MACHINE LEARNING: SUPERVISED LEARNING

Classify A Rare Event Using 5 Machine Learning Algorithms

Which one works best for unbalanced data? Any tradeoffs?

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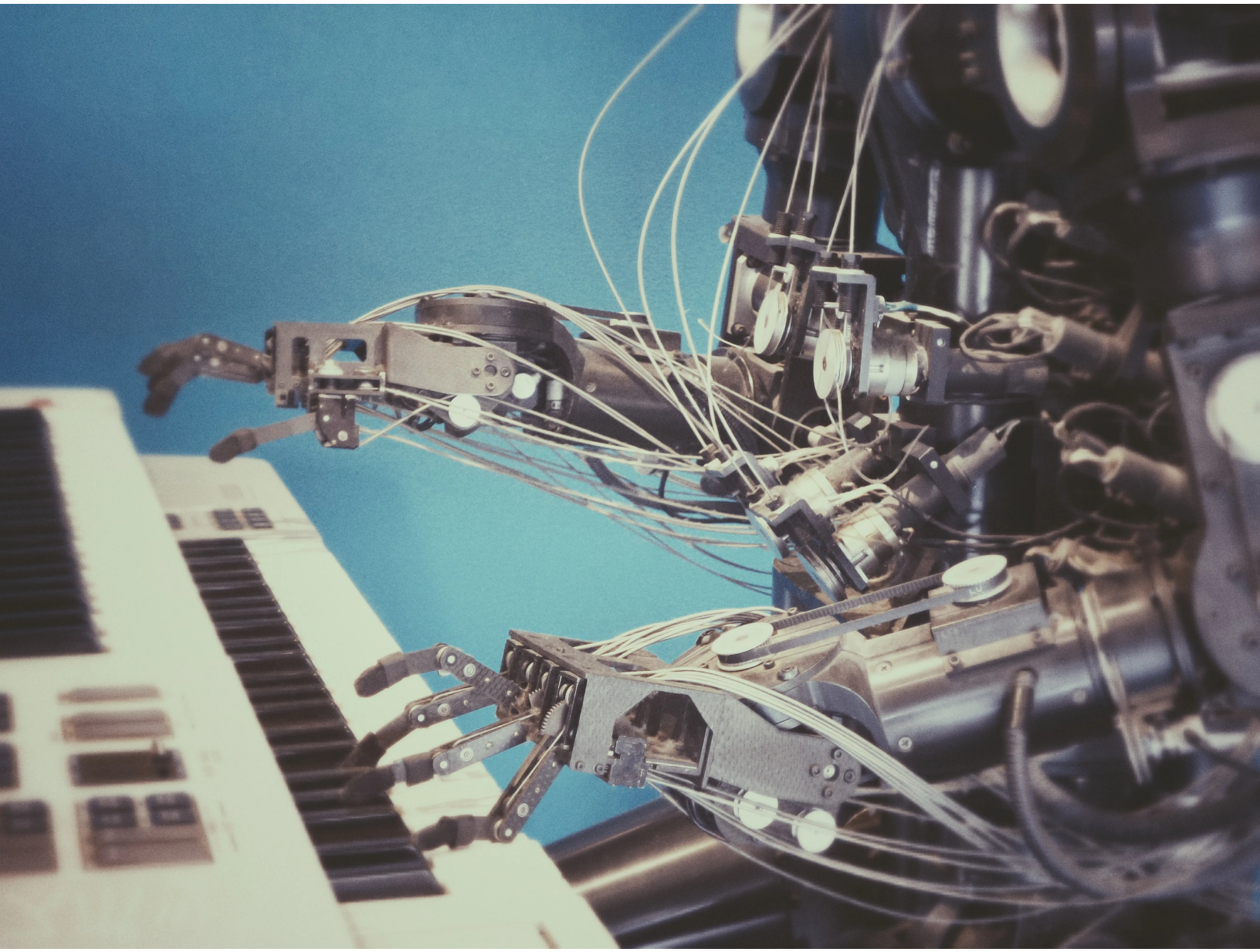

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***** Recent update on 12–28–2019 *****

> Machine Learning is the crown of Data Science;
>
> Supervised Learning is the crown jewel of Machine Learning.

