Entrega 6

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https://github.com/JusSolo/Mineria_Proyecto2.git

1. Exploración de los datos

Observaciones: - La variable respuesta `precio_categoria` está balanceada en torno a 25–50% por clase. - Existen variables numéricas que requieren centrado y escalado, y posibles valores faltantes.

2. Preparación de los datos

Para SVM es crucial que las variables numéricas estén normalizadas y no existan NA. Además, convertiremos factores a dummies.

```
# 1) Eliminación de predictores de varianza casi cero
nzv <- nearZeroVar(train, saveMetrics = TRUE)
train <- train[, !nzv$zeroVar]
test  <- test[, colnames(test) %in% colnames(train)]

# 2) Imputación de valores faltantes + centrado y escalado
pp <- preProcess(train %>% select(-SalePrice, -precio_categoria),
                 method = c("center","scale","knnImpute"))
train_pp <- predict(pp, train)
test_pp  <- predict(pp, test)

# 3) Codificación de factores en dummies para predictores categóricos
dummies <- dummyVars(~ ., data = train_pp %>% select(-SalePrice, -precio_categoria))
train_x <- predict(dummies, newdata = train_pp)
test_x  <- predict(dummies, newdata = test_pp)

# Preparamos data para caret
x_train <- as.data.frame(train_x)
y_train <- train_pp$precio_categoria
x_test  <- as.data.frame(test_x)
y_test  <- test_pp$precio_categoria
```

3. Definición de control de entrenamiento

```
ctrl <- trainControl(method = "repeatedcv", number = 5, repeats = 3,
                     classProbs = TRUE, summaryFunction = multiClassSummary)
```

4. Modelos SVM

4.1 SVM Lineal

```
grid_lin <- expand.grid(C = c(0.1, 1, 10))
svm_lin <- train(x_train, y_train, method = "svmLinear",
                 trControl = ctrl, tuneGrid = grid_lin)
svm_lin
```

```
## Support Vector Machines with Linear Kernel
##
## 1024 samples
##   35 predictor
##    3 classes: 'Economica', 'Intermedia', 'Cara'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold, repeated 3 times)
## Summary of sample sizes: 818, 821, 819, 819, 819, 819, ...
## Resampling results across tuning parameters:
##
##   C     logLoss    AUC        prAUC      Accuracy   Kappa      Mean_F1
##    0.1  0.4274141  0.9482423  0.8884803  0.8466445  0.7509514  0.8443582
##    1.0  0.4455822  0.9473231  0.8864311  0.8414285  0.7408239  0.8377079
##   10.0  0.4664172  0.9461297  0.8844024  0.8381939  0.7332534  0.8329701
##   Mean_Sensitivity  Mean_Specificity  Mean_Pos_Pred_Value  Mean_Neg_Pred_Value
##   0.8362863         0.9114446         0.8561436            0.9164732
##   0.8262286         0.9069208         0.8555335            0.9149067
##   0.8163159         0.9027783         0.8614337            0.9150557
##   Mean_Precision  Mean_Recall  Mean_Detection_Rate  Mean_Balanced_Accuracy
##   0.8561436       0.8362863    0.2822148            0.8738654
##   0.8555335       0.8262286    0.2804762            0.8665747
##   0.8614337       0.8163159    0.2793980            0.8595471
##
## Accuracy was used to select the optimal model using the largest value.
## The final value used for the model was C = 0.1.
```

