn_split)
```

Simple Logistic Regression

Fit two generalized linear models to predict attrition.

```r
model1 <- glm(Attrition ~ MonthlyIncome, family = "binomial",
              data = churn_train)

model2 <- glm(Attrition ~ OverTime, family = "binomial",
              data = churn_train)
```

```r
churn_train2 <- churn_train %>% mutate(prob = ifelse(Attrition == "Yes", 1, 0))
churn_train2 <- broom::augment(model2, churn_train2) %>% mutate(.fitted = exp(.fitted))

p1 <- ggplot(churn_train2, aes(MonthlyIncome, prob)) +
   geom_point(alpha = 0.15) +
   geom_smooth(method = "glm", method.args = list(family = "binomial")) +
   ggtitle("Predicted probabilities for model1") +
   xlab("Monthly Income") +
   ylab("Probability of Attrition")

p2 <- ggplot(churn_train2, aes(OverTime, .fitted, color = OverTime)) +
   geom_boxplot(show.legend = F) +
   geom_rug(sides = "b", position = "jitter", alpha = 0.2, show.legend = F) +
   ggtitle("Predicted probabilities for model2") +
   xlab("Over Time") +
   scale_y_continuous("Probability of Attrition", limits = c(0, 1))

gridExtra::grid.arrange(p1, p2, nrow = 1)
```



Model Diagnostics

```r
tidy(model1)
```

```
# A tibble: 2 x 5
  term           estimate std.error statistic       p.value
  <chr>             <dbl>     <dbl>     <dbl>         <dbl>
1 (Intercept)   -0.924    0.155         -5.96 0.00000000259
2 MonthlyIncome -0.000130 0.0000264     -4.93 0.000000836
```

```r
tidy(model2)
```

```
# A tibble: 2 x 5
  term        estimate std.error statistic  p.value
  <chr>          <dbl>     <dbl>     <dbl>    <dbl>
1 (Intercept)    -2.18     0.122    -17.9  6.76e-72
2 OverTimeYes     1.41     0.176      8.00 1.20e-15
```

```r
exp(coef(model1))
```

```
  (Intercept) MonthlyIncome
    0.3970771     0.9998697
```

```r
exp(coef(model2))
```

```
(Intercept) OverTimeYes
  0.1126126   4.0812121
```

```r
confint(model1)
```

```
Waiting for profiling to be done...
                      2.5 %        97.5 %
```

```
(Intercept)   -1.2267754960 -0.61800619157
MonthlyIncome -0.0001849796 -0.00008107634
```

```
confint(model2)
```

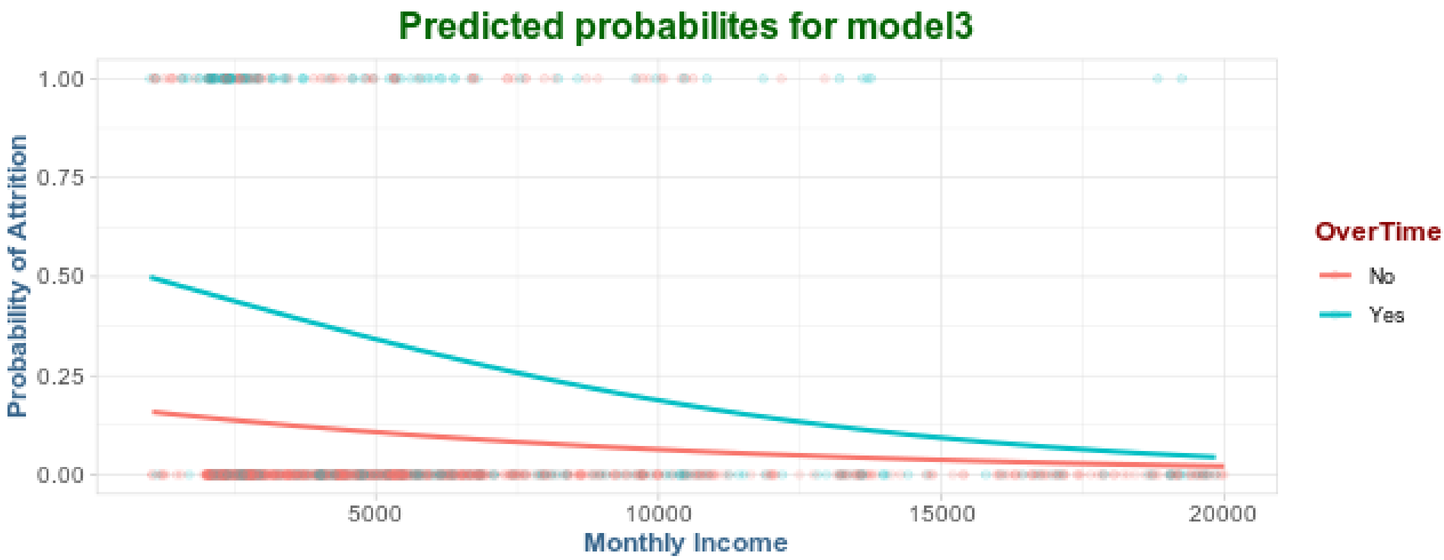
```
Waiting for profiling to be done...

