# Performance measures & kNN

### Setup

```
# devtools::install_github("dkahle/ggmap")
#library(learnr)
library(RSocrata)
library(ggplot2)
library(ggmap)
library(e1071)
library(class)
library(caret)
library(PRROC)
library(pROC)
library(tidyverse)
```

### Data

For this notebook we use data on incidents of crime in the City of Chicago. This data "… is extracted from the Chicago Police Department's CLEAR (Citizen Law Enforcement Analysis and Reporting) system." It contains a number of basic information about each crime incident, such as date, location, type and whether there was an arrest. Here we only pull in data from January 2018.

Source: https://data.cityofchicago.org/Public-Safety/Crimes-2001-to-present/ijzp-q8t2

```
ccj2018 <- read.socrata("https://data.cityofchicago.org/resource/6zsd-86xi.json?$where=date 

#str(ccj2018)
head(ccj2018)
```

```
        id case_number                date              block iucr
1 11193699    JB101825 2018-01-02 10:00:00    014XX S HOMAN AVE 0610
2 11192212    JB100020 2018-01-01 00:10:00  028XX N NATCHEZ AVE 143B
3 11192218    JB100041 2018-01-01 00:01:00 084XX S MANISTEE AVE 1310
4 11192223    JB100017 2018-01-01 00:09:00   009XX W ADDISON ST 0460
5 11192225    JB100070 2018-01-01 00:52:00   039XX S ARCHER AVE 2022
6 11192228    JB100029 2018-01-01 00:27:00   022XX S KEDZIE AVE 143A
       primary_type                 description   location_description arrest
1          BURGLARY              FORCIBLE ENTRY          CHA APARTMENT  FALSE
2 WEAPONS VIOLATION UNLAWFUL POSS OTHER FIREARM                  ALLEY  FALSE
3   CRIMINAL DAMAGE                 TO PROPERTY              RESIDENCE  FALSE
4           BATTERY                      SIMPLE VEHICLE NON-COMMERCIAL   TRUE
5         NARCOTICS               POSS: COCAINE                 STREET   TRUE
6 WEAPONS VIOLATION    UNLAWFUL POSS OF HANDGUN                  ALLEY   TRUE
  domestic beat district ward community_area fbi_code x_coordinate y_coordinate
1    FALSE 1021      010   24             29       05      1153932      1892909
2    FALSE 2511      025   36             19       15      1132592      1918227
3    FALSE 0423      004    7             46       14      1195962      1849465
4    FALSE 1924      019   44              6      08B      1169144      1924100
5    FALSE 0921      009   12             58       18      1159000      1878185
6    FALSE 1024      010   24             30       15      1155375      1888899
  year          updated_on    latitude     longitude location.type
1 2018 2018-05-04 15:51:04 41.861974172 -87.710418378         Point
2 2018 2018-05-04 15:51:04 41.931848306  -87.78816484         Point
3 2018 2018-05-04 15:51:04 41.741821184 -87.557574799         Point
4 2018 2018-05-04 15:51:04 41.947247732  -87.65367048         Point
5 2018 2018-05-04 15:51:04 41.821467456 -87.692217949         Point
6 2018 2018-05-04 15:51:04 41.850941431 -87.705229007         Point
  location.coordinates location_address location_city location_state
1  -87.71042, 41.86197
2  -87.78816, 41.93185
3  -87.55757, 41.74182
4  -87.65367, 41.94725
5  -87.69222, 41.82147
6  -87.70523, 41.85094
  location_zip
1
2
3
4
5
6
```

```r
names(ccj2018)
```

```
 [1] "id"                   "case_number"          "date"
 [4] "block"                "iucr"                 "primary_type"
 [7] "description"          "location_description" "arrest"
[10] "domestic"             "beat"                 "district"
[13] "ward"                 "community_area"       "fbi_code"
[16] "x_coordinate"         "y_coordinate"         "year"
[19] "updated_on"           "latitude"             "longitude"
[22] "location.type"        "location.coordinates" "location_address"
[25] "location_city"        "location_state"       "location_zip"
```

