Churn Analysis with logistic regression and random forests

Daniel Moscoe

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Abstract

Churn analysis is a fundamental problem in data science. The investigator obtains information on customer behavior and attributes and uses this information to predict whether the customer will terminate a contract, or not. In this study, I conduct a churn analysis based on simulated cell phone customer data from a Kaggle competition, Customer Churn Prediction 2020. I combine this data with information on Google searches pertaining to each of the four major cell phone carriers in the US. The study addresses three main questions:

Does the mean total daytime charge for customers vary by area code?

Does the mean number of customer service calls vary depending on whether a customer carries an international plan?

How can a customer's characteristics be used to predict whether they will terminate their contract?

The study follows the OSEMN workflow. The main strategy for data exploration, in addition to visualization, is hypothesis testing. In the modeling section, I build a logistic regression as well as a random forest model to predict customer churn. I conclude with a summary of my findings.

Data collection

Kaggle Customer Churn Prediction 2020

```
k1.dat <- read_csv("https://raw.githubusercontent.com/dmoscoe/SPS/main/churn_train.csv")
str(k1.dat)
```

```
## spec_tbl_df [4,250 x 20] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ state                        : chr [1:4250] "OH" "NJ" "OH" "OK" ...
##  $ account_length               : num [1:4250] 107 137 84 75 121 147 117 141 65 74 ...
##  $ area_code                    : chr [1:4250] "area_code_415" "area_code_415" "area_code_408" "area_code_415" ...
##  $ international_plan           : chr [1:4250] "no" "no" "yes" "yes" ...
##  $ voice_mail_plan              : chr [1:4250] "yes" "no" "no" "no" ...
##  $ number_vmail_messages        : num [1:4250] 26 0 0 0 24 0 0 37 0 0 ...
##  $ total_day_minutes            : num [1:4250] 162 243 299 167 218 ...
##  $ total_day_calls              : num [1:4250] 123 114 71 113 88 79 97 84 137 127 ...
##  $ total_day_charge             : num [1:4250] 27.5 41.4 50.9 28.3 37.1 ...
##  $ total_eve_minutes            : num [1:4250] 195.5 121.2 61.9 148.3 348.5 ...
##  $ total_eve_calls              : num [1:4250] 103 110 88 122 108 94 80 111 83 148 ...
##  $ total_eve_charge             : num [1:4250] 16.62 10.3 5.26 12.61 29.62 ...
##  $ total_night_minutes          : num [1:4250] 254 163 197 187 213 ...
##  $ total_night_calls            : num [1:4250] 103 104 89 121 118 96 90 97 111 94 ...
##  $ total_night_charge           : num [1:4250] 11.45 7.32 8.86 8.41 9.57 ...
##  $ total_intl_minutes           : num [1:4250] 13.7 12.2 6.6 10.1 7.5 7.1 8.7 11.2 12.7 9.1 ...
##  $ total_intl_calls             : num [1:4250] 3 5 7 3 7 6 4 5 6 5 ...
##  $ total_intl_charge            : num [1:4250] 3.7 3.29 1.78 2.73 2.03 1.92 2.35 3.02 3.43 2.46 ...
##  $ number_customer_service_calls: num [1:4250] 1 0 2 3 3 0 1 0 4 0 ...
##  $ churn                        : chr [1:4250] "no" "no" "no" "no" ...
```

Response variable, `churn`

```
k3.dat %>%
  select(churn) %>%
  table()
```

```
## .
## FALSE  TRUE
##  3652   598
```

