Classification

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September 25, 2022

How do linear models for classification work?

Linear models for classification create boundaries for decisions, which separate the observations into different categories that are of the same class. The decision boundaries in classification are linear combinations of different parameters for each side of the boundary. Strengths for these linear models include: the ability to add new data and update the graph with an easier approach, better probabilistic interpretations, and the avoidance of overfitting with algorithms. A few weaknesses for linear models in classification are: tendencies to fail with an increase in non-linear decision boundaries and less flexibility to adopt relationships as they get more complex.

Select a dataset

Data set: Adult Data Set

Source: https://archive.ics.uci.edu/ml/datasets/Adult

Target column: 'predicted_salary_range'

No. of rows: 48,842 rows

Load the data

```
adult <- read.csv("adult.data", header=FALSE)

# Adds columns names to the data table
colnames(adult) <- c('age', 'workclass', 'fnlwgt', 'education', 'education_num', 'marital_status', 'occu
```

Data Cleaning

```
# Changes the character values in the predicted_salary_range column to integer values
adult$predicted_salary_range[adult$predicted_salary_range == " <=50K"] <- "0"
adult$predicted_salary_range[adult$predicted_salary_range == " >50K"] <- "1"
adult$predicted_salary_range <- as.integer(adult$predicted_salary_range)
```

Split data into train and test data

```r
set.seed(1234)
sample <- sample(1:nrow(adult), nrow(adult)*0.8, replace=FALSE)
train <- adult[sample,]
test <- adult[-sample,]
```

Data exploration on the train data

```r
attach(train)

# Prints the first 10 rows of the train data for adults
head(train, n=10)
```

```
##       age workclass fnlwgt     education education_num      marital_status
## 7452   17   Private 110798          11th             7       Never-married
## 8016   34   Private 202450       HS-grad             9  Married-civ-spouse
## 7162   24   Private 259351  Some-college            10       Never-married
## 8086   67         ?  81761       HS-grad             9            Divorced
## 23653  25   Private 109532          12th             8       Never-married
## 9196   24   Private 237928     Bachelors            13       Never-married
## 623    65   Private 109351           9th             5             Widowed
## 15241  44   Private 368757  Some-college            10  Married-civ-spouse
## 10885  45   Private 189225       HS-grad             9       Never-married
## 934    23   Private 375871       HS-grad             9  Married-civ-spouse
##              occupation  relationship                race     sex
## 7452              Sales     Own-child               White  Female
## 8016       Craft-repair       Husband               White    Male
## 7162       Craft-repair     Unmarried  Amer-Indian-Eskimo    Male
## 8086                  ?     Own-child               White    Male
## 23653      Craft-repair     Own-child               White    Male
## 9196     Prof-specialty Not-in-family               White    Male
## 623     Priv-house-serv     Unmarried               Black  Female
## 15241 Machine-op-inspct       Husband               White    Male
## 10885     Other-service     Unmarried               Black  Female
## 934        Adm-clerical          Wife               White  Female
##       capital_gain capital_loss hours_per_week native_country
## 7452             0            0             20  United-States
## 8016             0            0             55  United-States
## 7162             0            0             40         Mexico
## 8086             0            0             20  United-States
## 23653            0            0             40  United-States
## 9196             0            0             39  United-States
## 623              0            0             24  United-States
## 15241            0            0             40  United-States
## 10885            0            0             40  United-States
## 934              0            0             40         Mexico
##       predicted_salary_range
## 7452                       0
## 8016                       1
## 7162                       0
## 8086                       0
## 23653                      0
```

```
## 9196                         0
## 623                          0
## 15241                        0
## 10885                        0
## 934                          0
```

```r
# Prints the mean of education_num
mean(education_num)
```

```
## [1] 10.08561
```

```r
# Prints the median of hours worked per week for adults
median(hours_per_week)
```

```
## [1] 40
```

```r
# Prints the smallest and largest capital_gain across the adults
range(capital_gain)
```