Background

A couple years ago, Harvard Business Review released an article with the following title "Data Scientist: The Sexiest Job of the 21st Century." Ever since its release, Data Science or Statistics Departments become widely pursued by college students and, and Data Scientists (Nerds), for the first time, is referred to as being sexy.

For some industries, Data Scientists have reshaped the corporation structure and reallocated a lot of decision-makings to the "front-line" workers. Being able to generate useful business insights from data has never been so easy.

According to Andrew Ng (Machine Learning Yearning, p.9),

> Supervised Learning algorithms contribute the majority value to the industry.

There is no doubt why SL generates so much business value. Banks use it to detect credit card fraud, traders make purchase decisions based on what models tell them to, and factory filter through the production line for defective units (this is an area where AI and ML can help traditional companies, according to Andrew Ng).

These business scenarios share two common features:

1. **Binary Results**: fraud VS not fraud, to buy VS not to buy, and defective VS not defective.
2. **Imbalanced Data Distribution**: one majority group VS one minority group.

As Andrew Ng points out recently, small data, robustness, and human factor are three obstacles to successful AI projects. To a certain degree, our rare event question with one minority group is also a small data question: **the ML algorithm learns more from the majority group and may easily misclassify the small data group.**

Here are the million-dollar questions:

For these rare events, which ML method performs better?

What metrics?

Tradeoffs?

In this post, we try to answer these questions by applying 5 ML methods to a real-life dataset with comprehensive R implementations.

For the full description and the original dataset, please check the original dataset; For the complete R code, please check my Github.

Business Question

A bank in Portugal carries out a marketing strategy of a new banking service (a term deposit) and wants to know which types of clients have subscribed to the service. So, the bank can adjust its marketing strategy and target specific groups of populations in the future. Data Scientists have teamed up with the sells and marketing teams to come up with statistical solutions to identify future subscribers.

R Implementations

Here comes the pipeline of model selection and R implementations.

1. Importation, Data Cleaning, and Exploratory Data Analysis

Let's load and clean the raw dataset.