                2.5 %    97.5 %
(Intercept) -2.430458 -1.952330
OverTimeYes  1.063246  1.752879
```

Multiple Logistic Regression

```
model3 <- glm(
   Attrition ~ MonthlyIncome + OverTime,
   family = "binomial",
   data = churn_train
)

tidy(model3)
```

```
# A tibble: 3 x 5
  term           estimate std.error statistic  p.value
  <chr>             <dbl>     <dbl>     <dbl>    <dbl>
1 (Intercept)   -1.43     0.176         -8.11 5.25e-16
2 MonthlyIncome -0.000139 0.0000270     -5.15 2.62e- 7
3 OverTimeYes    1.47     0.180          8.16 3.43e-16
```

```
churn_train3 <- churn_train %>% mutate(prob = ifelse(Attrition == "Yes", 1, 0))
churn_train3 <- broom::augment(model3, churn_train3) %>% mutate(.fitted = exp(.fitted))

ggplot(churn_train3, aes(MonthlyIncome, prob, color = OverTime)) +
   geom_point(alpha = .15) +
   geom_smooth(method = "glm", method.args = list(family = "binomial"), se = F) +
   ggtitle("Predicted probabilites for model3") +
   xlab("Monthly Income") +
   ylab("Probability of Attrition")
```



Assessing Model Accuracy

```r
set.seed(123)

cv_model1 <- train(
   Attrition ~ MonthlyIncome,
   data = churn_train,
   method = "glm",
   family = "binomial",
   trControl = trainControl(method = "cv", number = 10)
)

set.seed(123)

cv_model2 <- train(
   Attrition ~ MonthlyIncome + OverTime,
   data = churn_train,
   method = "glm",
   family = "binomial",
   trControl = trainControl(method = "cv", number = 10)
)

set.seed(123)

cv_model3 <- train(
   Attrition ~ .,
   data = churn_train,
```

```r
   method = "glm",
   family = "binomial",
   trControl = trainControl(method = "cv", number = 10)
)

# extract out of sample performance measurse

summary(
   resamples(
      list(
         model_1 = cv_model1,
         model_2 = cv_model2,
         model_3 = cv_model3
      )
   )
)$statistics$Accuracy
```

```
             Min.   1st Qu.    Median      Mean   3rd Qu.      Max. NA's
model_1 0.8349515 0.8349515 0.8365385 0.8388478 0.8431373 0.8446602    0
model_2 0.8349515 0.8349515 0.8365385 0.8388478 0.8431373 0.8446602    0
model_3 0.8365385 0.8495146 0.8792476 0.8757893 0.8907767 0.9313725    0
```

```r
# predicted class
pred_class <- predict(cv_model3, churn_train)

# create confusion matrix
confusionMatrix(
   data = relevel(pred_class, ref = "Yes"),
   reference = relevel(churn_train$Attrition, ref = "Yes")
)
```

```
Confusion Matrix and Statistics

          Reference
Prediction Yes  No
       Yes  93  25
       No   73 839

               Accuracy : 0.9049
                 95% CI : (0.8853, 0.9221)
    No Information Rate : 0.8388
    P-Value [Acc > NIR] : 0.000000000536