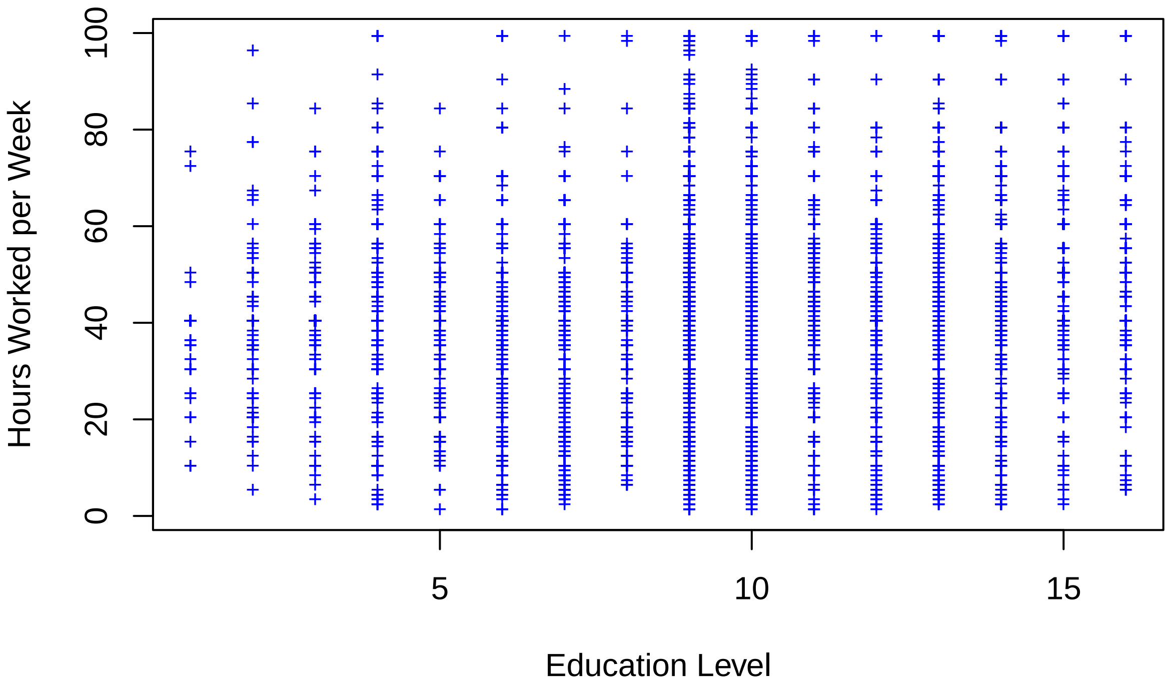
```
## [1]     0 99999
```

```r
# Prints statistics for the age across the adults data
summary(age)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   17.00   28.00   37.00   38.59   48.00   90.00
```

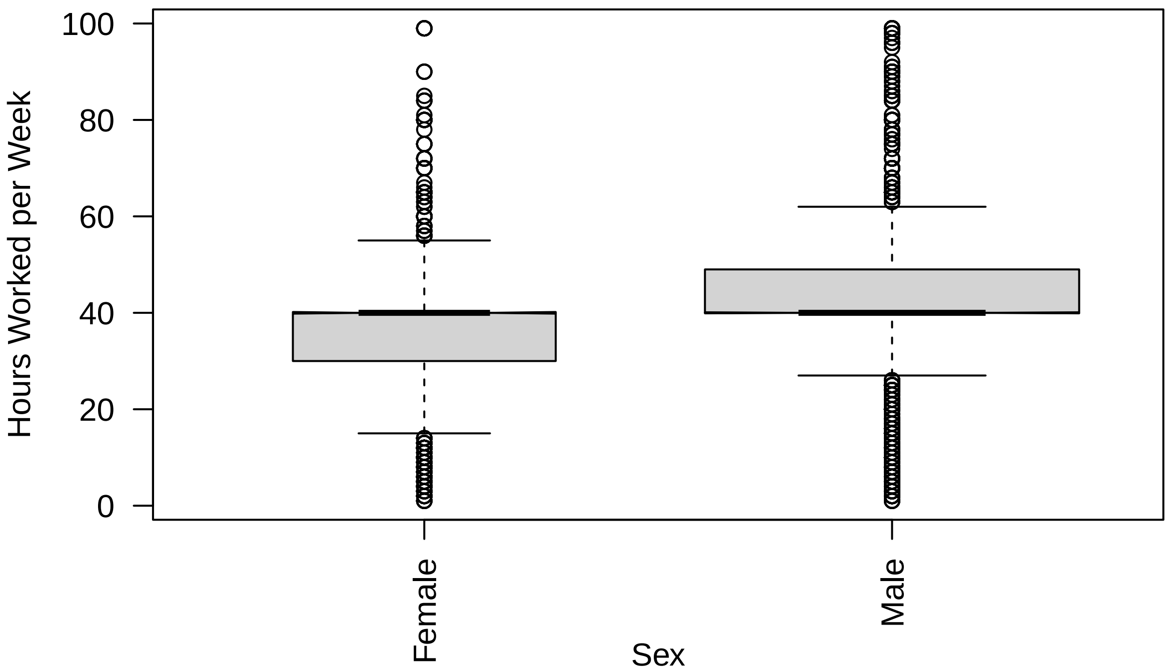
Informative graphs of train data

```r
# Scatterplot of education level vs. hours worked per week
plot(train$education_num, train$hours_per_week, pch='+', cex=0.75, col="blue", xlab="Education Level", y
```




```r
# Boxplot of hours worked per week based on sex
boxplot(train$hours_per_week~train$sex, varwidth=TRUE, notch=TRUE, xlab="Sex", ylab="Hours Worked per We
```

```
## Warning in (function (z, notch = FALSE, width = NULL, varwidth = FALSE, : some
## notches went outside hinges ('box'): maybe set notch=FALSE
```



