Module 2: Supervised Learning

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```
# If a package is installed, it will be loaded. If any
## are not, the missing package(s) will be installed
## from CRAN and then loaded.
## First specify the packages of interest
packages <- c(
  "dplyr", "PheCAP", "glmnet", "randomForestSRC", "PheNorm",
  "MAP", "pROC", "mltools", "data.table", "ggplot2", "parallel"
## Now load or install&load all
package.check <- lapply(</pre>
 packages,
  FUN = function(x) {
   if (!require(x, character.only = TRUE)) {
      install.packages(x, dependencies = TRUE)
      library(x, character.only = TRUE)
   }
 }
# load environment from example 1
load("environment.RData")
```

Prepare data for algorithm development

- Split data into training and testing set
- Training 106(60%), Testing 75(40%)

```
data <- PhecapData(PheCAP::ehr_data, "healthcare_utilization", "label", 75,
    patient_id = "patient_id", seed = 123
)

# Data with non-missing labels
labeled_data <- ehr_data %>% dplyr::filter(!is.na(label))

# All Features
all_x <- ehr_data %>% dplyr::select(
    starts_with("COD"), starts_with("NLP"),
    starts_with("main"), healthcare_utilization
)
```

```
health_count <- ehr_data$healthcare_utilization
# Training Set
train_data <- ehr_data %>% dplyr::filter(patient_id %in% data$training_set)
train_x <- train_data %>%
  dplyr::select(
   starts_with("COD"), starts_with("NLP"),
   starts_with("main"), healthcare_utilization
  ) %>%
  as.matrix()
train_y <- train_data %>%
  dplyr::select(label) %>%
 pull()
# Testing Set
test_data <- ehr_data %>% dplyr::filter(patient_id %in% data$validation_set)
test_x <- test_data %>%
 dplyr::select(
    starts_with("COD"), starts_with("NLP"),
    starts_with("main"), healthcare_utilization
  ) %>%
  as.matrix()
test_y <- test_data %>%
  dplyr::select(label) %>%
 pull()
```

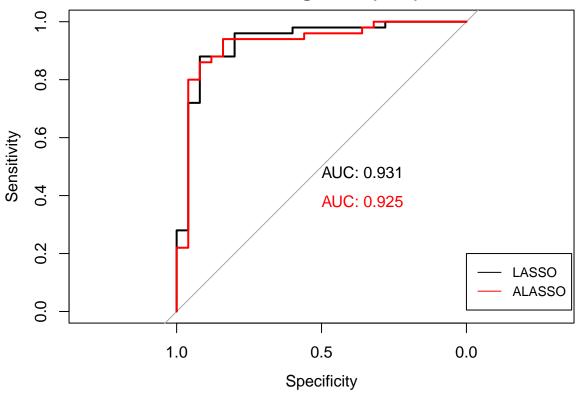
Penalized logistic regression

• Fit LASSO and Adaptive LASSO(ALASSO)

```
# Choose best lambda using CV
beta.lasso <- lasso_fit(</pre>
  x = train_x, y = train_y,
  tuning = "cv", family = "binomial"
# Features Selected
names(beta.lasso[abs(beta.lasso) > 0])[-1]
## [1] "NLP93"
                                                            "NLP304"
                                  "NLP104"
## [4] "main_NLP"
                                  "main_ICDNLP"
                                                            "healthcare_utilization"
# prediction on testing set
y_hat.lasso <- linear_model_predict(</pre>
  beta = beta.lasso, x = test_x,
  probability = TRUE
# Fit Adaptive LASSO
beta.alasso <- adaptive_lasso_fit(</pre>
 x = train_x, y = train_y,
  tuning = "cv", family = "binomial"
y_hat.alasso <- linear_model_predict(</pre>
beta = beta.alasso, x = test_x,
```

```
probability = TRUE
# Features Selected
names(beta.alasso[abs(beta.alasso) > 0])[-1]
## [1] "NLP304"
                                 "main NLP"
                                                           "healthcare_utilization"
roc.lasso <- roc(test_y, y_hat.lasso)</pre>
roc.alasso <- roc(test_y, y_hat.alasso)</pre>
plot(roc.lasso,
  print.auc = TRUE, main = "n_training = 106 (40%)"
plot(roc.alasso,
  print.auc = TRUE, col = "red", add = TRUE, print.auc.y = 0.4
legend(0, 0.2,
 legend = c("LASSO", "ALASSO"), col = c("black", "red"),
  lty = 1, cex = 0.8
```

n_training = 106 (40%)