4.2 SVM Radial (RBF)

```
grid_rad <- expand.grid(sigma = c(0.001, 0.01, 0.1), C = c(0.1, 1, 10))
svm_rad <- train(x_train, y_train, method = "svmRadial",
                 trControl = ctrl, tuneGrid = grid_rad)
svm_rad
```

```
## Support Vector Machines with Radial Basis Function Kernel
##
## 1024 samples
##   35 predictor
##    3 classes: 'Economica', 'Intermedia', 'Cara'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold, repeated 3 times)
## Summary of sample sizes: 819, 819, 819, 820, 819, 819, ...
## Resampling results across tuning parameters:
##
##   sigma  C     logLoss    AUC        prAUC      Accuracy   Kappa      Mean_F1
```

```
##   0.001   0.1  0.5546005  0.9402993  0.8787211  0.7796430  0.6634994  0.7852081
##   0.001   1.0  0.4338778  0.9430833  0.8836443  0.8196625  0.7116493  0.8198889
##   0.001  10.0  0.4050926  0.9492930  0.8937655  0.8385261  0.7396542  0.8373561
##   0.010   0.1  0.4572172  0.9423134  0.8866822  0.8001279  0.6876875  0.8039683
##   0.010   1.0  0.3814616  0.9512624  0.9011152  0.8346268  0.7336363  0.8332279
##   0.010  10.0  0.3704936  0.9548218  0.9073267  0.8433835  0.7464197  0.8412003
##   0.100   0.1  0.5861882  0.9224454  0.8444093  0.7770254  0.6359824  0.7726574
##   0.100   1.0  0.4640849  0.9365448  0.8720024  0.8115020  0.6877312  0.8043564
##   0.100  10.0  0.4908162  0.9307737  0.8606447  0.7994583  0.6671215  0.7913346
##   Mean_Sensitivity  Mean_Specificity  Mean_Pos_Pred_Value  Mean_Neg_Pred_Value
##   0.8189915         0.8910883         0.7752766            0.8845414
##   0.8211449         0.9003409         0.8217873            0.9001308
##   0.8333548         0.9086425         0.8445294            0.9113104
##   0.8206834         0.8958344         0.7973943            0.8908246
##   0.8305185         0.9068425         0.8391678            0.9090471
##   0.8349799         0.9102960         0.8507995            0.9144289
##   0.7615673         0.8707949         0.7898349            0.8774352
##   0.7848582         0.8863123         0.8370010            0.9004611
##   0.7707599         0.8789249         0.8268624            0.8939269
##   Mean_Precision  Mean_Recall  Mean_Detection_Rate  Mean_Balanced_Accuracy
##   0.7752766       0.8189915    0.2598810            0.8550399
##   0.8217873       0.8211449    0.2732208            0.8607429
##   0.8445294       0.8333548    0.2795087            0.8709986
##   0.7973943       0.8206834    0.2667093            0.8582589
##   0.8391678       0.8305185    0.2782089            0.8686805
##   0.8507995       0.8349799    0.2811278            0.8726379
##   0.7898349       0.7615673    0.2590085            0.8161811
##   0.8370010       0.7848582    0.2705007            0.8355852
##   0.8268624       0.7707599    0.2664861            0.8248424
##
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were sigma = 0.01 and C = 10.
```