Logistic regression model of train data

```
glm1 <- glm(predicted_salary_range~education_num, data=train)
glm1
```

```
##
## Call:  glm(formula = predicted_salary_range ~ education_num, data = train)
##
## Coefficients:
##   (Intercept)  education_num
##      -0.32142        0.05566
##
## Degrees of Freedom: 26047 Total (i.e. Null);  26046 Residual
## Null Deviance:       4750
## Residual Deviance: 4213  AIC: 26470
```

```
# Outputs the summary of the model
summary(glm1)
```

```
##
## Call:
## glm(formula = predicted_salary_range ~ education_num, data = train)
##
```

```
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -0.5691  -0.2352  -0.1795   0.1544   1.2101
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -0.3214220  0.0100529  -31.97   <2e-16 ***
## education_num  0.0556599  0.0009657   57.64   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.1617512)
##
##     Null deviance: 4750.4  on 26047  degrees of freedom
## Residual deviance: 4213.0  on 26046  degrees of freedom
## AIC: 26473
##
## Number of Fisher Scoring iterations: 2
```

The residual deviance in the model summary shows how well the predicted_salary_range can be predicted by the model with education_num as the predictor variable. AIC is a measure of how well-fit the model is to the data set. A lower AIC value indiciates a better-fitting model. The AIC value for this model is fairly large, meaning this model is underfit for the data.