Some quick data preparation since most variables seem to be of type `character` by default. We also exclude cases with missing values.

```r
ccj2018$arrest <- as.factor(ccj2018$arrest)
ccj2018$latitude <- as.numeric(ccj2018$latitude)
ccj2018$longitude <- as.numeric(ccj2018$longitude)

ccj2018 <- subset(ccj2018, complete.cases(ccj2018[,c(9,20,21)]))
```

### Train and test set

Next, we split the data into a train and test set.

```r
set.seed(765)
train <- sample(1:nrow(ccj2018), 0.8*nrow(ccj2018))
c_train <- ccj2018[train,]
c_test <- ccj2018[-train,]
```

In addition, we also need X and y data frames for both data pieces as input for `knn()`. In the next sections, the outcome will be `arrest` and we use (only) `latitude` and `longitude` as features.

```r
X_train <- ccj2018[train,c(20,21)]
X_test <- ccj2018[-train,c(20,21)]
y_train <- ccj2018[train,9]
y_test <- ccj2018[-train,9]
```

A quick look at our outcome variable.

```
summary(y_train)
```

```
FALSE  TRUE 
12357  3268 
```

```
summary(y_test)
```

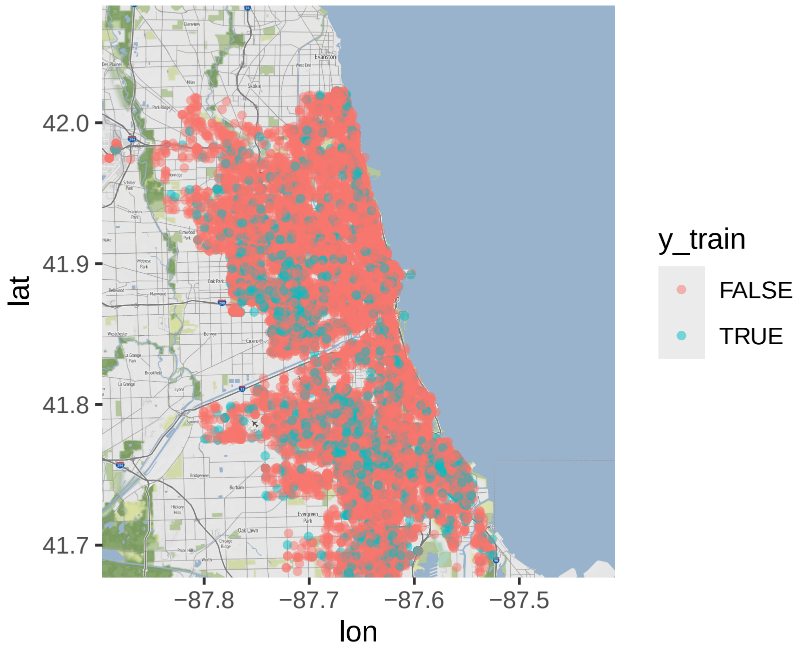
```
FALSE  TRUE 
 3108   799 
```

As a nice illustration of our prediction problem, we can use `qmap()` to build a map of Chicago and then plot the crime incidents colored by `arrest` on top.

```
api_keys <- read_csv("~/repos/api-keys.csv")

register_stadiamaps(api_keys |>
                      filter(key_id == "stadiamaps_key") |>
                      pull(key) )


bbox <- c(left = -87.896805, bottom = 41.677015, right = -87.409286, top = 42.082936)
map <-get_stadiamap(bbox = bbox, zoom = 12, maptype = "stamen_terrain")
map <- ggmap(map)
```

```
map +
  geom_point(data = X_train, aes(x = longitude, y = latitude, color = y_train), size = 1, al
```

```
Warning: Removed 305 rows containing missing values or values outside the scale range
(`geom_point()`).
```