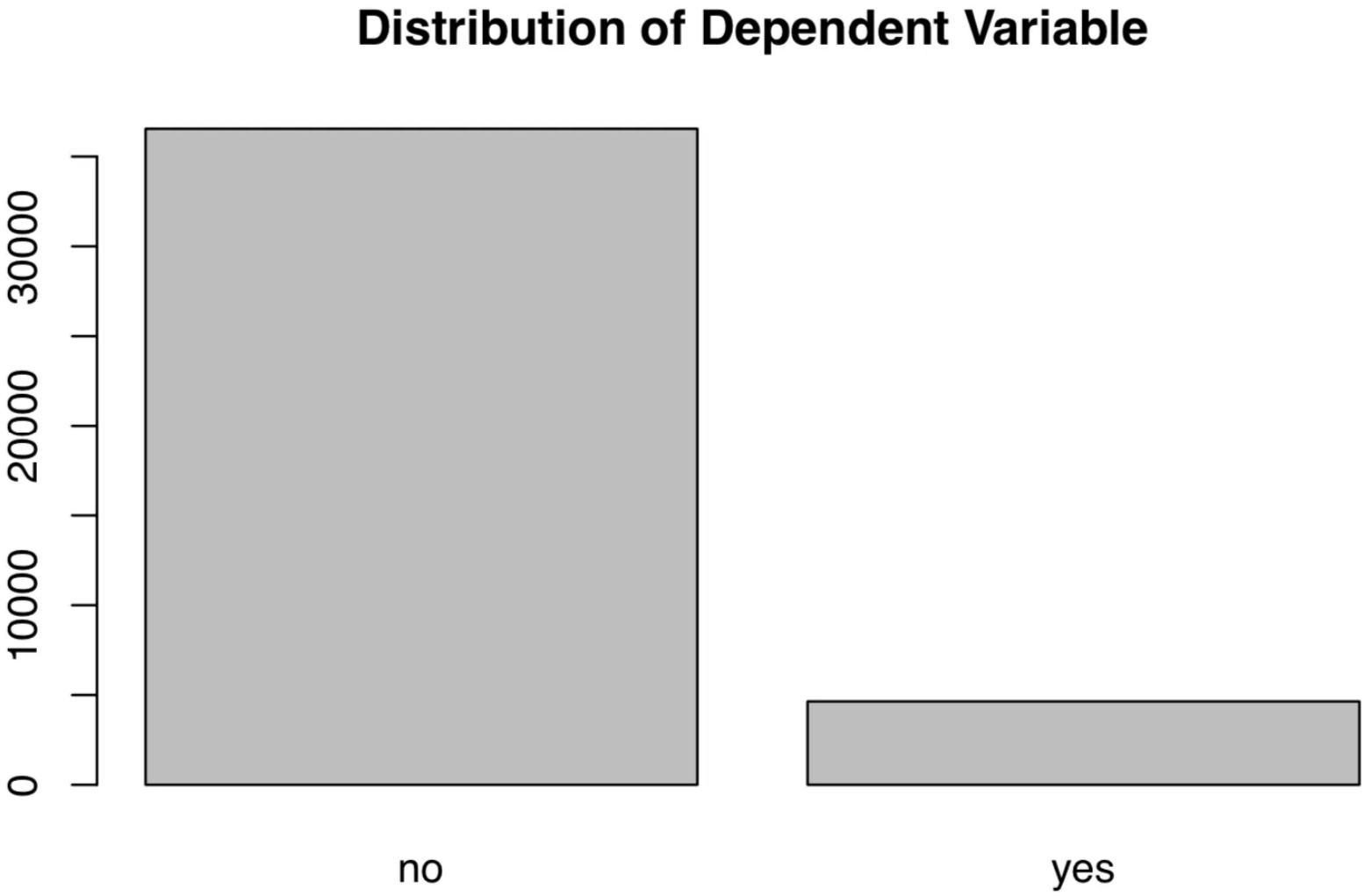
```
####load the dataset
banking=read.csv("bank-additional-full.csv",sep =";",header=T)

##check for missing data and make sure no missing data
banking[!complete.cases(banking),]

#re-code qualitative (factor) variables into numeric
banking$job= recode(banking$job, "'admin.'=1;'blue-
collar'=2;'entrepreneur'=3;'housemaid'=4;'management'=5;'retired'=6;'
self-
employed'=7;'services'=8;'student'=9;'technician'=10;'unemployed'=11;
'unknown'=12")

#recode variable again
banking$marital = recode(banking$marital,
"'divorced'=1;'married'=2;'single'=3;'unknown'=4")

banking$education = recode(banking$education,
"'basic.4y'=1;'basic.6y'=2;'basic.9y'=3;'high.school'=4;'illiterate'=
5;'professional.course'=6;'university.degree'=7;'unknown'=8")
```

```
banking$default = recode(banking$default,
“‘no’=1;’yes’=2;’unknown’=3”)

banking$housing = recode(banking$housing,
“‘no’=1;’yes’=2;’unknown’=3”)

banking$loan = recode(banking$loan, “‘no’=1;’yes’=2;’unknown’=3”)
banking$contact = recode(banking$loan, “‘cellular’=1;’telephone’=2;”)

banking$month = recode(banking$month,
“‘mar’=1;’apr’=2;’may’=3;’jun’=4;’jul’=5;’aug’=6;’sep’=7;’oct’=8;’nov
’=9;’dec’=10”)

banking$day_of_week = recode(banking$day_of_week,
“‘mon’=1;’tue’=2;’wed’=3;’thu’=4;’fri’=5;”)

banking$poutcome = recode(banking$poutcome,
“‘failure’=1;’nonexistent’=2;’success’=3;”)

#remove variable “pdays”, b/c it has no variation
banking$pdays=NULL

#remove variable “pdays”, b/c itis collinear with the DV
banking$duration=NULL
```