Data collection

Google Trends for wireless carrier names, March 2020. `library(gtrendsR)`

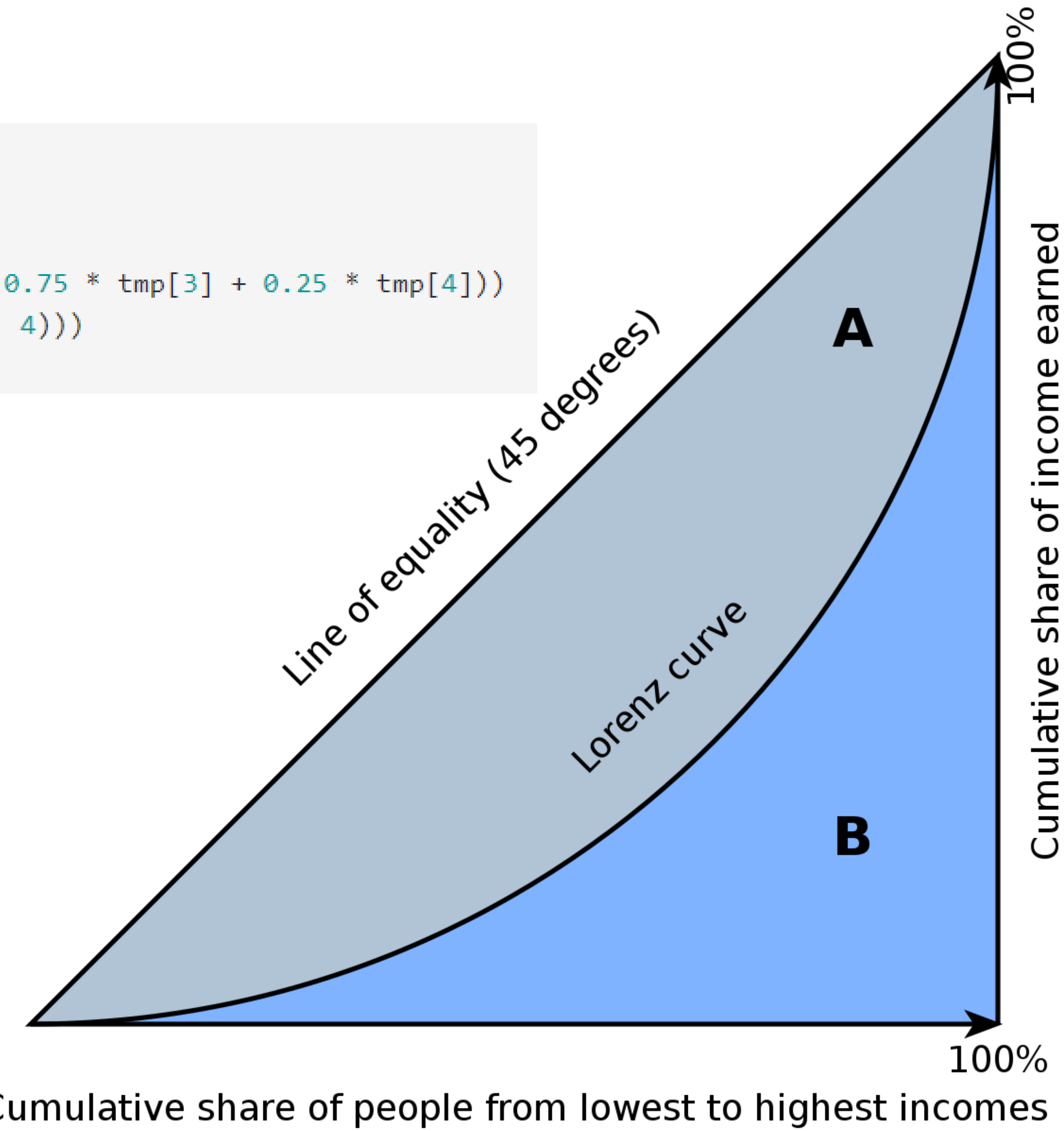
```
gtrends(keyword = gtrends_search_terms[1:4], geo = states[i], time = "2020-03-01 2020-03-30")
```

```
## 'data.frame':    120 obs. of  7 variables:
##  $ date    : POSIXct, format: "2020-03-01" "2020-03-02" ...
##  $ hits    : int  44 20 84 34 36 76 32 38 69 59 ...
##  $ keyword : chr  "att" "att" "att" "att" ...
##  $ geo     : chr  "US-AL" "US-AL" "US-AL" "US-AL" ...
##  $ time    : chr  "2020-03-01 2020-03-30" "2020-03-01 2020-03-30" "2020-03-01 2020-03-30" "2020-03-01 2020-03-30" ...
##  $ gprop   : chr  "web" "web" "web" "web" ...
##  $ category: int  0 0 0 0 0 0 0 0 0 0 ...
```