### kNN

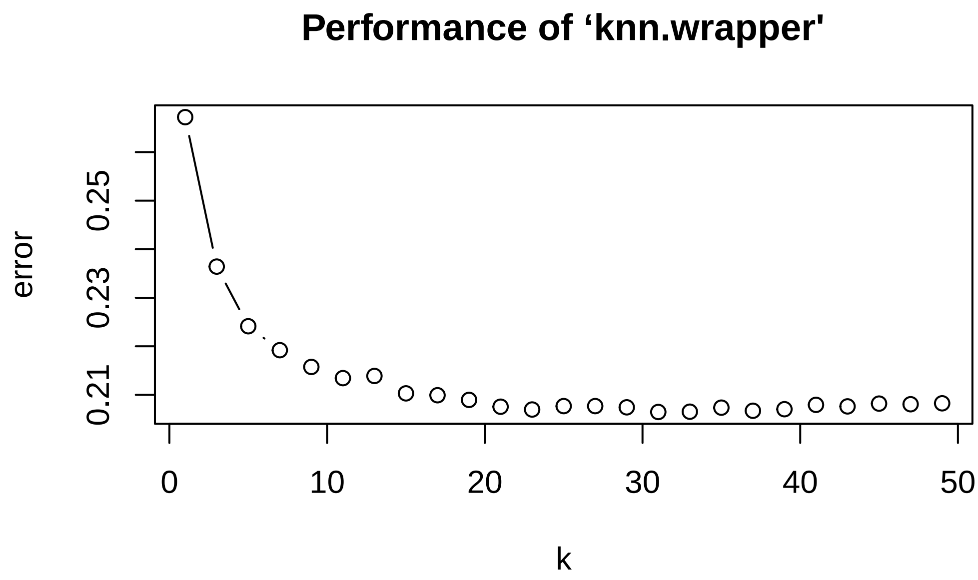
In order to find a useful kNN setup, we tune k using 10-Fold Cross-Validation. This can be done e.g. with `tune.knn()`.

```
set.seed(761)
tune <- tune.knn(X_train, y_train,
                 # k takes 1 to 25
                 k = seq(1, 50, 2),
                 # 10 fold cross validation
                 tunecontrol = tune.control(sampling = "cross"), cross = 10)
summary(tune)
```

```
Parameter tuning of 'knn.wrapper':

- sampling method: 10-fold cross validation

- best parameters:
```

```
  k
 31

- best performance: 0.2064655

- Detailed performance results:
    k     error  dispersion
1    1 0.2672029 0.015061210
2    3 0.2364194 0.014246301
3    5 0.2241308 0.011805896
4    7 0.2192023 0.009756644
5    9 0.2157459 0.009500124
6   11 0.2134408 0.006422457
7   13 0.2138895 0.007676999
8   15 0.2103054 0.007052546
9   17 0.2099213 0.007424717
10  19 0.2089611 0.007295530
11  21 0.2075529 0.005690947
12  23 0.2069770 0.006215810
13  25 0.2076812 0.006889022
14  27 0.2076810 0.007416950
15  29 0.2074252 0.006496074
16  31 0.2064655 0.007106230
17  33 0.2065295 0.007311366
18  35 0.2073613 0.006667115
19  37 0.2067217 0.008560472
20  39 0.2070416 0.008217489
21  41 0.2079378 0.008729263
22  43 0.2076174 0.008000268
23  45 0.2081936 0.009049583
24  47 0.2080653 0.008055665
25  49 0.2082573 0.008150788
```

```r
# used to tune value, choose lowest error
# about 20% of the time we were wrong on our predictions
plot(tune)
```




Seems like `k = 23` is a good choice. We pass this information to `knn()`, together with X from the test data. Note that the resulting object are the test set predictions, since with kNN there is no separate model to be stored.

```
y_knn <- knn(X_train, X_test, y_train, k = 23, prob = TRUE)
```