It appears to be tedious to clean the raw data as we have to recode missing variables and transform qualitative into quantitative variables. It takes even more time to clean the data in the real world. **There is a saying “data scientists spend 80% of their time cleaning data and 20% building a model.”**

Next, let’s explore the distribution of our outcome variables.

```
#EDA of the DV
plot(banking$y,main="Plot 1: Distribution of Dependent Variable")
```



As can be seen, the dependent variables (service subscription) are not equally distributed, with more "No"s than "Yes"s. **The unbalanced distribution should flash some warning signs because data distribution affects the final statistical model**. It can easily misclassify the minority case using a model developed out of a majority case.

2. Data Split

Next, let's split the dataset into two parts: training and test sets. As a rule of thumb, we stick to the 80–20 division: 80% as the training set and 20% as the test test. For Time Series data, we train models based on 90% of the data and leave the rest 10% as the test dataset.

```
#split the dataset into training and test sets randomly
set.seed(1)#set seed so as to generate the same value each time we
run the code

#create an index to split the data: 80% training and 20% test
index = round(nrow(banking)*0.2,digits=0)

#sample randomly throughout the dataset and keep the total number
equal to the value of index
test.indices = sample(1:nrow(banking), index)

#80% training set
banking.train=banking[-test.indices,]
```

```
#20% test set
banking.test=banking[test.indices,]

#Select the training set except the DV
YTrain = banking.train$y
XTrain = banking.train %>% select(-y)

# Select the test set except the DV
YTest = banking.test$y
XTest = banking.test %>% select(-y)
```

Here, let's create an empty tracking record.

```
records = matrix(NA, nrow=5, ncol=2)
colnames(records) <- c("train.error","test.error")
rownames(records) <- c("Logistic","Tree","KNN","Random
Forests","SVM")
```

3. Train Models

In this section, we define a new function (**calc_error_rate**) and apply it to calculate training and test errors of each ML model.

```
calc_error_rate <- function(predicted.value, true.value)
                    {return(mean(true.value!=predicted.value))}
```

This function calculates the rate when the predicted label does not equal to the true value.

#1 Logistic Regression Model

For a brief introduction of logistic model, please check my other posts: **Machine Learning 101**and **Machine Learning 102**.

Let's fit a logistic model including all other variables except the outcome variable. Since the outcome is binary, we set the model to binomial distribution ("family=binomial").

```
glm.fit = glm(y ~
age+factor(job)+factor(marital)+factor(education)+factor(default)+fac
tor(housing)+factor(loan)+factor(contact)+factor(month)+factor(day_of
_week)+campaign+previous+factor(poutcome)+emp.var.rate+cons.price.idx
+cons.conf.idx+euribor3m+nr.employed, data=banking.train,
family=binomial)
```

The next step is to obtain the train error. We set the type to response since we are predicting the types of the outcome and adopt a majority rule: if the prior probability exceeding or equal to 0.5, we predict the outcome to be a yes; otherwise, a no.

```
prob.training = predict(glm.fit,type="response")
```

```
banking.train_glm = banking.train %>% #select all rows of the train
 mutate(predicted.value=as.factor(ifelse(prob.training<=0.5, “no”,
“yes”))) #create a new variable using mutate and set a majority rule
using ifelse

# get the training error
logit_traing_error <-
calc_error_rate(predicted.value=banking.train_glm$predicted.value,
true.value=YTrain)

# get the test error of the logistic model
prob.test = predict(glm.fit,banking.test,type=”response”)

banking.test_glm = banking.test %>% # select rows
 mutate(predicted.value2=as.factor(ifelse(prob.test<=0.5, “no”,
“yes”))) # set rules

logit_test_error <-
calc_error_rate(predicted.value=banking.test_glm$predicted.value2,
true.value=YTest)

# write down the training and test errors of the logistic model
records[1,] <- c(logit_traing_error,logit_test_error)#write into the
first row
```