The Gini Index

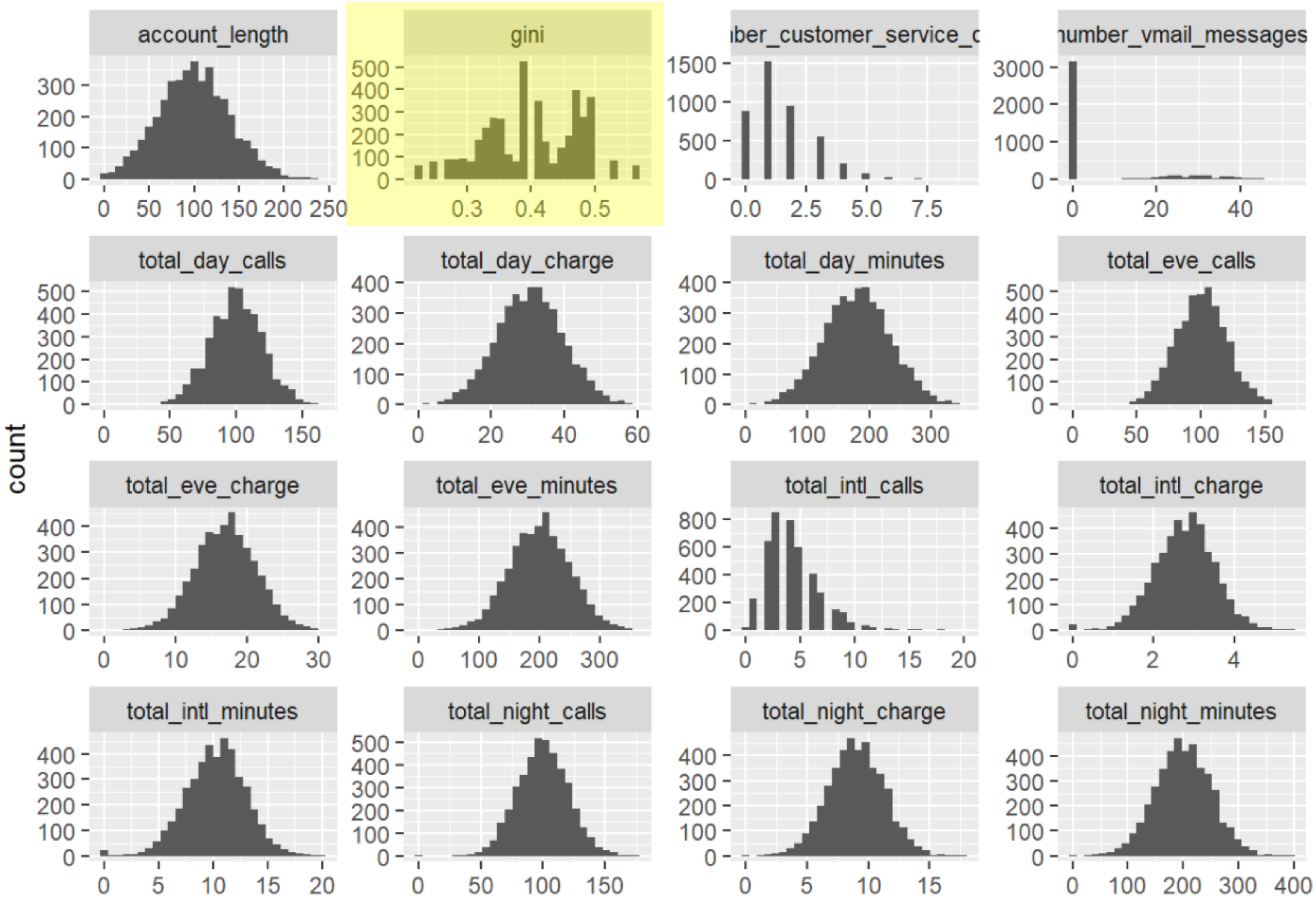
```
ginis <- data.frame("geo" = "x", "gini" = "-1")
for(i in seq(nrow(tmp_query_summaries))) {
  tmp <- sort(as.integer(tmp_query_summaries[i,2:5]))
  tmp.gini <- 1 - ((1/sum(tmp)) * (1.75 * tmp[1] + 1.25 * tmp[2] + 0.75 * tmp[3] + 0.25 * tmp[4]))
  ginis <- rbind(ginis, c(tmp_query_summaries[i,1], round(tmp.gini, 4)))
}
```

- Computed from Google Trends data
- $0 \leq A/(A+B) \leq 1$ (perfect equality to perfect inequality)
- ***Inequality in searches implies inequality in number of customers across providers***



Explanatory variables

```
k3.dat %>%
  keep(is.numeric) %>%
  gather() %>%
  ggplot(aes(value)) +
  facet_wrap(~ key, scales = "free") +
  geom_histogram()
```