4.3 SVM Polinomial

```
grid_poly <- expand.grid(degree = c(2, 3, 4), scale = c(0.001, 0.01), C = c(0.1, 1, 10))
svm_poly <- train(x_train, y_train, method = "svmPoly",
                  trControl = ctrl, tuneGrid = grid_poly)
svm_poly
```

```
## Support Vector Machines with Polynomial Kernel
##
## 1024 samples
##   35 predictor
##    3 classes: 'Economica', 'Intermedia', 'Cara'
##
## No pre-processing
## Resampling: Cross-Validated (5 fold, repeated 3 times)
## Summary of sample sizes: 818, 820, 819, 819, 820, 820, ...
## Resampling results across tuning parameters:
##
##   degree  scale  C     logLoss    AUC        prAUC      Accuracy   Kappa
##   2       0.001   0.1  0.5547119  0.9407783  0.8793010  0.7880650  0.6765371
##   2       0.001   1.0  0.4488754  0.9431750  0.8835717  0.8267821  0.7224443
```

```
##   2       0.001  10.0  0.4308580  0.9487165  0.8896987  0.8437230  0.7480515
##   2       0.010   0.1  0.4534784  0.9432156  0.8831891  0.8284177  0.7240475
##   2       0.010   1.0  0.4310074  0.9503482  0.8935556  0.8486059  0.7552878
##   2       0.010  10.0  0.4185081  0.9533077  0.8994385  0.8577180  0.7689501
##   3       0.001   0.1  0.5554992  0.9407919  0.8790649  0.7851318  0.6721808
##   3       0.001   1.0  0.4469091  0.9439705  0.8840543  0.8254972  0.7178635
##   3       0.001  10.0  0.4300125  0.9497345  0.8914850  0.8486059  0.7554221
##   3       0.010   0.1  0.4568495  0.9461173  0.8863397  0.8310272  0.7264445
##   3       0.010   1.0  0.4245633  0.9532113  0.8983660  0.8518595  0.7600920
##   3       0.010  10.0  0.4399155  0.9497044  0.8927726  0.8492547  0.7539326
##   4       0.001   0.1  0.5477613  0.9409291  0.8794674  0.7919627  0.6812866
##   4       0.001   1.0  0.4474038  0.9444859  0.8847576  0.8287381  0.7233971
##   4       0.001  10.0  0.4221668  0.9508839  0.8937518  0.8547801  0.7653234
##   4       0.010   0.1  0.4555103  0.9476547  0.8880317  0.8355770  0.7339521
##   4       0.010   1.0  0.4358625  0.9521212  0.8951291  0.8505571  0.7569469
##   4       0.010  10.0  0.4419496  0.9460407  0.8876642  0.8362179  0.7317523
##   Mean_F1    Mean_Sensitivity  Mean_Specificity  Mean_Pos_Pred_Value
##   0.7942952  0.8282762         0.8959976         0.7851914
##   0.8270452  0.8267359         0.9037241         0.8301292
##   0.8426950  0.8384627         0.9115382         0.8491390
##   0.8280667  0.8254009         0.9036446         0.8335407
##   0.8472204  0.8410499         0.9134910         0.8555946
##   0.8556017  0.8471176         0.9174673         0.8675905
##   0.7914854  0.8258732         0.8944699         0.7823350
##   0.8240811  0.8180291         0.9005955         0.8332190
##   0.8472374  0.8418896         0.9137749         0.8550174
##   0.8292080  0.8223481         0.9033409         0.8394880
##   0.8503491  0.8431882         0.9149365         0.8602862
##   0.8463913  0.8344297         0.9112775         0.8633767
##   0.7982165  0.8290772         0.8969853         0.7891983
##   0.8271575  0.8221301         0.9027566         0.8350181
##   0.8533524  0.8477533         0.9170992         0.8612136
##   0.8337466  0.8275622         0.9060859         0.8428419
##   0.8481590  0.8384009         0.9130352         0.8624420
##   0.8327719  0.8193941         0.9032750         0.8530852
##   Mean_Neg_Pred_Value  Mean_Precision  Mean_Recall  Mean_Detection_Rate
##   0.8888253            0.7851914       0.8282762    0.2626883
##   0.9039080            0.8301292       0.8267359    0.2755940
##   0.9139269            0.8491390       0.8384627    0.2812410
##   0.9050101            0.8335407       0.8254009    0.2761392
##   0.9169902            0.8555946       0.8410499    0.2828686
##   0.9228799            0.8675905       0.8471176    0.2859060
##   0.8874352            0.7823350       0.8258732    0.2617106
##   0.9039257            0.8332190       0.8180291    0.2751657
##   0.9168844            0.8550174       0.8418896    0.2828686
##   0.9073925            0.8394880       0.8223481    0.2770091
##   0.9189511            0.8602862       0.8431882    0.2839532
##   0.9189884            0.8633767       0.8344297    0.2830849
##   0.8898935            0.7891983       0.8290772    0.2639876
##   0.9057492            0.8350181       0.8221301    0.2762460
##   0.9204674            0.8612136       0.8477533    0.2849267
##   0.9097172            0.8428419       0.8275622    0.2785257
##   0.9193086            0.8624420       0.8384009    0.2835190
##   0.9119312            0.8530852       0.8193941    0.2787393
```

```
##   Mean_Balanced_Accuracy
##   0.8621369
##   0.8652300
##   0.8750005
##   0.8645227
##   0.8772704
##   0.8822925
##   0.8601715
##   0.8593123
##   0.8778323
##   0.8628445
##   0.8790623
##   0.8728536
##   0.8630312
##   0.8624433
##   0.8824263
##   0.8668240
##   0.8757180
##   0.8613346
##
## Accuracy was used to select the optimal model using the largest value.
## The final values used for the model were degree = 2, scale = 0.01 and C = 10.
```