Naive Bayes Model

```
#install.packages('e1071', dependencies=TRUE)
library(e1071)
nb <- naiveBayes(predicted_salary_range~., data=train)
nb
```

```
##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
##         0         1
## 0.7600584 0.2399416
##
## Conditional probabilities:
##    age
## Y       [,1]     [,2]
##   0 36.81897 14.08123
##   1 44.21488 10.41266
##
##    workclass
## Y              ?  Federal-gov    Local-gov  Never-worked      Private
##   0 0.0673805435 0.0232851803 0.0596524902  0.0003030609 0.7177997778
##   1 0.0244800000 0.0483200000 0.0795200000  0.0000000000 0.6326400000
```

```
##    workclass
## Y    Self-emp-inc  Self-emp-not-inc    State-gov  Without-pay
##   0  0.0196484493      0.0739468633 0.0374785332 0.0005051015
##   1  0.0803200000      0.0902400000 0.0444800000 0.0000000000
##
##    fnlwgt
## Y       [,1]     [,2]
##   0 189674.5 105991.1
##   1 187899.4 101477.8
##
##    education
## Y          10th        11th        12th     1st-4th     5th-6th     7th-8th
##   0 0.036013739 0.044751995 0.016314779 0.006566320 0.012779069 0.025659157
##   1 0.007360000 0.007680000 0.004320000 0.000800000 0.001760000 0.004160000
##    education
## Y           9th  Assoc-acdm   Assoc-voc   Bachelors   Doctorate     HS-grad
##   0 0.019345388 0.032983130 0.041266795 0.127891706 0.004293363 0.354278210
##   1 0.003360000 0.035200000 0.044640000 0.287680000 0.038240000 0.210240000
##    education
## Y       Masters   Preschool  Prof-school  Some-college
##   0 0.031467825 0.002171937  0.006566320   0.237650268
##   1 0.121280000 0.000000000  0.053920000   0.179360000
##
##    education_num
## Y        [,1]     [,2]
##   0  9.597939 2.452206
##   1 11.630400 2.359654
##
##    marital_status
## Y       Divorced  Married-AF-spouse  Married-civ-spouse  Married-spouse-absent
##   0 0.1597131023       0.0005556117        0.3353369027           0.0159106981
##   1 0.0614400000       0.0016000000        0.8544000000           0.0043200000
##    marital_status
## Y    Never-married    Separated      Widowed
##   0   0.4139812102 0.0374785332 0.0370239418
##   1   0.0596800000 0.0086400000 0.0099200000
##
##    occupation
## Y             ?  Adm-clerical  Armed-Forces  Craft-repair  Exec-managerial
##   0 0.0676836044  0.1323365997  0.0003535711  0.1277906859     0.0854631781
##   1 0.0244800000  0.0652800000  0.0001600000  0.1190400000     0.2483200000
##    occupation
## Y    Farming-fishing  Handlers-cleaners  Machine-op-inspct  Other-service
##   0     0.0354581271       0.0518234165       0.0708657440   0.1273866047
##   1     0.0129600000       0.0105600000       0.0331200000   0.0179200000
##    occupation
## Y    Priv-house-serv  Prof-specialty  Protective-serv        Sales
##   0     0.0057581574    0.0923325588     0.0175270229 0.1080412163
##   1     0.0001600000    0.2382400000     0.0272000000 0.1265600000
##    occupation
## Y    Tech-support  Transport-moving
##   0  0.0257096676      0.0514698454
##   1  0.0352000000      0.0408000000
##
```

```
##    relationship
## Y      Husband  Not-in-family  Other-relative  Own-child  Unmarried       Wife
##   0 0.29487827     0.30361653      0.03732700 0.20097990 0.12996262 0.03323568
##   1 0.75488000     0.10864000      0.00368000 0.00832000 0.02784000 0.09664000
##
##    race
## Y    Amer-Indian-Eskimo  Asian-Pac-Islander      Black      Other      White
##   0          0.01136478          0.03101323 0.10940499 0.00989999 0.83831700
##   1          0.00480000          0.03440000 0.05184000 0.00352000 0.90544000
##
##    sex
## Y      Female      Male
##   0 0.3863522 0.6136478
##   1 0.1529600 0.8470400
##
##    capital_gain
## Y        [,1]       [,2]
##   0  149.6236   970.3204
##   1 4018.6848 14581.7440
##
##    capital_loss
## Y        [,1]     [,2]
##   0  51.62001 307.1221
##   1 194.93104 594.0050
##
##    hours_per_week
## Y       [,1]     [,2]
##   0 38.84317 12.29426
##   1 45.44384 10.94613
##
##    native_country
## Y              ?     Cambodia       Canada        China     Columbia
##   0 1.818365e-02 5.051015e-04 2.980099e-03 2.121426e-03 2.070916e-03
##   1 1.872000e-02 8.000000e-04 5.120000e-03 2.720000e-03 1.600000e-04
##    native_country
## Y           Cuba  Dominican-Republic      Ecuador  El-Salvador      England
##   0 2.929589e-03        2.727548e-03 1.111223e-03 3.687241e-03 2.474997e-03
##   1 2.560000e-03        3.200000e-04 4.800000e-04 1.280000e-03 3.840000e-03
##    native_country
## Y         France      Germany       Greece    Guatemala        Haiti
##   0 6.061218e-04 4.040812e-03 6.566320e-04 2.778058e-03 1.515305e-03
##   1 1.120000e-03 5.760000e-03 1.120000e-03 1.600000e-04 6.400000e-04
##    native_country
## Y    Holand-Netherlands     Honduras         Hong      Hungary        India
##   0        5.051015e-05 4.040812e-04 6.061218e-04 4.040812e-04 2.323467e-03
##   1        0.000000e+00 1.600000e-04 4.800000e-04 3.200000e-04 4.480000e-03
##    native_country
## Y           Iran      Ireland        Italy      Jamaica        Japan
##   0 1.010203e-03 9.091827e-04 2.121426e-03 2.778058e-03 1.363774e-03
##   1 2.080000e-03 4.800000e-04 3.520000e-03 1.120000e-03 2.400000e-03
##    native_country
## Y           Laos       Mexico    Nicaragua  Outlying-US(Guam-USVI-etc)
##   0 6.566320e-04 2.429538e-02 1.111223e-03                6.566320e-04
##   1 1.600000e-04 4.000000e-03 3.200000e-04                0.000000e+00
```

```
##    native_country
## Y           Peru  Philippines       Poland     Portugal  Puerto-Rico
##   0 1.212244e-03 5.909688e-03 1.969896e-03 1.262754e-03 3.737751e-03
##   1 3.200000e-04 8.480000e-03 1.280000e-03 6.400000e-04 1.600000e-03
##    native_country
## Y       Scotland        South       Taiwan     Thailand  Trinadad&Tobago
##   0 3.535711e-04 2.626528e-03 1.060713e-03 7.071421e-04     8.586726e-04
##   1 4.800000e-04 2.240000e-03 2.400000e-03 1.600000e-04     3.200000e-04
##    native_country
## Y    United-States      Vietnam   Yugoslavia
##   0   8.902919e-01 2.576018e-03 3.535711e-04
##   1   9.166400e-01 4.800000e-04 6.400000e-04
```