                  Kappa : 0.6016
```

```
 Mcnemar's Test P-Value : 0.000002057257

            Sensitivity : 0.56024
            Specificity : 0.97106
         Pos Pred Value : 0.78814
         Neg Pred Value : 0.91996
             Prevalence : 0.16117
         Detection Rate : 0.09029
   Detection Prevalence : 0.11456
      Balanced Accuracy : 0.76565

       'Positive' Class : Yes
```

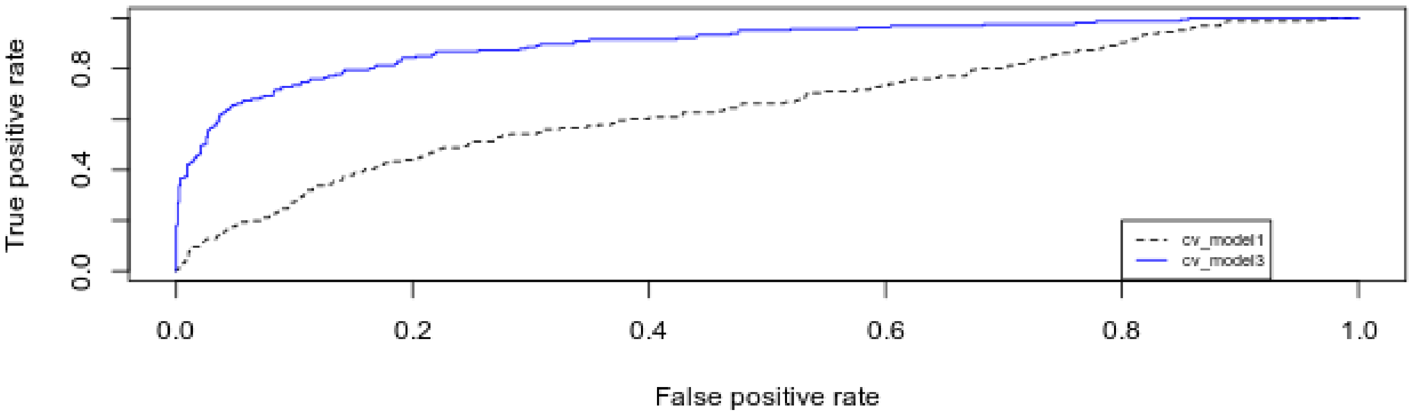
No-information rate

```
table(churn_train$Attrition) %>% prop.table()
```

```
      No      Yes
0.838835 0.161165
```

Basically, this is saying if we just predicted “No” for every instance we would have 83.8% accuracy.

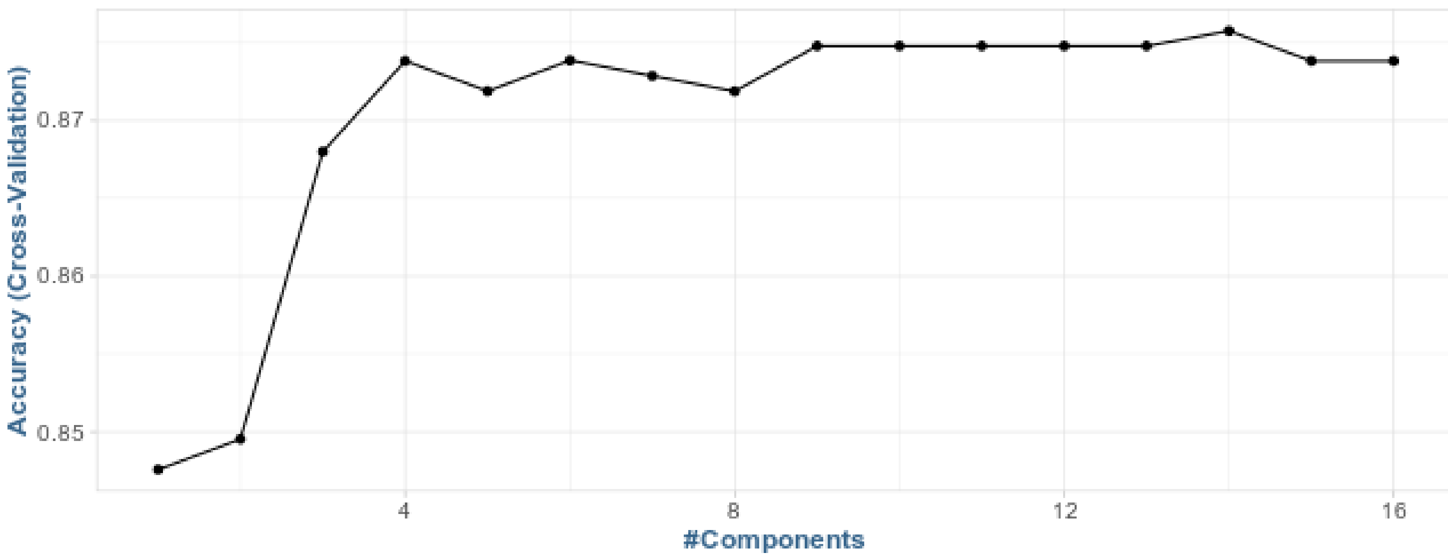
```
# Compute predicted probabilities
m1_prob <- predict(cv_model1, churn_train, type = "prob")$Yes
m3_prob <- predict(cv_model3, churn_train, type ="prob")$Yes