5. Predicción y matrices de confusión

```
# Mejor modelo según Accuracy (ejemplo: svm_rad)
best <- svm_rad
pred_test <- predict(best, x_test)
confusionMatrix(pred_test, y_test)
```

```
## Confusion Matrix and Statistics
##
##             Reference
## Prediction   Economica Intermedia Cara
##   Economica         86         16    0
##   Intermedia        23        190   18
##   Cara               0         13   90
##
## Overall Statistics
##
##                Accuracy : 0.8394
##                  95% CI : (0.8016, 0.8727)
##     No Information Rate : 0.5023
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.7397
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: Economica Class: Intermedia Class: Cara
## Sensitivity                    0.7890            0.8676      0.8333
## Specificity                    0.9511            0.8111      0.9604
```

```
## Pos Pred Value                 0.8431           0.8225      0.8738
## Neg Pred Value                 0.9311           0.8585      0.9459
## Prevalence                     0.2500           0.5023      0.2477
## Detection Rate                 0.1972           0.4358      0.2064
## Detection Prevalence           0.2339           0.5298      0.2362
## Balanced Accuracy              0.8700           0.8393      0.8968
```

```r
# Confusion matrices para cada modelo
a_list <- list(
  Linear = svm_lin,
  Radial = svm_rad,
  Poly   = svm_poly
)
for(name in names(a_list)){
  cat("\nModelo:", name, "\n")
  print(confusionMatrix(predict(a_list[[name]], x_test), y_test))
}
```

```
##
## Modelo: Linear
## Confusion Matrix and Statistics
##
##             Reference
## Prediction   Economica Intermedia Cara
##   Economica         88         17    0
##   Intermedia        21        191   24
##   Cara               0         11   84
##
## Overall Statistics
##
##                Accuracy : 0.8326
##                  95% CI : (0.7941, 0.8664)
##     No Information Rate : 0.5023
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.7273
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: Economica Class: Intermedia Class: Cara
## Sensitivity                    0.8073           0.8721      0.7778
## Specificity                    0.9480           0.7926      0.9665
## Pos Pred Value                 0.8381           0.8093      0.8842
## Neg Pred Value                 0.9366           0.8600      0.9296
## Prevalence                     0.2500           0.5023      0.2477
## Detection Rate                 0.2018           0.4381      0.1927
## Detection Prevalence           0.2408           0.5413      0.2179
## Balanced Accuracy              0.8777           0.8324      0.8721
##
## Modelo: Radial
## Confusion Matrix and Statistics
##
##             Reference
```

```
## Prediction   Economica Intermedia Cara
##   Economica         86         16    0
##   Intermedia        23        190   18
##   Cara               0         13   90
##
## Overall Statistics
##
##                Accuracy : 0.8394
##                  95% CI : (0.8016, 0.8727)
##     No Information Rate : 0.5023
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.7397
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: Economica Class: Intermedia Class: Cara
## Sensitivity                    0.7890            0.8676      0.8333
## Specificity                    0.9511            0.8111      0.9604
## Pos Pred Value                 0.8431            0.8225      0.8738
## Neg Pred Value                 0.9311            0.8585      0.9459
## Prevalence                     0.2500            0.5023      0.2477
## Detection Rate                 0.1972            0.4358      0.2064
## Detection Prevalence           0.2339            0.5298      0.2362
## Balanced Accuracy              0.8700            0.8393      0.8968
##
## Modelo: Poly
## Confusion Matrix and Statistics
##
##             Reference
## Prediction   Economica Intermedia Cara
##   Economica         86         17    0
##   Intermedia        23        191   22
##   Cara               0         11   86
##
## Overall Statistics
##
##                Accuracy : 0.8326
##                  95% CI : (0.7941, 0.8664)
##     No Information Rate : 0.5023
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.7273
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: Economica Class: Intermedia Class: Cara
## Sensitivity                    0.7890            0.8721      0.7963
## Specificity                    0.9480            0.7926      0.9665
## Pos Pred Value                 0.8350            0.8093      0.8866
```

```
## Neg Pred Value                0.9309           0.8600      0.9351
## Prevalence                    0.2500           0.5023      0.2477
## Detection Rate                0.1972           0.4381      0.1972
## Detection Prevalence          0.2362           0.5413      0.2225
## Balanced Accuracy             0.8685           0.8324      0.8814
```