The data above displays the probability of each result (salary <= 50K or salary > 50K) based on the value of each attribute.

Predict and evaluate on the test data

```r
probs <- predict(glm1, newdata=test, type="response")
pred <- ifelse(probs>0.5, 2, 1)

# Calculate accuracy
acc1 <- mean(pred==as.integer(test$predicted_salary_range))
print(paste("accuracy = ", acc1))
```

Logistic Regression Model

```
## [1] "accuracy =  0.220789190849071"
```

```r
# Table of predictions and true values
tab <- table(pred, as.integer(test$predicted_salary_range))
tab
```

```
##
## pred    0    1
##    1 4877 1438
##    2   45  153
```

```r
TP <- tab[1, 1]
FN <- tab[2, 1]
TN <- tab[2, 2]
FP <- tab[1, 2]

# Sensitivity
sens <- TP / (TP + FN)
print(paste("sensitivity = ", sens))
```

```
## [1] "sensitivity =  0.990857375050792"
```

```
# Specificity
spec <- TN / (TN + FP)
print(paste("specificity = ", spec))
```

```
## [1] "specificity =  0.0961659333752357"
```

```
p1 <- predict(nb, newdata=test, type="class")

# Calculate accuracy
acc2 <- mean(p1==(test$predicted_salary_range))
print(paste("accuracy = ", acc2))
```

Naive Bayes Model

```
## [1] "accuracy =  0.826193766313527"
```

```
# Table of predictions and true values
tab2 <- table(p1, test$predicted_salary_range)
tab2
```

```
##
## p1     0    1
##   0 4608  818
##   1  314  773
```

```
TP2 <- tab2[1, 1]
FN2 <- tab2[2, 1]
TN2 <- tab2[2, 2]
FP2 <- tab2[1, 2]

# Sensitivity
sens2 <- TP2 / (TP2 + FN2)
print(paste("sensitivity = ", sens2))
```

```
## [1] "sensitivity =  0.936204794798862"
```

```
# Specificity
spec2 <- TN2 / (TN2 + FP2)
print(paste("specificity = ", spec2))
```

```
## [1] "specificity =  0.48585795097423"
```

The naive bayes model has a much higher accuracy rate compared to the logistic regression model. This can be explained by the fact that the naive bayes model uses all attributes as predictors to make a more accurate prediction of the target variable (predicted_salary_range).

Strengths and weaknesses of Naive Bayes and Logistic Regression

Logistic regression is accurate for simpler, more linear data sets. However, it can only be useful for data sets that follow a linear trend. The naive bayes algorithm computes a model quickly in a short amount of time. However, the model assumes that all predictor attributes are independent of each other, which is rarely true.

Classification metrics

The most common and simplest classification metric is accuracy. This represents the proportion of predictions made by the model that are accurate. Sensitivity measures the rate of true positives. Specificity measures the rate of true negatives.