

## 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(
  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("../data/CAD_norm_pub.rda")
```

### Prepare data for algorithm development

- Split data into training and testing set
- Training 106, Testing 75

```
ehr_data <- cbind(1:nrow(x), y, x)
colnames(ehr_data) <- c("patient_id", "label", colnames(x))
data <- PhecapData(ehr_data, "healthcare_utilization", "label", 75,
  patient_id = "patient_id", seed = 123
)

# Transform Features log(x + 1)
labeled_data <- ehr_data %>% dplyr::filter(!is.na(label))

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

```

    surrogate, 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"),
    surrogate, 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"),
    surrogate, 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(x = train_x, y = train_y,
  tuning = "cv", family = "binomial")

# Features Selected
names(beta.lasso[abs(beta.lasso)>0])[-1]

## [1] "NLP93" "NLP304" "surrogate"
## [4] "healthcare_utilization"

# prediction on testing set
y_hat.lasso <- linear_model_predict(beta = beta.lasso, x = test_x,
  probability = TRUE)

# Fit Adaptive LASSO
beta.alasso <- adaptive_lasso_fit(x = train_x, y = train_y,
  tuning = "cv", family = "binomial")
y_hat.alasso <- linear_model_predict(beta = beta.alasso, x = test_x,
  probability = TRUE)

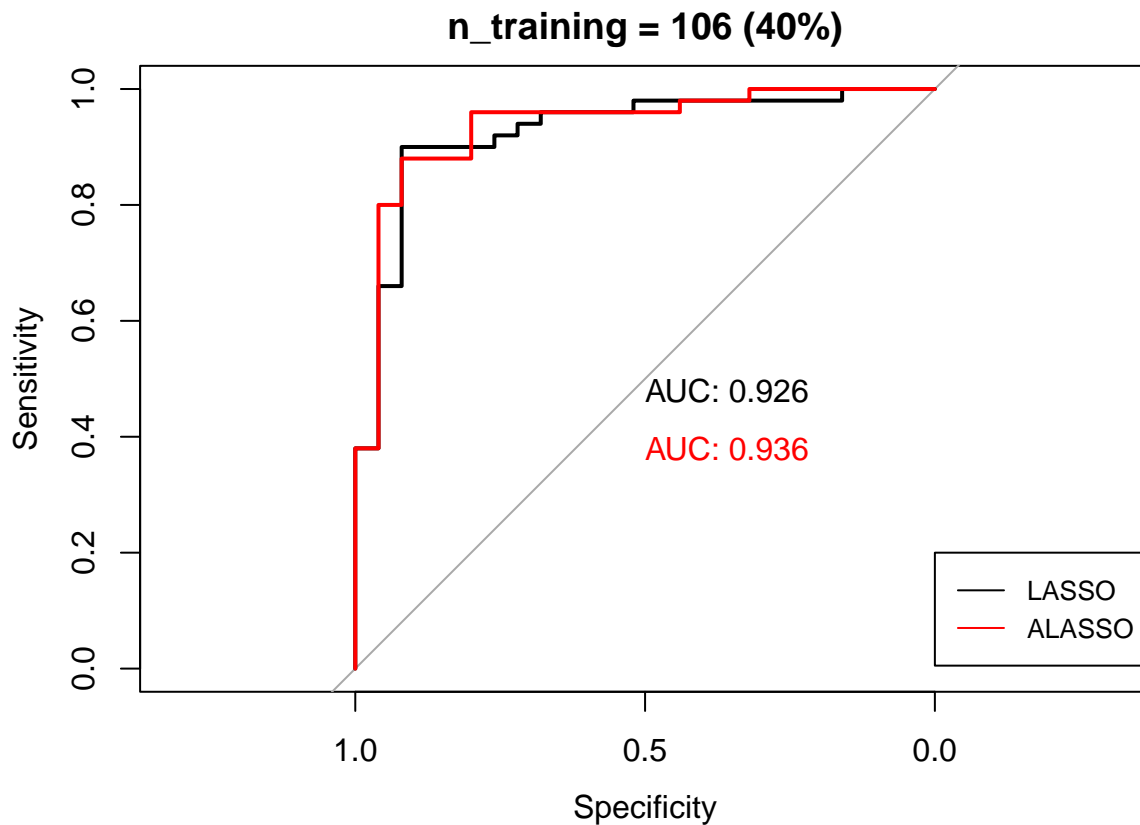
# Features Selected
names(beta.alasso[abs(beta.alasso)>0])[-1]

```

```
## [1] "NLP304"                "surrogate"                "healthcare_utilization"

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

plot(roc.lasso,
     print.auc = TRUE, main = "n_training = 106 (40%)")
)
plot(roc.lasso,
     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)
```



```
roc_full.lasso <- get_roc(y_true = test_y, y_score = y_hat.lasso)
head(roc_full.lasso, 10)
```

##	cutoff	pos.rate	FPR	TPR	PPV	NPV	F1
## [1,]	0.9438312	0.006666667	0.00	0.18050	1.0000000	0.3789314	0.3058026
## [2,]	0.9033418	0.093333333	0.00	0.28025	1.0000000	0.4099201	0.4378051
## [3,]	0.8628523	0.260000000	0.02	0.38000	0.9743590	0.4414414	0.5467626
## [4,]	0.8605276	0.266666667	0.04	0.45000	0.9574468	0.4660194	0.6122449
## [5,]	0.8582029	0.273333333	0.04	0.52000	0.9629630	0.5000000	0.6753247
## [6,]	0.8015623	0.400000000	0.04	0.59000	0.9672131	0.5393258	0.7329193
## [7,]	0.7449217	0.460000000	0.06	0.66000	0.9565217	0.5802469	0.7810651
## [8,]	0.7430289	0.466666667	0.08	0.72000	0.9473684	0.6216216	0.8181818
## [9,]	0.7411362	0.473333333	0.08	0.78000	0.9512195	0.6764706	0.8571429
## [10,]	0.6939832	0.573333333	0.08	0.84000	0.9545455	0.7419355	0.8936170

```
roc_full.lasso <- get_roc(y_true = test_y, y_score = y_hat.lasso)
head(roc_full.lasso,10)
```

##		cutoff	pos.rate	FPR	TPR	PPV	NPV	F1
##	[1,]	0.9438312	0.006666667	0.00	0.18050	1.0000000	0.3789314	0.3058026
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