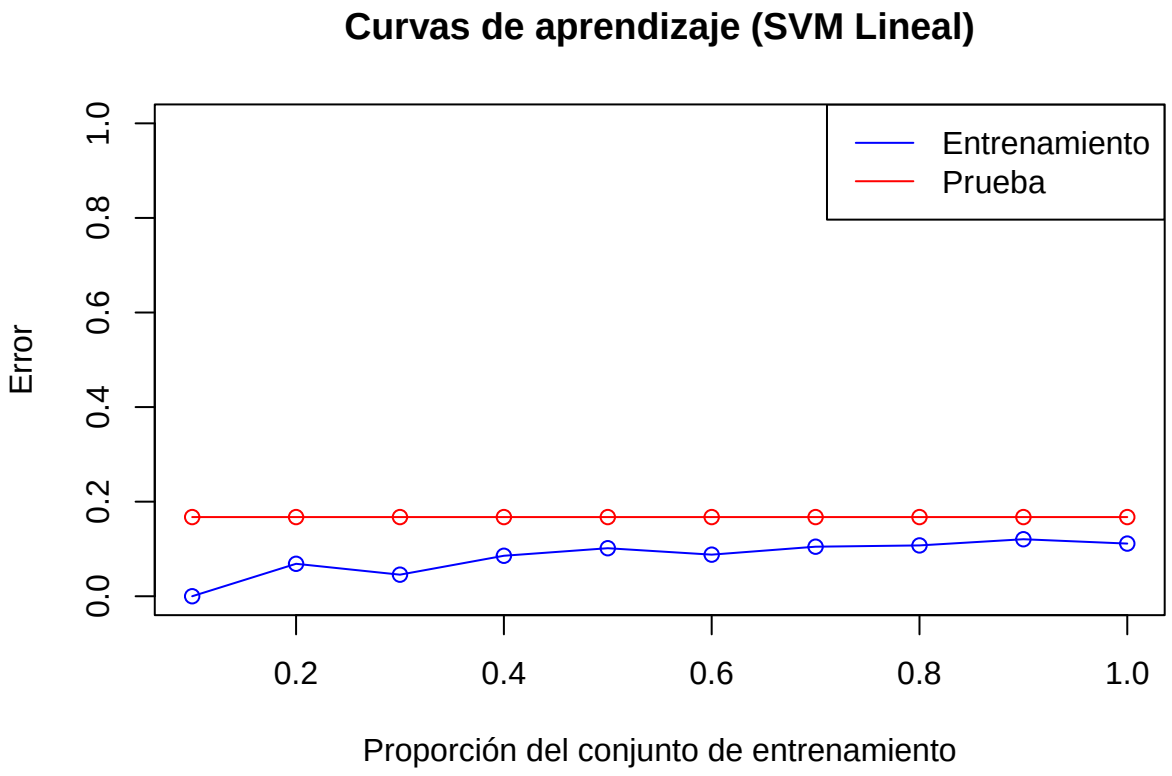
EL rendimiento de los modelos en general SVM en el conjunto de prueba indica que el modelo linea alcanzó un accuaracy del 83%, el modelo radial con una mejora de 83.94% y el modelo polinomio un acuaracy de 83.26%. Los intervalos de confianza del 95% para la accuaracy sugeren una variabilidad razonabla en las estimaciones.

Según las metricas por clase, observamos que el modelo radial tiente una sensibilidad ligeramente mejor para la clase cara en comparacion con los modelos, lineal y poliómico. Para la clase intermedia los tres modelos muestran una sensibilidad similares alta. La especificidad es generalmente alta para clase económica y cara pra los tres modelos, teniendo buena capaciad para identificar de manera correctamente las casas que no están en esta categoría.

```r
library(e1071)
library(Metrics)

tamaños <- seq(0.1, 1, by = 0.1)
errores_train_lin <- c()
errores_test_lin <- c()

for (t in tamaños) {

  idx <- sample(1:nrow(x_train), size = floor(t * nrow(x_train)))
  sub_x_train <- x_train[idx, ]
  sub_y_train <- y_train[idx]

  # Entrenar un modelo SVM lineal con el subconjunto
  sub_svm_lin <- svm(sub_x_train, sub_y_train, kernel = "linear")

  # Predecir en el subconjunto de entrenamiento y en el conjunto de prueba completo
  pred_train_lin <- predict(sub_svm_lin, newdata = sub_x_train)
  pred_test_lin <- predict(svm_lin, newdata = x_test) # Usamos el modelo lineal completo entrenado prev

  # Calcular el error de clasificación
  errores_train_lin <- c(errores_train_lin, mean(pred_train_lin != sub_y_train))
  errores_test_lin <- c(errores_test_lin, mean(pred_test_lin != y_test))
}
```

```
## Warning in svm.default(sub_x_train, sub_y_train, kernel = "linear"):
## Variable(s) 'PoolArea' constant. Cannot scale data.
```

```r
# Graficar curvas de aprendizaje para el modelo lineal
plot(tamaños, errores_train_lin, type = "o", col = "blue", ylim = c(0, 1),
     ylab = "Error", xlab = "Proporción del conjunto de entrenamiento",
     main = "Curvas de aprendizaje (SVM Lineal)")
lines(tamaños, errores_test_lin, type = "o", col = "red")
legend("topright", legend = c("Entrenamiento", "Prueba"),
       col = c("blue", "red"), lty = 1)
```



Según la gráfica anterior, la curva de error de entrenamiento muestra un error bajo que tiende a disminuir ligeramente a medidad que se utiliza una mayor cantidad de datos para el entrenamiento, por lo que el modelo es capaz de aprender de los patrones. por el lado de la curva de prueba se mantiene consistente mas alta, sugiendo un pequeño sobreajuste.