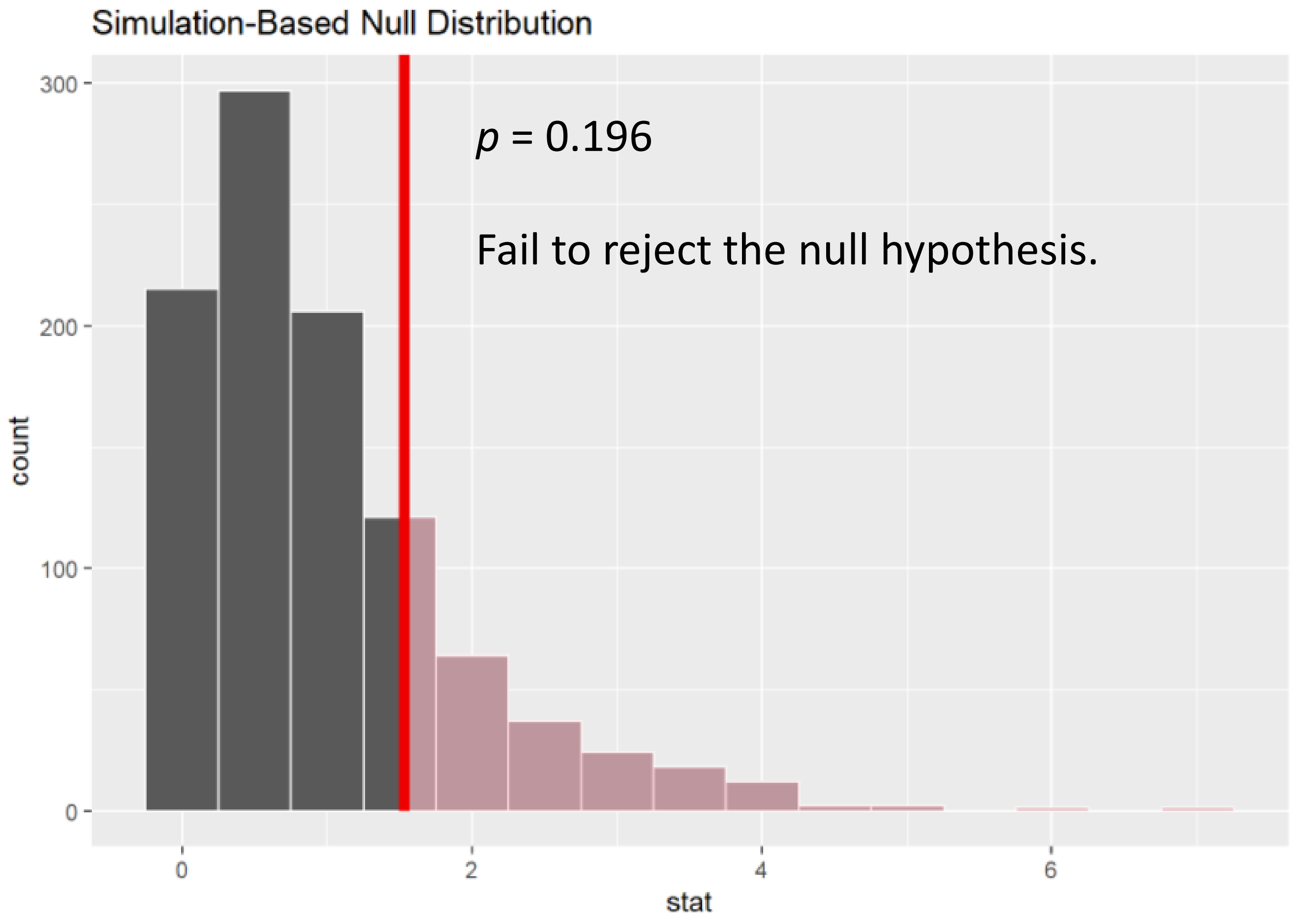
Does mean total daytime charge vary by area code?

```r
#Compute the point estimate
F_hat <- k3.dat %>%
  specify(total_day_charge ~ area_code) %>%
  calculate(stat = "F")

#Generate the null distribution (the sampling distribution of the test stat
null_f_distn <- k3.dat %>%
  specify(total_day_charge ~ area_code) %>%
  hypothesize(null = "independence") %>%
  generate(reps = 1000, type = "permute") %>%
  calculate(stat = "F")

#Get the p-value for your test statistic with respect to the null distribut
null_f_distn %>%
  get_p_value(obs_stat = F_hat, direction = "greater")
```

```r
#Visualize the result
visualize(null_f_distn, method = "simulation") +
  shade_p_value(obs_stat = F_hat, direction = "greater")
```