#2 Decision Tree

For DT, we follow cross-validation and identify the best nodes of split. For a quick intro to DT, please refer to a post (link) by Prashant Gupta.

```
# finding the best nodes
# the total number of rows
nobs = nrow(banking.train)

#build a DT model;
#please refer to this document (here) for constructing a DT model
bank_tree = tree(y~., data= banking.train,na.action = na.pass,
 control = tree.control(nobs , mincut =2, minsize = 10, mindev = 1e-
3))

#cross validation to prune the tree
set.seed(3)
cv = cv.tree(bank_tree,FUN=prune.misclass, K=10)
cv

#identify the best cv
best.size.cv = cv$size[which.min(cv$dev)]
best.size.cv#best = 3

bank_tree.pruned<-prune.misclass(bank_tree, best=3)
summary(bank_tree.pruned)
```

The best size of cross-validation is 3.

```
# Training and test errors of bank_tree.pruned
pred_train = predict(bank_tree.pruned, banking.train, type=”class”)
pred_test = predict(bank_tree.pruned, banking.test, type=”class”)

# training error
DT_training_error <- calc_error_rate(predicted.value=pred_train,
true.value=YTrain)

# test error
DT_test_error <- calc_error_rate(predicted.value=pred_test,
true.value=YTest)

# write down the errors
records[2,] <- c(DT_training_error,DT_test_error)
```

#3 K-Nearest Neighbors

As a non-parametric method, KNN does not require any prior knowledge of the distribution. In simple words, KNN assigns a k number of nearest neighbors to the unit of interest.

For a quick start, please check my post on KNN: **Beginner's Guide to K-Nearest Neighbors in R: from Zero to Hero.** For detailed explanations of Cross-Validation and the do.chunk function, please redirect to my post.

Using cross-validation, we find the minimal cross-validation error when k=20.

```
nfold = 10
set.seed(1)

# cut() divides the range into several intervals
folds = seq.int(nrow(banking.train)) %>%
     cut(breaks = nfold, labels=FALSE) %>%
     sample

do.chunk <- function(chunkid, folddef, Xdat, Ydat, k){
     train = (folddef!=chunkid)# training index

Xtr = Xdat[train,] # training set by the index

Ytr = Ydat[train] # true label in training set

Xvl = Xdat[!train,] # test set

Yvl = Ydat[!train] # true label in test set

predYtr = knn(train = Xtr, test = Xtr, cl = Ytr, k = k) # predict
training labels

predYvl = knn(train = Xtr, test = Xvl, cl = Ytr, k = k) # predict
test labels

data.frame(fold =chunkid, # k folds
train.error = calc_error_rate(predYtr, Ytr),#training error per fold
 val.error = calc_error_rate(predYvl, Yvl)) # test error per fold
 }

# set error.folds to save validation errors
error.folds=NULL

# create a sequence of data with an interval of 10
kvec = c(1, seq(10, 50, length.out=5))

set.seed(1)

for (j in kvec){
 tmp = ldply(1:nfold, do.chunk, # apply do.function to each fold
 folddef=folds, Xdat=XTrain, Ydat=YTrain, k=j) # required arguments
 tmp$neighbors = j # track each value of neighbors
 error.folds = rbind(error.folds, tmp) # combine the results
 }

#melt() in the package reshape2 melts wide-format data into long-
format data
errors = melt(error.folds, id.vars=c("fold","neighbors"), value.name=
"error")
```

Then, let's find the best k number that minimizes validation error.

```
val.error.means = errors %>%
 filter(variable== "val.error" ) %>%
 group_by(neighbors, variable) %>%
 summarise_each(funs(mean), error) %>%
 ungroup() %>%
 filter(error==min(error))
```

```
#the best number of neighbors =20
numneighbor = max(val.error.means$neighbors)
numneighbor

## [20]
```