We can also add a logistic regression model for comparison, although this is unlikely to perform well given the prediction task at hand.

```
logit <- glm(arrest ~ latitude + longitude, data = c_train, family = binomial)
summary(logit)
```

```
Call:
glm(formula = arrest ~ latitude + longitude, family = binomial,
    data = c_train)
```

```
Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -143.5878    29.3471  -4.893 9.94e-07 ***
latitude      -2.8208     0.2748 -10.266  < 2e-16 ***
longitude     -2.9689     0.3878  -7.656 1.92e-14 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 16026  on 15624  degrees of freedom
Residual deviance: 15913  on 15622  degrees of freedom
AIC: 15919

Number of Fisher Scoring iterations: 4
```

Given the `logit` object, we can generate predicted risk scores for the test set and transform those into predicted classes. Note that we are using an arbitrary classification threshold (0.5), which might not be the best option.

```r
yp_logit <- predict(logit, newdata = c_test, type = "response")
y_logit <- as.factor(ifelse(yp_logit > 0.5, "TRUE", "FALSE"))
```

### Prediction performance

Now we can inspect the prediction performance of kNN and the logit model using `confusionMatrix()` from `caret`, which can be used to (also) display a lot of performance measures, given predicted classes.

```r
confusionMatrix(y_knn, y_test, mode = "everything", positive = "TRUE")
```

```
Confusion Matrix and Statistics

          Reference
Prediction FALSE TRUE
     FALSE  2995  680
     TRUE    113  119
```

```
               Accuracy : 0.797
                 95% CI : (0.7841, 0.8095)
    No Information Rate : 0.7955
    P-Value [Acc > NIR] : 0.4151

                  Kappa : 0.1529

 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.14894
            Specificity : 0.96364
         Pos Pred Value : 0.51293
         Neg Pred Value : 0.81497
              Precision : 0.51293
                 Recall : 0.14894
                     F1 : 0.23084
             Prevalence : 0.20450
         Detection Rate : 0.03046
   Detection Prevalence : 0.05938
      Balanced Accuracy : 0.55629

       'Positive' Class : TRUE
```

```r
confusionMatrix(y_logit, y_test, mode = "everything", positive = "TRUE")
```

```
Warning in confusionMatrix.default(y_logit, y_test, mode = "everything", :
Levels are not in the same order for reference and data. Refactoring data to
match.

Confusion Matrix and Statistics

          Reference
Prediction FALSE TRUE
     FALSE  3108  799
     TRUE      0    0

               Accuracy : 0.7955
                 95% CI : (0.7825, 0.808)
    No Information Rate : 0.7955
    P-Value [Acc > NIR] : 0.5095
```

```
                  Kappa : 0

 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.0000
            Specificity : 1.0000
         Pos Pred Value :    NaN
         Neg Pred Value : 0.7955
              Precision :     NA
                 Recall : 0.0000
                     F1 :     NA
             Prevalence : 0.2045
         Detection Rate : 0.0000
   Detection Prevalence : 0.0000
      Balanced Accuracy : 0.5000

       'Positive' Class : TRUE
```

Additionally, ROC and PR curves are helpful for evaluating prediction performance with categorical outcomes. Here we could (e.g.) use the `PRROC` package. As an example, we only consider the knn model.

First, get predicted risk scores.

```
yp_knn <- 1 - attributes(y_knn)$prob
```

Then, create helper objects…

```
pc <- yp_knn[y_test == "TRUE"]
nc <- yp_knn[y_test == "FALSE"]
```

…that can be passed to `roc.curve()` (see `?roc.curve`).