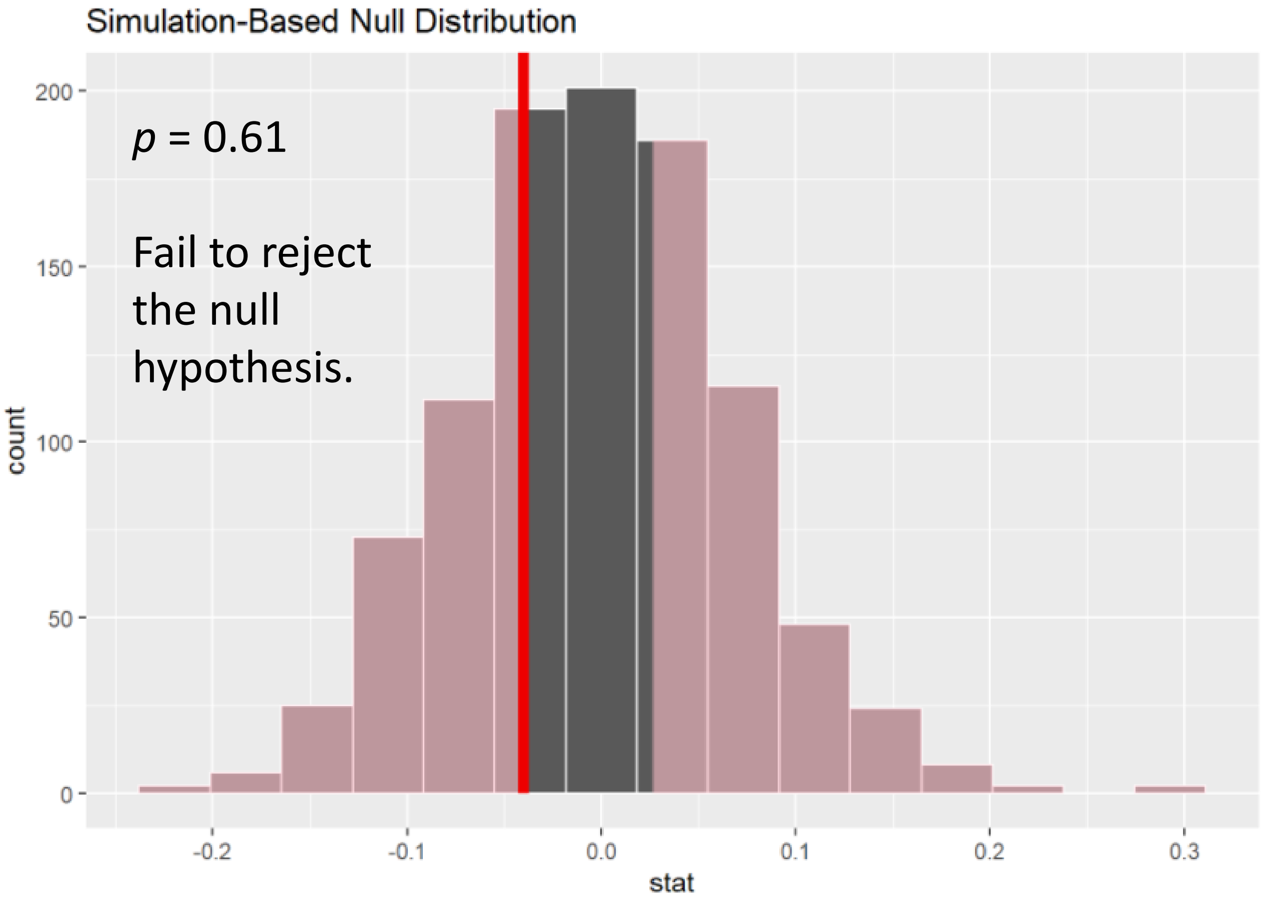


Does the mean number of customer service calls vary depending on whether a customer carries an international plan?

```r
obs_diff <- k3.dat %>%
  specify(number_customer_service_calls ~ international_plan) %>%
  calculate(stat = "diff in means", order = c(TRUE, FALSE))

null_t_distn <- k3.dat %>%
  specify(number_customer_service_calls ~ international_plan) %>%
  hypothesize(null = "independence") %>%
  generate(reps = 1000, type = "permute") %>%
  calculate(stat = "diff in means", order = c(TRUE, FALSE))
```

```r
visualize(null_t_distn, method = "simulation") +
  shade_p_value(obs_stat = obs_diff, direction = "two_sided")
```



Logistic Regression

- Address class imbalance
- Prune model with backward selection

```
## Call:
## glm(formula = churn ~ total_day_minutes + total_eve_minutes +
##     total_night_minutes + number_customer_service_calls + international_plan +
##     voice_mail_plan, family = binomial(link = "logit"), data = k4_train.dat)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.55164  -0.78148  -0.03148   0.82985   2.67961
##
## Coefficients:
##                                Estimate Std. Error z value Pr(>|z|)
## (Intercept)                   -6.060681   0.612370  -9.897  < 2e-16 ***
## total_day_minutes              0.014621   0.001472   9.936  < 2e-16 ***
## total_eve_minutes              0.006237   0.001579   3.951 7.79e-05 ***
## total_night_minutes            0.003483   0.001645   2.117   0.0343 *
## number_customer_service_calls  0.630234   0.061077  10.319  < 2e-16 ***
## international_planTRUE         2.487112   0.255333   9.741  < 2e-16 ***
## voice_mail_planTRUE           -1.356577   0.217122  -6.248 4.16e-10 ***
```

Interpreting coefficients of the logistic regression

$$\frac{p}{1-p} = \sum_{i,j} \exp(\beta_i x_{ij})$$

A unit increase in x_i increases the odds of churn by a *factor* of $\exp(\beta_i)$.

