DS5559-Final_proj-NHAMCS-Report_2

June 28, 2020

1 Final Project: Admission Prediction from NHAMCS

- 1.1 Progress report: Inital model evaluation
- 1.1.1 DS5559: Big Data Analysis
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Created: 6/28/20

In this report we demonstrate a logistic regression model. We use patient characteristics as input and create a model to prediction hospital admission. We transform our variables and create a vector of features. We then loop through values of reg for standard, ridge, and lasso methods. All the models use weights for the outcomes since there is class imbalance. The best hyperparameters were selected based on AUC.

The following is a summary of the best LR model:

- Type of model:
 - Logistic Regression
- Best hyperparameters used:
 - Method: Ridge regression
 - Regularization parameter: 1.0
- Size of the saved model:
 - Disk usage: 52k
- Performance metrics:
 - Accuracy: 0.713
 - Area under ROC curve (AUROC): 0.755
 - F1 score: 0.183
 - Confusion matrix:

tn: 1473 fn: 45 fp: 587 tp: 99

1.2 Configuration

```
[1]: # set data directory
  data_dir = "../data"
  results_dir = "../results"
```

1.3 Import libraries and set up Spark

```
[2]: # import python libraries
import os
import pandas as pd
import numpy as np
from functools import reduce
```

```
[3]: # set up pyspark
from pyspark.sql import *
from pyspark.sql import SparkSession
from pyspark.sql.functions import *
from pyspark.sql.types import IntegerType
```

```
[4]: from pyspark.ml import Pipeline from pyspark.ml.feature import * from pyspark.ml.classification import LogisticRegression from pyspark.ml.evaluation import BinaryClassificationEvaluator
```

```
[5]: spark = SparkSession.builder.getOrCreate()
```

1.4 Read in data

```
[6]: NHAMCS = spark.read.parquet(data_dir + "/NHAMCS_processed.2007-2017")
```

1.5 Transform data

```
[7]: # perform string indexing to prepare for OHE for residence variable
rsi = StringIndexer(inputCol="RESIDNCE", outputCol="RESINDEX")
simodel = rsi.fit(NHAMCS)
NHAMCS = simodel.transform(NHAMCS)
```

```
[8]: # perform OHE on residence variable
rohe = OneHotEncoder(inputCol='RESINDEX', outputCol='RESONE')
NHAMCS = rohe.transform(NHAMCS)
```

1.6 Train and test model

→elasticNetParam=0)

elif method=="Lasso":

```
[10]: # split into training and testing set
      training, testing = NHAMCS.randomSplit([0.8, 0.2], 42)
[11]: # handle class imbalance
      # calculate balance ratio
      balRatio = training.select("ADM_OUTCOME").where('ADM_OUTCOME == 0').count() / ___
      →training.count()
      # add weights
      training = training.withColumn("classWeights", when(training.ADM_OUTCOME ==__
       →1,balRatio).otherwise(1-balRatio))
[12]: # function for logistic regression
      def lr_nhamcs (training_set, testing_set, reg_param=0, method="Standard"):
          if method=="Standard":
              lr = LogisticRegression(featuresCol="features", labelCol="ADM_OUTCOME", |
       ⇔weightCol="classWeights", \
                                        maxIter=10, regParam=0, elasticNetParam=0)
          elif method=="Ridge":
              lr = LogisticRegression(featuresCol="features", labelCol="ADM_OUTCOME", __
       ⇔weightCol="classWeights", \
                                        maxIter=10, regParam=reg_param,__
```