# Compute AUC metrics for cv_model1 and cv_model3
perf1 <- prediction(m1_prob, churn_train$Attrition) %>%
   performance(measure = "tpr", x.measure = "fpr")

perf2 <- prediction(m3_prob, churn_train$Attrition) %>%
   performance(measure = "tpr", x.measure = "fpr")

# Plot ROC curves for cv_model1 and cv_model3
plot(perf1, col = "black", lty = 2)
plot(perf2, col = "blue", add = T)

legend(0.8, 0.2, legend = c("cv_model1", "cv_model3"),
       col = c("black", "blue"), lty = 2:1, cex = 0.6)
```




```r
set.seed(123)
cv_model_pls <- train(
   Attrition ~ .,
   data = churn_train,
   method = "pls",
   family = "binomial",
   trControl = trainControl(method = "cv", number = 10),
   preProcess = c("zv", "center", "scale"),
   tuneLength = 16
)

cv_model_pls$bestTune
```

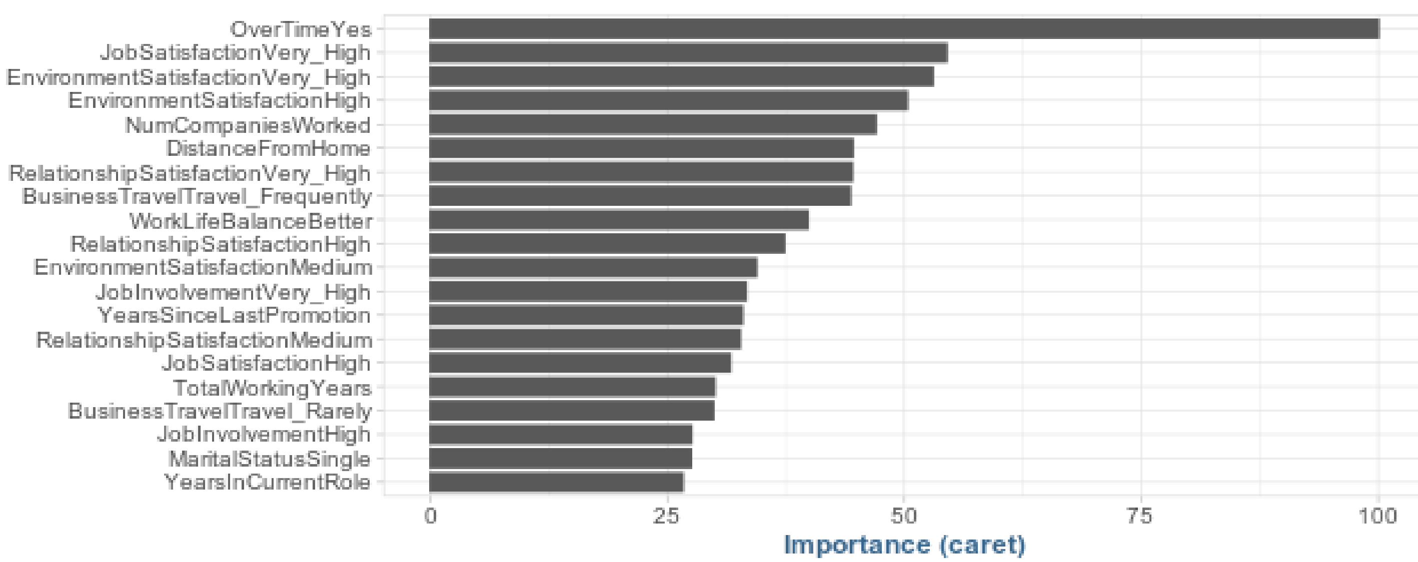
```
   ncomp
14    14
```