Variable	Estimate	Odds change by factor of
total_day_minutes	0.015	1.015
total_eve_minutes	0.0062	1.006
total_night_ minutes	0.0035	1.004
number_customer_ service_calls	0.6302	1.878
international_plan	2.4871	12.026
voicemail_plan	-1.357	0.257

Logistic Regression Cutoffs

Maximize detection of true positives:
Cutoff = 0.0857

```
k4_train_preds <- ifelse(k4_train_preds >= optimal_cutoff, TRUE, FALSE)
k4_train_preds_table <- table(k3_test.dat$churn, k4_train_preds)
k4_train_preds_table
```

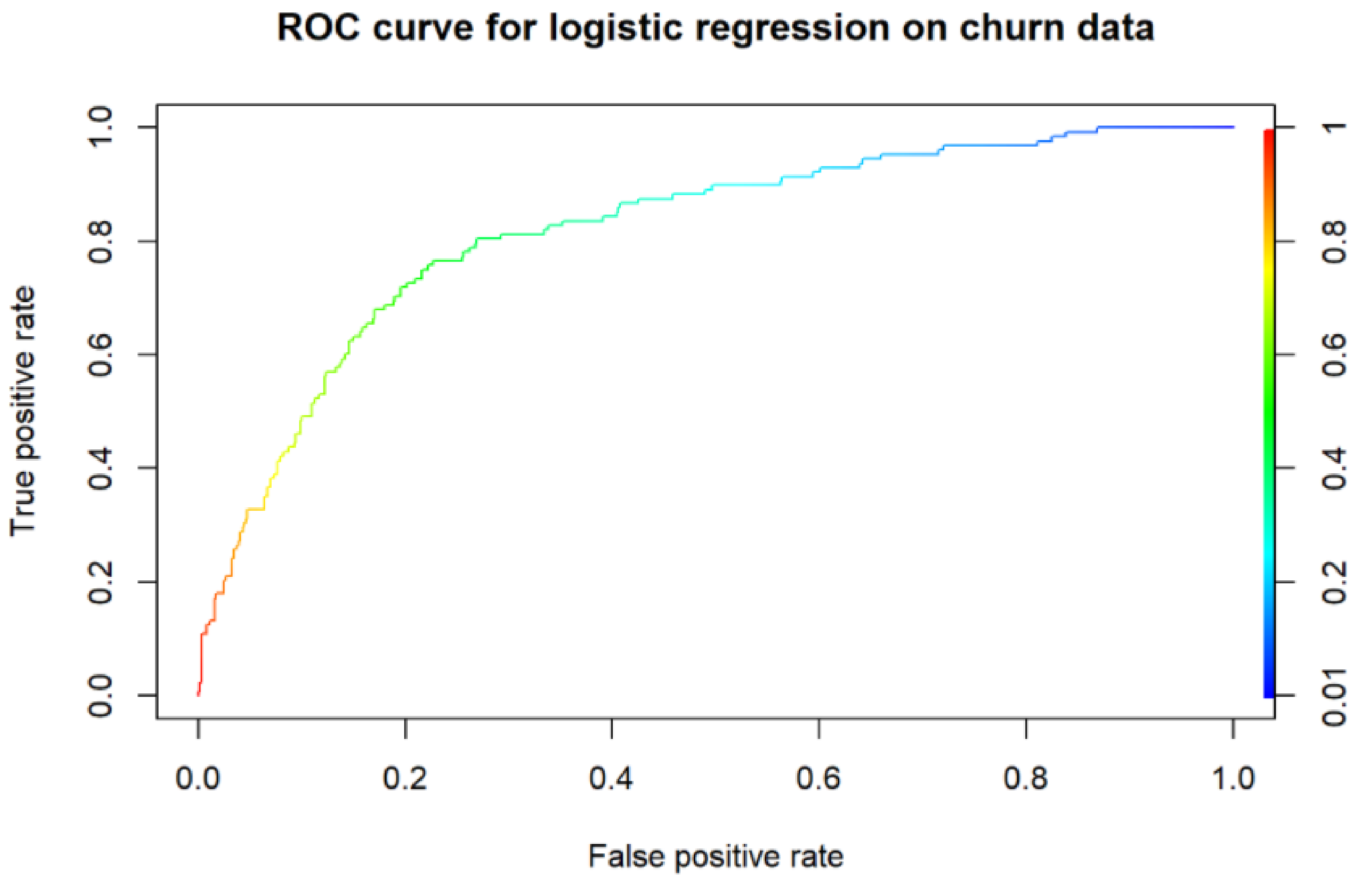
```
##        k4_train_preds
##         FALSE  TRUE
##   FALSE    95   627
##   TRUE      0   128
```