Following the same step, we find the training and test errors.

```
#training error
set.seed(20)
pred.YTtrain = knn(train=XTrain, test=XTrain, cl=YTrain, k=20)
knn_traing_error <- calc_error_rate(predicted.value=pred.YTtrain,
true.value=YTrain)

#test error =0.095

set.seed(20)
pred.YTest = knn(train=XTrain, test=XTest, cl=YTrain, k=20)
knn_test_error <- calc_error_rate(predicted.value=pred.YTest,
true.value=YTest)

records[3,] <- c(knn_traing_error,knn_test_error)
```

#4 Random Forests

We follow standard steps of constructing a Random Forests model. A quick intro to RF (link) by Tony Yiu.

```
# build a RF model with default settings
set.seed(1)
RF_banking_train = randomForest(y ~ ., data=banking.train,
importance=TRUE)

# predicting outcome classes using training and test sets

pred_train_RF = predict(RF_banking_train, banking.train,
type="class")

pred_test_RF = predict(RF_banking_train, banking.test, type="class")

# training error
RF_training_error <- calc_error_rate(predicted.value=pred_train_RF,
true.value=YTrain)

# test error
RF_test_error <- calc_error_rate(predicted.value=pred_test_RF,
true.value=YTest)

records[4,] <- c(RF_training_error,RF_test_error)
```

#5 Support Vector Machines

Similarly, we follow standard steps of constructing SVM. A good intro to the method, please refer to a post (Link) by Rohith Gandhi.

```
set.seed(1)
tune.out=tune(svm, y ~., data=banking.train,
kernel="radial",ranges=list(cost=c(0.1,1,10)))

# find the best parameters
summary(tune.out)$best.parameters

# the best model
best_model = tune.out$best.model

svm_fit=svm(y~.,
data=banking.train,kernel="radial",gamma=0.05555556,cost=1,probabilit
```

```
y=TRUE)

# using training/test sets to predict outcome classes
svm_best_train = predict(svm_fit,banking.train,type="class")
svm_best_test = predict(svm_fit,banking.test,type="class")

# training error
svm_training_error <- calc_error_rate(predicted.value=svm_best_train,
true.value=YTrain)

# test error
svm_test_error <- calc_error_rate(predicted.value=svm_best_test,
true.value=YTest)

records[5,] <- c(svm_training_error,svm_test_error)
```

4. Model Metrics

We have constructed all ML models following model selection procedures and obtained their training and test errors. In this section, we are going to select the best model using some model metrics.

4.1 Train/Test Errors

Is it possible to find the best model using the train/test errors?

Now, let's check the results.

```
records
```

```
##                train.error test.error
## Logistic        0.10139605 0.10002428
## Tree            0.10100152 0.09966011
## KNN             0.10121396 0.11009954
## Random Forests  0.04430956 0.10609371
## SVM             0.09848255 0.09881039
```

Here, Random Forests have the minimal training error, though with a similar test error with the other methods. As you may notice, the training and test errors are very close, and it's difficult to tell which one is clearly winning.

Besides, classification accuracy, either train error or test error, should not be the metrics for highly imbalanced dataset. This is so because the dataset is dominated by the majority cases, and even a random guess gives you 50–50 chance of getting it right (50% accuracy). Even worse, a highly accuracy model may severely penalize the minority case. For that reason, let's check another metrics ROC Curve.