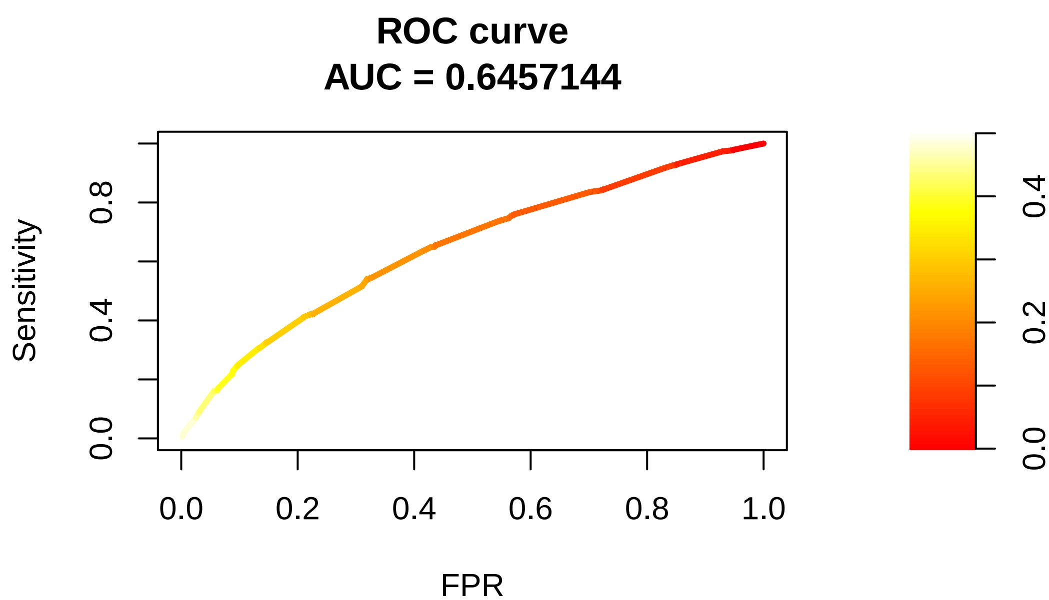
```
roc <- roc.curve(scores.class0 = pc, scores.class1 = nc, curve = T)
```

Finally, we can print and plot the resulting roc object.

```
roc
```

```
ROC curve

   Area under curve:
    0.6457144

   Curve for scores from  0  to  0.5
   ( can be plotted with plot(x) )
```

```
plot(roc, scale.color = heat.colors(100))
```