Maximize accuracy:
Cutoff = 0.9457

```
k4_train_preds <- ifelse(k4_train_preds >= optimal_cutoff, TRUE, FALSE)
k4_train_preds_table <- table(k3_test.dat$churn, k4_train_preds)
k4_train_preds_table
```

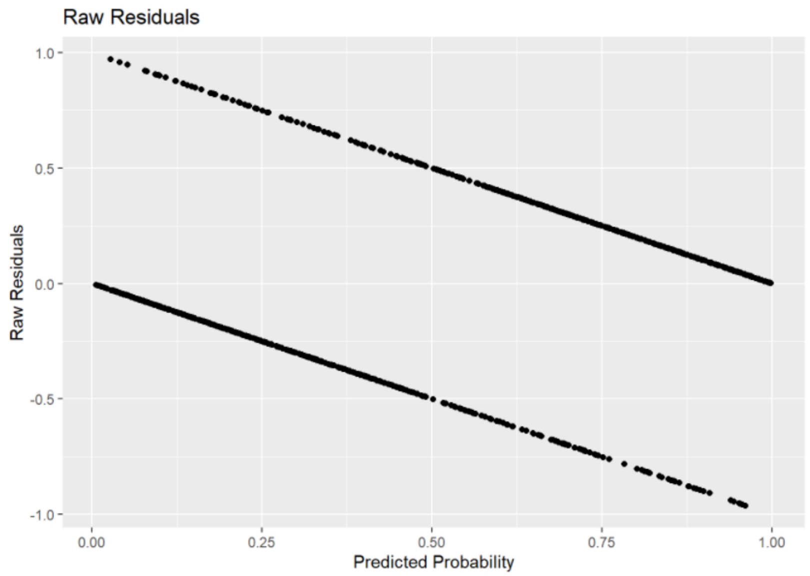
```
##        k4_train_preds
##         FALSE  TRUE
##   FALSE   719     3
##   TRUE    114    14
```

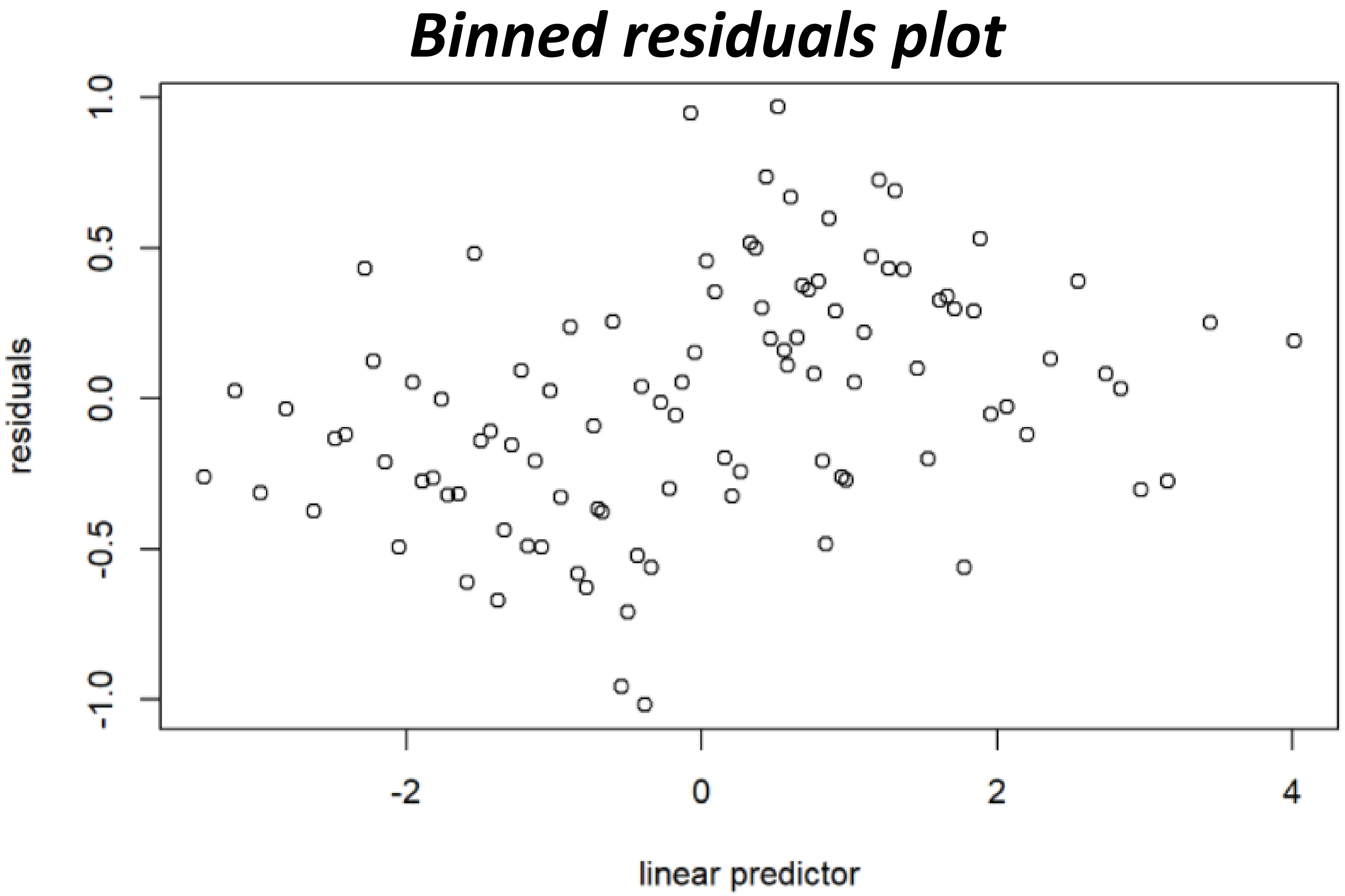
```
k4_train_preds <- predict(k4_train.glm, k3_test.dat, type = "response")
pred <- ROCR::prediction(k4_train_preds, k3_test.dat$churn)
perf <- ROCR::performance(pred, "tpr", "fpr")
plot(perf, colorize = TRUE, main = "ROC curve for logistic regression on churn data")
```