```
roc_full.lasso <- get_roc(y_true = test_y, y_score = y_hat.lasso)</pre>
roc_full.lasso %>% data.frame() %>% filter(FPR <= 0.1)</pre>
```

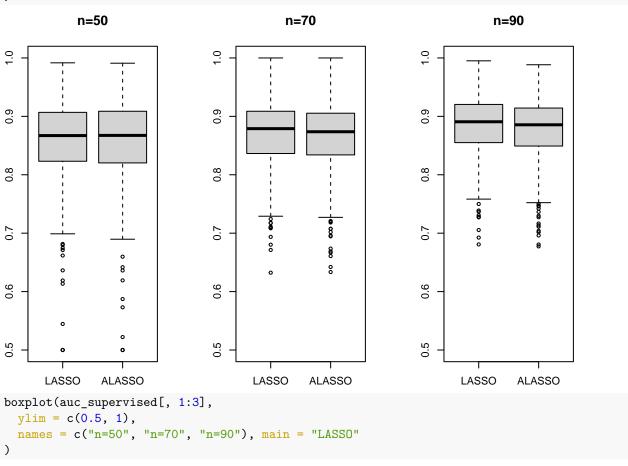
cutoff pos.rate FPR PPVNPV ## 1 0.9468465 0.006666667 0.00 0.1306667 1.0000000 0.3651412 0.2311321 ## 2 0.9140868 0.066666667 0.00 0.2053333 1.0000000 0.3861998 0.3407080