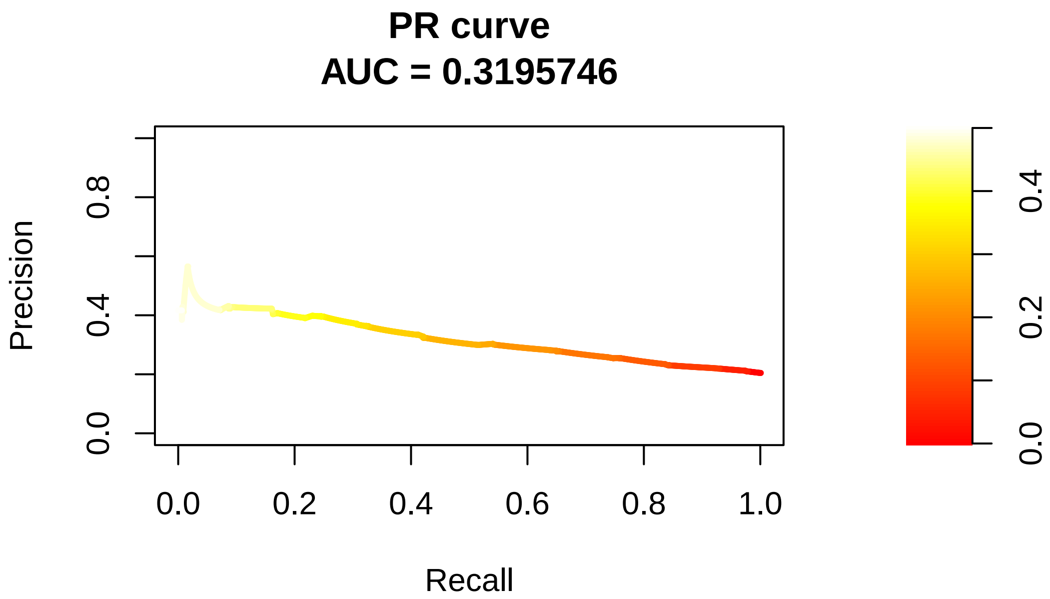

Same for PR curve.

```
pr <- pr.curve(scores.class0 = pc, scores.class1 = nc, curve = T)
pr
```

```
Precision-recall curve

   Area under curve (Integral):
    0.3195746
```

```
Area under curve (Davis & Goadrich):
 0.3195753

Curve for scores from  0  to  0.5
( can be plotted with plot(x) )
```

```
plot(pr, scale.color = heat.colors(100))
```




Try to calculate precision at top 100, i.e. the expected precision when classifying the 100 test incidents with the highest risk scores as being arrests (`TRUE`). For this, we need to create a new prediction vector. The function `order()` might be helpful here.

```
yp <- data.frame(yp_knn, y_test)
yp <- yp[order(-yp_knn),]
yp$yt_knn <- "FALSE"
yp[1:100,]$yt_knn <- "TRUE"
```

Next, compute the precision given the new predicted classes and `y_test`.

```
precision(as.factor(yp$yt_knn), yp$y_test, relevant = "TRUE")
```

```
[1] 0.46
```

### Classification thresholds

In the previous plots, we have seen that performance measures such as sensitivity and specificity are highly dependent on the underlying classification threshold. Therefore, lets try to find a threshold that satisfies some optimality criterion, instead of simply using 0.5. For this purpose, we have to create another roc object for the knn result, now using the `pROC` package.

```
roc2 <- roc(y_test, yp_knn)
```

```
Setting levels: control = FALSE, case = TRUE
```

```
Setting direction: controls < cases
```

```
roc2
```

```
Call:
roc.default(response = y_test, predictor = yp_knn)

Data: yp_knn in 3108 controls (y_test FALSE) < 799 cases (y_test TRUE).
Area under the curve: 0.6457
```

This package provides the function `coords()`, which can be used for threshold optimization (see `?coords`). Note that in an actual application, we couldn't use the test set for this purpose, so another hold-out set would be needed.

```
knn_t <- coords(roc2, x = "best", best.method = "closest.topleft", best.weights = c(1, 0.2))
knn_t
```

```
  threshold specificity sensitivity
1 0.2939815   0.7892535   0.4117647
```

We can now use this new threshold to predict class membership.

```
y_knn2 <- as.factor(ifelse(yp_knn > unlist(knn_t[1]), "TRUE", "FALSE"))
```

And finally build a confusion matrix using the predicted classes from above.

```r
confusionMatrix(y_knn2, y_test, mode = "everything", positive = "TRUE")
```

```
Confusion Matrix and Statistics

          Reference
Prediction FALSE TRUE
     FALSE  2453  470
     TRUE    655  329

               Accuracy : 0.7121
                 95% CI : (0.6976, 0.7262)
    No Information Rate : 0.7955
    P-Value [Acc > NIR] : 1

                  Kappa : 0.1851

 Mcnemar's Test P-Value : 4.116e-08

            Sensitivity : 0.41176
            Specificity : 0.78925
         Pos Pred Value : 0.33435
         Neg Pred Value : 0.83921
              Precision : 0.33435
                 Recall : 0.41176
                     F1 : 0.36904
             Prevalence : 0.20450
         Detection Rate : 0.08421
   Detection Prevalence : 0.25186
      Balanced Accuracy : 0.60051

       'Positive' Class : TRUE
```

## References


- https://dev.socrata.com/foundry/data.cityofchicago.org/6zsd-86xi