LR Residuals

```
k5_train.dat <- k4_train.dat %>%
mutate("residuals" = residuals(k4_train.glm), linpred = predict(k4_train.glm))
gdf <- group_by(k5_train.dat, cut(linpred, breaks = unique(quantile(linpred, (1:100)/101))))
diagdf <- summarise(gdf, residuals = mean(residuals), linpred = mean(linpred))
plot(residuals ~ linpred, diagdf, xlab = "linear predictor")
```





Tuned Random Forest Model

```
k4_train.for <- randomForest(as.factor(churn) ~ ., k4_train.dat, ntree = 200, mtry = 14, importance = TRUE, proximity = TRU
E)
print(k4_train.for)
```

```
##
## Call:
##  randomForest(formula = as.factor(churn) ~ ., data = k4_train.dat,      ntree = 200, mtry = 14, importance = TRUE, proxim
ity = TRUE)
##                Type of random forest: classification
##                      Number of trees: 200
## No. of variables tried at each split: 14
##
##         OOB estimate of  error rate: 15.85%
## Confusion matrix:
##       FALSE TRUE class.error
## FALSE   386   84   0.1787234
## TRUE     65  405   0.1382979
```

Applying the new model to the test set:

```
k4_test_preds_for <- predict(k4_train.for, k3_test.dat) #predictions on the k3_test.dat data based on the model trained on k
4_train.dat.
confusionMatrix(k4_test_preds_for, as.numeric(k3_test.dat$churn)) #A confusion matrix comparing predicted values for k3_tes
t.dat with actual values.
```

```
##   FALSE TRUE
## 0   603  119
## 1    20  108
```

Choosing a model

Act.↓ Pred. →	Churn	Remain	Pro	Con
LR max true +			***Detects about 100% of churn. Use if cost of churn is much greater than cost of promo.***	***Low accuracy. Detects many false positives. Many non-churners will receive promo.*** acc = 0.26, prec = 0.17, rec = 1, spec = 0.13
Churn	0.15	0		
Remain	0.74	0.11		
LR max acc.			***High accuracy.***	***Essentially equivalent to predicting majority class for all obs's.*** acc = 0.87, prec = 0.83, Rec = 0.13, spec = 0.99
Churn	0.02	0.13		
Remain	0.004	0.85		
Random Forest			***Detects almost all churn. Detects majority of non-churn. High accuracy.***	***Some false positives.*** acc = 0.84, prec = 0.48, Rec = 0.87, spec = 0.84
Churn	0.13	0.02		
Remain	0.14	0.71		

Submission and Description	Private Score	Public Score
sub_set.csv 2 minutes ago by Daniel Moscoe	0.81333	0.80444

Conclusion

- Finding value doesn’t always mean improving accuracy.

- The LR yields “collateral insights.”