## Code Appendix

```
library(tidyverse)
library(MASS)
library(caret)
library(caretEnsemble)
library(glmnet)
library(corrplot)
library(lubridate)
set.seed(578)
# glimpse(raw_data)
data <- raw_data %>%
  mutate(vdate_month = month(parse_date(vdate, "%m/%d/%Y"))) %>%
  sample_n(size = 8000) # actually, take 8k samples so we can save 4k for a
# final test of the CV models
# summary(data)
ggplot(data, aes(lengthofstay)) +
  geom_histogram(binwidth = 1) +
  theme_bw()
d1 <- data %>%
  dplyr::select(5:15) %>%
  pivot_longer(cols = everything()) %>%
  group_by(name, value) %>%
  summarize(count = n()) %>%
  pivot_wider(id_cols = name, names_from = value, values_from = count)
knitr::kable(d1, caption = "Summary of categorical predictors")
numdata <- data %>%
  dplyr::select(16:24) %>%
  pivot_longer(everything())
ggplot(numdata, aes(value)) +
  geom_histogram() +
 facet_wrap(~name, scales = "free") +
 theme bw()
cmat <- cor(data[, c(16:24, 28)], method = "spearman")</pre>
corrplot(cmat, type = "upper")
# 1 - set up a for loop for 10-fold cross validation
#2 - set up train and test indices from data (df); nested for loop?
#3 - each model will use a different data structure, so just make sure to use
# the same indices to
```

```
# subset test and train prior to creating the required data structures.
# 4 - apply models and record MSE.
# lm and lasso can use the same data struc (pq. 120 class notes)
# decision tree
# maybe use gams
# 5 - caretEnsemble will actually do this through model methods
set.seed(578)
# split data equally into train and test sets; cross validate using train.
# Apply final models to the test set.
# ToDo drop extra cols that aren't predictors; address recount variable. Could
# try one-hot encoding. Need to think carefully about how to handle this. It
# is a strange mix of ordinal and numeric data. I think you can make the
# argument to convert the 5+ values to 5?
# first center and scale numeric predictors
los <- data$lengthofstay</pre>
data_cent_scale <- data %>%
  dplyr::select(-lengthofstay) %>%
  dplyr::mutate_if(is.numeric, scale) %>%
  dplyr::mutate_if(is.numeric, scale) %>%
  bind_cols(., lengthofstay = los)
train <- sample(1:nrow(data_cent_scale), nrow(data_cent_scale) / 2)</pre>
test <- (-train)</pre>
train_set <- data_cent_scale[train, -c(1, 2, 3, 13, 25, 26, 28)] # drop id, vdate, discharged,
# vdate_month, fibrosisandother
test_set <- data_cent_scale[test, -c(1, 2, 3, 13, 25, 26, 28)]
library(skimr)
skimmed <- skim_to_wide(data_cent_scale[, -c(1, 2, 3, 13, 25, 26, 28)])
# skimmed
# There's a large list of model algos available in caret.
# To get the details, use
# modelLookup(<algorithm>)
knitr::kable(models <- bind_rows(</pre>
  modelLookup("rpart"),
  modelLookup("glm"),
  modelLookup("lasso"),
  modelLookup("glm.nb")
), caption = "List of models in caret")
# set up for caretEnsemble to CV all models in one go.
library(caretEnsemble)
grid \leftarrow 10^seq(10, -2, length = 100)
trainControl_args <- trainControl(</pre>
  method = "cv",
 number = 10,
  savePredictions = "final",
  index = createFolds(
    test_set$lengthofstay,
    10
  )
)
```

```
# createFolds sets up k folds to use across all models
algorithmList <- c(
  "lm",
  "lasso".
  "rpart",
  "glm.nb"
tune_list <- list(poisson = caretModelSpec(method = "glm", family = "poisson"))</pre>
# family is required for qlm and must be passed via caretModelSpec (instead of algorithmList)
set.seed(578)
models <- caretList(lengthofstay ~ ., # model formula</pre>
 data = train_set, # training set
 trControl = trainControl_args, # cv params
 methodList = algorithmList, # which models
 tuneList = tune_list, # glm needs this
 continue_on_fail = FALSE # stop if something fails
out <- resamples(models)</pre>
options(digits = 4)
model_results <- data.frame(</pre>
 LM = min(models$lm$results$RMSE),
 POISSON = min(models$poisson$results$RMSE),
 LASSO = min(models$lasso$results$RMSE),
 RPART = min(models$rpart$results$RMSE),
 NB = min(models$glm.nb$results$RMSE)
  pivot_longer(cols = everything(), names_to = "Model", values_to = "RMSE") %>%
 arrange(RMSE)
NB_link_tune <- models[["glm.nb"]][["results"]]</pre>
knitr::kable(NB_link_tune, caption = "Negative binomial CV results for link function")
# ?resamples
resamples <- resamples(models)</pre>
dotplot(resamples, metric = "RMSE")
plot(varImp(models$rpart))
rpart.plot::rpart.plot(models$rpart$finalModel)
plot(varImp(models$glm.nb))
# evaluate final models on test data
pred_lm <- predict.train(models$lm, newdata = test_set)</pre>
pred_poisson <- predict.train(models$poisson, newdata = test_set)</pre>
pred_lasso <- predict.train(models$lasso, newdata = test_set)</pre>
pred rpart <- predict.train(models$rpart, newdata = test set)</pre>
pred_glm <- predict.train(models$glm.nb, newdata = test_set)</pre>
pred_RMSE <- data.frame(</pre>
 LM = RMSE(pred_lm, test_set$lengthofstay),
```

```
POISSON = RMSE(pred_poisson, test_set$lengthofstay),
LASSO = RMSE(pred_lasso, test_set$lengthofstay),
RPART = RMSE(pred_rpart, test_set$lengthofstay),
NB = RMSE(pred_glm, test_set$lengthofstay)
) %>%
   pivot_longer(cols = everything(), names_to = "Model", values_to = "RMSE") %>%
   arrange(RMSE)
knitr::kable(pred_RMSE, caption="RMSE of final models across the test data")

nb_coeffs <- as.data.frame(models$glm.nb$finalModel$coefficients) %>%
   set_names("coefficient") %>%
   arrange(desc(abs(coefficient)))
knitr::kable(nb_coeffs, caption = "Negative binomial model coefficients")
```