```
## 3 0.8813270 0.193333333 0.02 0.2800000 0.9655172 0.4049587 0.4341085
## 4 0.8781599 0.200000000 0.04 0.3900000 0.9512195 0.4403670 0.5531915
## 5 0.8749928 0.206666667 0.04 0.5000000 0.9615385 0.4897959 0.6578947
## 6 0.8130579 0.413333333 0.04 0.6100000 0.9682540 0.5517241 0.7484663
## 7 0.7511229 0.500000000 0.06 0.7200000 0.9600000 0.6266667 0.8228571
## 8 0.7445305 0.506666667 0.08 0.7600000 0.9500000 0.6571429 0.8444444
## 9 0.7379380 0.513333333 0.08 0.8000000 0.9523810 0.6969697 0.8695652
## 10 0.6905611 0.586666667 0.08 0.8400000 0.9545455 0.7419355 0.8936170
## 11 0.6431842 0.620000000 0.10 0.8800000 0.9462366 0.7894737 0.9119171
roc_full.alasso <- get_roc(y_true = test_y, y_score = y_hat.alasso)</pre>
roc_full.alasso %>% data.frame() %>% filter(FPR <= 0.1)</pre>
        cutoff
                  pos.rate FPR
                                               PPV
                                                         NPV
                                      TPR.
                                                                    F1
## 1 0.9882448 0.006666667 0.00 0.1008333 1.0000000 0.3573556 0.1831945
## 3 0.9631681 0.153333333 0.02 0.2200000 0.9565217 0.3858268 0.3577236
## 4 0.9631509 0.160000000 0.04 0.3650000 0.9480519 0.4304933 0.5270758
## 5 0.9631337 0.166666667 0.04 0.5100000 0.9622642 0.4948454 0.6666667
## 6 0.8722516 0.480000000 0.04 0.6550000 0.9703704 0.5818182 0.7820896
## 7 0.7813696 0.553333333 0.06 0.8000000 0.9638554 0.7014925 0.8743169
## 8 0.7756834 0.560000000 0.08 0.8150000 0.9532164 0.7131783 0.8787062
## 9 0.7699971 0.566666667 0.08 0.8300000 0.9540230 0.7301587 0.8877005
## 10 0.7512328 0.600000000 0.08 0.8450000 0.9548023 0.7479675 0.8965517
## 11 0.7324685 0.606666667 0.10 0.8600000 0.9450549 0.7627119 0.9005236
Different train size
  • randomly sample training size = 50, 70, 90
  • rest as testing set
  • repeat 600 times
start <- Sys.time()</pre>
auc_supervised <- validate_supervised(</pre>
 dat = labeled_data, nsim = 600,
 n.train = c(50, 70, 90)
)
end <- Sys.time()</pre>
end - start
## Time difference of 3.267942 mins
# median AUC
apply(auc_supervised, 2, median)
## n=50,LASSO n=70,LASSO n=90,LASSO n=50,ALASSO n=70,ALASSO n=90,ALASSO
##
    0.8670982
              0.8789683
                           0.8907670 0.8673935
                                                   0.8736602
# SE
apply(auc_supervised, 2, sd)
## n=50,LASSO n=70,LASSO n=90,LASSO n=50,ALASSO n=70,ALASSO n=90,ALASSO
## 0.07197811 0.05588511 0.05184181 0.07300341 0.05871336 0.05415953
```

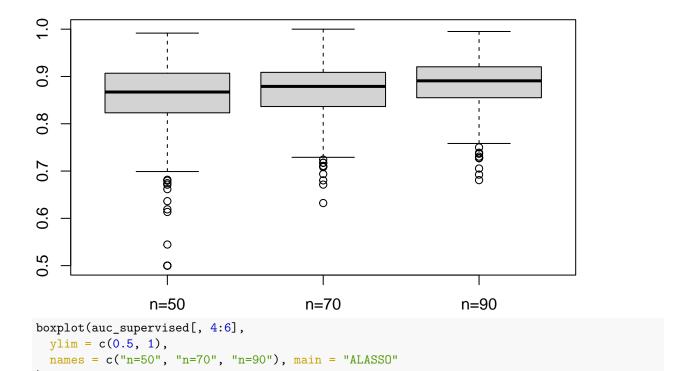
par(mfrow = c(1, 3))

boxplot(auc_supervised %>% select(starts_with("n=50")),

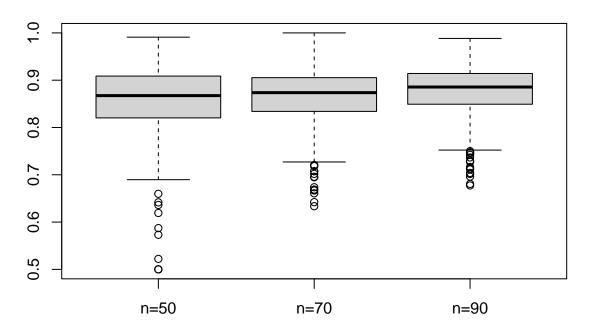
```
ylim = c(0.5, 1),
  names = c("LASSO", "ALASSO"), main = "n=50"
)
boxplot(auc_supervised %>% select(starts_with("n=70")),
  ylim = c(0.5, 1),
  names = c("LASSO", "ALASSO"), main = "n=70"
)
boxplot(auc_supervised %>% select(starts_with("n=90")),
  ylim = c(0.5, 1),
  names = c("LASSO", "ALASSO"), main = "n=90"
)
```



LASSO



ALASSO



Appendix

)

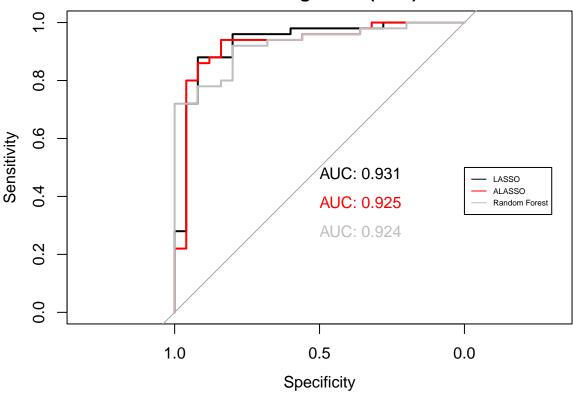
Random Forest

```
model_rf <- rfsrc(y ~ ., data = data.frame(y = train_y, x = train_x))
y_hat.rf <- predict(model_rf, newdata = data.frame(x = test_x))$predicted

roc.rf <- roc(test_y, y_hat.rf)

plot(roc.lasso,
    print.auc = TRUE, main = "n_training = 106 (40%)"
)
plot(roc.alasso,
    print.auc = TRUE, col = "red", add = TRUE, print.auc.y = 0.4
)
plot(roc.rf,
    print.auc = TRUE, col = "grey", add = TRUE, print.auc.y = 0.3
)
legend(0, 0.5,
    legend = c("LASSO", "ALASSO", "Random Forest"), col = c("black", "red", "grey"),
    lty = 1, cex = 0.5
)</pre>
```

n_training = 106 (40%)

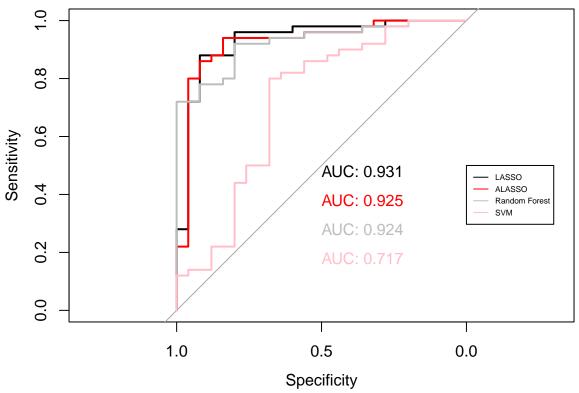


SVM