1.7 Determine best hyperparameters

```
[13]: # test standard LR model
     print("ROC-AUC for standard LR is: ", lr_nhamcs(training,testing))
     ROC-AUC for standard LR is: 0.7540790183387306
[14]: # test Ridge LR model for different values of the regularization parameter
     for i in np.arange(0.0, 1.1, 0.1):
         i = np.round(i,1)
         print("ROC-AUC for Ridge LR with reg_param=", i, \
               " is: ", lr_nhamcs(training,testing, i,"Ridge"))
     ROC-AUC for Ridge LR with reg param = 0.0 is: 0.7540790183387306
     ROC-AUC for Ridge LR with reg_param= 0.1 is: 0.7540419363538331
     ROC-AUC for Ridge LR with reg_param= 0.2 is: 0.7540756472491944
     ROC-AUC for Ridge LR with reg_param= 0.3 is: 0.7542239751887837
     ROC-AUC for Ridge LR with reg_param= 0.4 is: 0.754362189859765
     ROC-AUC for Ridge LR with reg_param= 0.5 is: 0.7542273462783199
     ROC-AUC for Ridge LR with reg_param= 0.6 is: 0.754166666666701
     ROC-AUC for Ridge LR with reg_param= 0.7 is: 0.7541026159654836
     ROC-AUC for Ridge LR with reg_param= 0.8 is: 0.7540756472491945
     ROC-AUC for Ridge LR with reg_param= 0.9 is: 0.7544869201726022
     ROC-AUC for Ridge LR with reg_param= 1.0 is: 0.7550094390507027
[15]: # test Lasso LR model for different values of the regularization parameter
     for i in np.arange(0.0, 1.1, 0.1):
         i = np.round(i,1)
         print("ROC-AUC for Lasso LR with reg_param=", i, \
```

```
" is: ", lr_nhamcs(training,testing, i,"Lasso"))
     ROC-AUC for Lasso LR with reg_param= 0.0 is: 0.7540790183387306
     ROC-AUC for Lasso LR with reg_param= 0.1
                                               is:
                                                    0.7391906014023741
     ROC-AUC for Lasso LR with reg_param= 0.2 is:
                                                    0.5
     ROC-AUC for Lasso LR with reg_param= 0.3 is:
                                                    0.5
     ROC-AUC for Lasso LR with reg_param= 0.4 is:
                                                    0.5
     ROC-AUC for Lasso LR with reg_param= 0.5 is:
                                                    0.5
     ROC-AUC for Lasso LR with reg_param= 0.6 is:
                                                    0.5
     ROC-AUC for Lasso LR with reg_param= 0.7 is:
                                                    0.5
     ROC-AUC for Lasso LR with reg_param= 0.8 is:
                                                    0.5
     ROC-AUC for Lasso LR with reg_param= 0.9 is: 0.5
     ROC-AUC for Lasso LR with reg_param= 1.0 is: 0.5
     1.8 Size of saved model
[16]: # create model with best hyperparameters (Ridge, regParam=1.0)
      lr = LogisticRegression(featuresCol="features", labelCol="ADM_OUTCOME", __
      ⇔weightCol="classWeights", \
                             maxIter=10, regParam=1.0, elasticNetParam=0)
      admModel = lr.fit(training)
[17]: # save model
      admModel.write().overwrite().save("../models/001-log_regress-no_RFV")
[18]: # qet size on disk
      !du -h ../models/001-log_regress-no_RFV
     28K
             ../models/001-log_regress-no_RFV/data
     20K
             ../models/001-log_regress-no_RFV/metadata
             ../models/001-log_regress-no_RFV
     52K
     1.9 Get evaluation metrics
[19]: # predict on testing set
      predict_test=admModel.transform(testing)
[20]: # calculate AUC
      evaluator=BinaryClassificationEvaluator(rawPredictionCol="rawPrediction", __
      →labelCol="ADM OUTCOME")
      print("ROC-AUC:", evaluator.evaluate(predict_test))
```

ROC-AUC: 0.7550094390507027

```
[21]: # calculate accuracy
      print("F1 score:",evaluator.setMetricName("areaUnderPR").evaluate(predict_test))
     F1 score: 0.18282251646509748
[22]: # calculate accuracy
      correct = predict_test.where('prediction == ADM_OUTCOME').count()
      total = predict_test.count()
      print("Accuracy:", correct/total)
     Accuracy: 0.7132486388384754
[24]: # compute confusion matrix
      tp = predict_test.where('prediction == 1 and ADM_OUTCOME==1').count()
      fp = predict_test.where('prediction == 1 and ADM_OUTCOME==0').count()
      tn = predict_test.where('prediction == 0 and ADM_OUTCOME==0').count()
      fn = predict_test.where('prediction == 0 and ADM_OUTCOME==1').count()
      print("\nConfusion Matrix:")
      print('tn:',tn,' fn:',fn)
      print('fp:',fp, ' tp:',tp,)
     Confusion Matrix:
     tn: 1473 fn: 45
     fp: 587 tp: 99
 []: # convert to PDF
      !jupyter nbconvert --to pdf `pwd`/DS5559-Final_proj-NHAMCS-Report_2.ipynb
 []:
```