```r
ggplot(cv_model_pls)
```



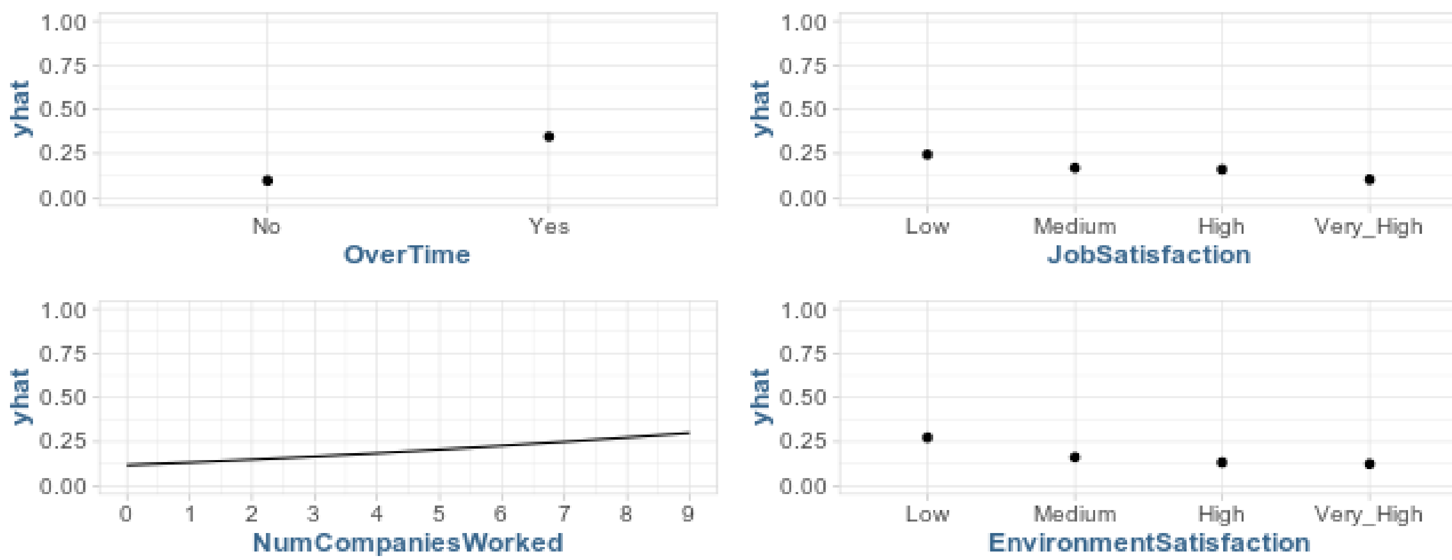
Feature Interpretation

```r
vip::vip(cv_model3, num_features = 20)
```




```r
pred.fun <- function(object, newdata) {
  Yes <- mean(predict(object, newdata, type = "prob")$Yes)
  as.data.frame(Yes)
}

p1 <- pdp::partial(cv_model3, pred.var = "OverTime", pred.fun = pred.fun ) %>%
  autoplot(rug = T) + ylim(c(0, 1))
```

```
p2 <- pdp::partial(cv_model3, pred.var = "JobSatisfaction", pred.fun = pred.fun) %>%
  autoplot() + ylim(c(0, 1))

p3 <- pdp::partial(cv_model3, pred.var = "NumCompaniesWorked", pred.fun = pred.fun, gr = 10) %>
  autoplot() + scale_x_continuous(breaks = 0:9) + ylim(c(0, 1))

p4 <- pdp::partial(cv_model3, pred.var = "EnvironmentSatisfaction", pred.fun = pred.fun) %>%
  autoplot() + ylim(c(0, 1))

grid.arrange(p1, p2, p3, p4, nrow = 2)
```




```
# clean up
rm(list = ls())
```