4.2 Receiver Operating Characteristic (ROC) Curve

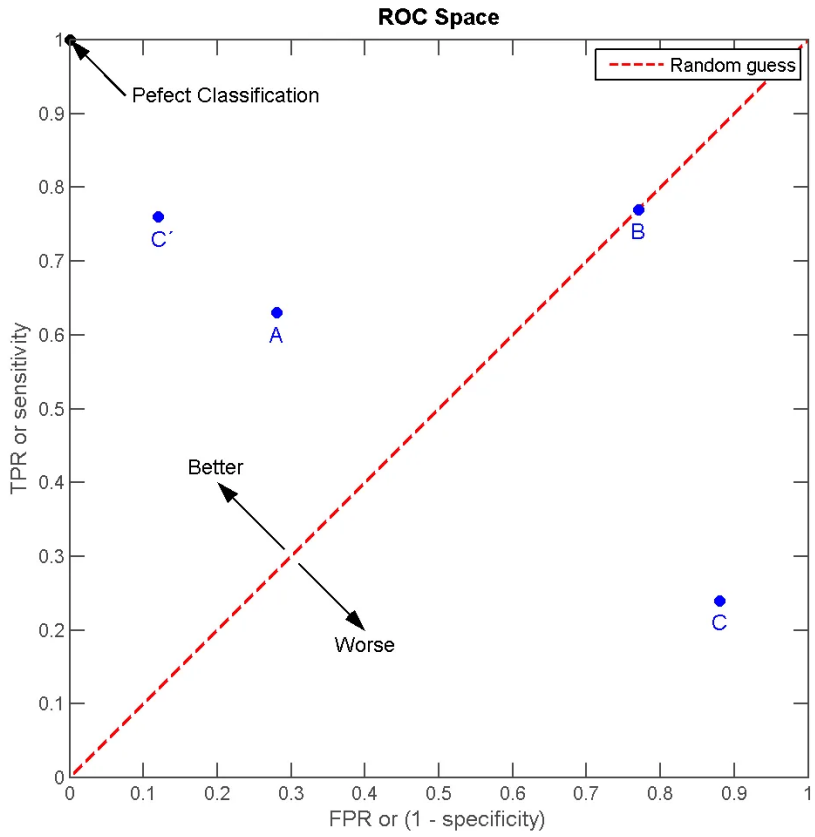
ROC is a graphic representation showing how a classification model performs at all classification thresholds. We prefer a classifier that

approaches to 1 quicker than others.

ROC Curve plots two parameters — True Positive Rate and False Positive Rate — at different thresholds in the same graph:

$$TPR\ (Recall) = TP/(TP+FN)$$

$$FPR = FP/(TN+FP)$$



Indon

To a large extent, ROC Curve does not only measure the level of classification accuracy but reaches a nice balance between TPR and FPR. This is quite desirable for rare events since we also want to reach a balance between the majority and minority cases.

```
# load the library
library(ROCR)

#creating a tracking record
Area_Under_the_Curve = matrix(NA, nrow=5, ncol=1)
colnames(Area_Under_the_Curve) <- c("AUC")
rownames(Area_Under_the_Curve) <- c("Logistic","Tree","KNN","Random
Forests","SVM")

############ logistic regression ############
# ROC
prob_test <- predict(glm.fit,banking.test,type="response")
```

```
pred_logit<- prediction(prob_test,banking.test$y)
performance_logit <- performance(pred_logit,measure = “tpr”,
x.measure=”fpr”)

########### Decision Tree ###########
# ROC
pred_DT<-predict(bank_tree.pruned, banking.test,type=”vector”)
pred_DT <- prediction(pred_DT[,2],banking.test$y)
performance_DT <- performance(pred_DT,measure = “tpr”,x.measure=
“fpr”)

########### KNN ###########
# ROC
knn_model = knn(train=XTrain, test=XTrain, cl=YTrain,
k=20,prob=TRUE)prob <- attr(knn_model, “prob”)
prob <- 2*ifelse(knn_model == “-1”, prob,1-prob) — 1
pred_knn <- prediction(prob, YTrain)
performance_knn <- performance(pred_knn, “tpr”, “fpr”)

########### Random Forests ###########
# ROC
pred_RF<-predict(RF_banking_train, banking.test,type=”prob”)
pred_class_RF <- prediction(pred_RF[,2],banking.test$y)
performance_RF <- performance(pred_class_RF,measure =
“tpr”,x.measure= “fpr”)

########### SVM ###########
# ROC
svm_fit_prob =
predict(svm_fit,type=”prob”,newdata=banking.test,probability=TRUE)
svm_fit_prob_ROCR = prediction(attr(svm_fit_prob,”probabilities”)
[,2],banking.test$y==”yes”)
performance_svm <- performance(svm_fit_prob_ROCR, “tpr”,”fpr”)
```