```
model_svm <- SVMMaj::svmmaj(X = train_x, y = train_y)
y_hat.svm <- predict(model_svm, test_x)
roc.svm <- roc(test_y, y_hat.svm)</pre>
```

```
plot(roc.lasso,
    print.auc = TRUE, main = "n_training = 106 (40%)"
)
plot(roc.alasso,
    print.auc = TRUE, col = "red", add = TRUE, print.auc.y = 0.4
)
plot(roc.rf,
    print.auc = TRUE, col = "grey", add = TRUE, print.auc.y = 0.3
)
plot(roc.svm,
    print.auc = TRUE, col = "pink", add = TRUE, print.auc.y = 0.2
)
legend(0, 0.5,
    legend = c("LASSO", "ALASSO", "Random Forest", "SVM"),
    col = c("black", "red", "grey", "pink"),
    lty = 1, cex = 0.5
)
```

n_training = 106 (40%)



Validation

```
start <- Sys.time()
auc_rfandsvm <- validate_svmandrf(dat = labeled_data, nsim = 600)
end <- Sys.time()
end - start
saveRDS(auc_rfandsvm, "appendix.rds")</pre>
```

```
auc_rfandsvm <- readRDS("appendix.rds")

# median AUC
apply(auc_rfandsvm, 2, median)

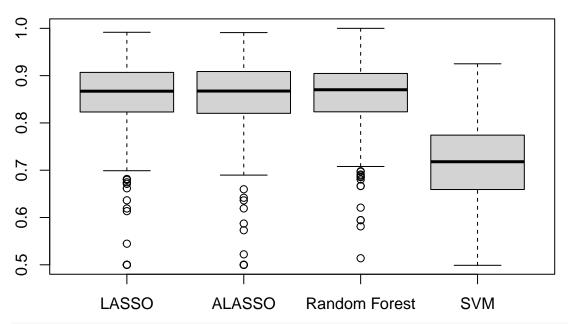
## n=50,rf n=70,rf n=90,rf n=50,svm n=70,svm n=90,svm
## 0.8701826 0.8873775 0.9008419 0.7179279 0.7540064 0.7848541

# SE
apply(auc_rfandsvm, 2, sd)

## n=50,rf n=70,rf n=90,rf n=50,svm n=70,svm n=90,svm
## 0.06771061 0.05256562 0.04799935 0.08221553 0.08092279 0.07128458

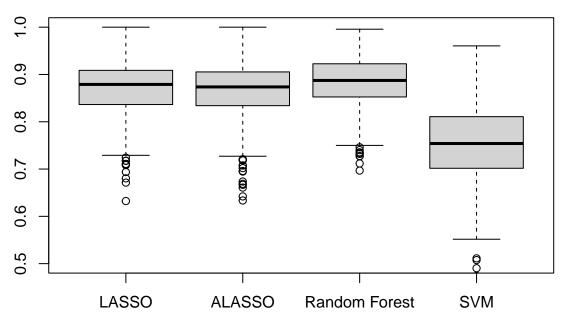
boxplot(cbind(auc_supervised, auc_rfandsvm) %>% select(starts_with("n=50")),
    ylim = c(0.5, 1),
    names = c("LASSO", "ALASSO", "Random Forest", "SVM"), main = "n=50"
)
```

n = 50



```
boxplot(cbind(auc_supervised, auc_rfandsvm) %>% select(starts_with("n=70")),
   ylim = c(0.5, 1),
   names = c("LASSO", "ALASSO", "Random Forest", "SVM"), main = "n=70"
)
```





```
boxplot(cbind(auc_supervised, auc_rfandsvm) %>% select(starts_with("n=90")),
   ylim = c(0.5, 1),
   names = c("LASSO", "ALASSO", "Random Forest", "SVM"), main = "n=90"
)
```

n=90