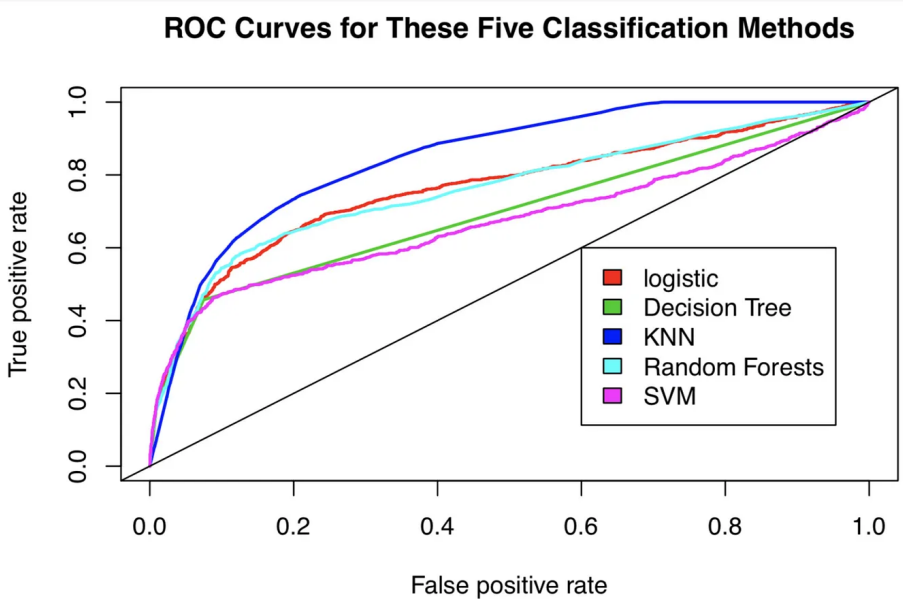
Let’s plot the ROC curves.

We put a abline to show the chance of random assignment. Our classifier should perform better than random guess, right?

```
#logit
plot(performance_logit,col=2,lwd=2,main=”ROC Curves for These Five
Classification Methods”)
```



```
#decision tree
plot(performance_DT,col=3,lwd=2,add=TRUE)

#knn
plot(performance_knn,col=4,lwd=2,add=TRUE)

#RF
plot(performance_RF,col=5,lwd=2,add=TRUE)

# SVM
plot(performance_svm,col=6,lwd=2,add=TRUE)

abline(0,1)
```



ROC

We have a winner here.

According to the ROC curve, KNN (the blue one) stands above all other methods.

4.3 Area Under the Curve (AUC)

As the name suggested, AUC is the area under the ROC curve. It is an arithmetic representation of the visual AUC curve. AUC provides an aggregated results of how classifiers perform across possible classifcation thresholds.

```
############ Logit ############
auc_logit = performance(pred_logit, “auc”)@y.values
Area_Under_the_Curve[1,] <-c(as.numeric(auc_logit))

############ Decision Tree ############
auc_dt = performance(pred_DT,”auc”)@y.values
Area_Under_the_Curve[2,] <- c(as.numeric(auc_dt))

############ KNN ############
auc_knn <- performance(pred_knn,”auc”)@y.values
Area_Under_the_Curve[3,] <- c(as.numeric(auc_knn))

############ Random Forests ############
auc_RF = performance(pred_class_RF,”auc”)@y.values
Area_Under_the_Curve[4,] <- c(as.numeric(auc_RF))

############ SVM ############
auc_svm<-performance(svm_fit_prob_ROCR,”auc”)@y.values[[1]]
Area_Under_the_Curve[5,] <- c(as.numeric(auc_svm))
```

Let’s check the AUC values.

```
Area_Under_the_Curve
```

```
##                      AUC
## Logistic       0.7632912
## Tree           0.6952220
## KNN            0.8470583
## Random Forests 0.7615868
## SVM            0.6723749
```

Also, KNN has the biggest AUC value (0.847).

Conclusion

In this post, we find KNN, a non-parametric classifier, performs better than its parametric counterparts. In terms of metrics, it's more reasonable to choose ROC Curve over classification accuracy for rare events.

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