

# Análisis de Datos y Aprendizaje Máquina con Tensorflow 2.0: Clasificación

2019/09/30

## Árboles de decision ID3

- Objetivo: Conocer los arboles ID3 para clasificación y como visualizarlos
- Los árboles de decisión (DT) son un método de aprendizaje supervisado relacionado con la entropía, se utiliza para la clasificación y la regresión. El algoritmo hace particiones en las características de los datos de forma que los va clasificando
- Los árboles de decisión son muy interpretables, lo que puede ser muy útil con algunos conjuntos de datos, pues indican que variable difiere de otra en cuanto a la cantidad de datos que se particionan

```
In [1]: import sklearn
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

## Análisis exploratorio

### Etiquetas de clase a valor numérico

- Diagnosis (M = malignant, B = benign)

```
In [2]: %matplotlib inline
```

```
df = pd.read_csv("data-breast.csv", index_col=0)

df.head(10)
```

```
Out[2]:
```

	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	\
id						
842302	M	17.99	10.38	122.80	1001.0	
842517	M	20.57	17.77	132.90	1326.0	
84300903	M	19.69	21.25	130.00	1203.0	
84348301	M	11.42	20.38	77.58	386.1	
84358402	M	20.29	14.34	135.10	1297.0	
843786	M	12.45	15.70	82.57	477.1	
844359	M	18.25	19.98	119.60	1040.0	

84458202	M	13.71	20.83	90.20	577.9
844981	M	13.00	21.82	87.50	519.8
84501001	M	12.46	24.04	83.97	475.9

	smoothness_mean	compactness_mean	concavity_mean	\
id				
842302	0.11840	0.27760	0.30010	
842517	0.08474	0.07864	0.08690	
84300903	0.10960	0.15990	0.19740	
84348301	0.14250	0.28390	0.24140	
84358402	0.10030	0.13280	0.19800	
843786	0.12780	0.17000	0.15780	
844359	0.09463	0.10900	0.11270	
84458202	0.11890	0.16450	0.09366	
844981	0.12730	0.19320	0.18590	
84501001	0.11860	0.23960	0.22730	

	concave points_mean	symmetry_mean	...	texture_worst	\
id			...		
842302	0.14710	0.2419	...	17.33	
842517	0.07017	0.1812	...	23.41	
84300903	0.12790	0.2069	...	25.53	
84348301	0.10520	0.2597	...	26.50	
84358402	0.10430	0.1809	...	16.67	
843786	0.08089	0.2087	...	23.75	
844359	0.07400	0.1794	...	27.66	
84458202	0.05985	0.2196	...	28.14	
844981	0.09353	0.2350	...	30.73	
84501001	0.08543	0.2030	...	40.68	

	perimeter_worst	area_worst	smoothness_worst	compactness_worst	\
id					
842302	184.60	2019.0	0.1622	0.6656	
842517	158.80	1956.0	0.1238	0.1866	
84300903	152.50	1709.0	0.1444	0.4245	
84348301	98.87	567.7	0.2098	0.8663	
84358402	152.20	1575.0	0.1374	0.2050	
843786	103.40	741.6	0.1791	0.5249	
844359	153.20	1606.0	0.1442	0.2576	
84458202	110.60	897.0	0.1654	0.3682	
844981	106.20	739.3	0.1703	0.5401	
84501001	97.65	711.4	0.1853	1.0580	

	concavity_worst	concave points_worst	symmetry_worst	\
id				
842302	0.7119	0.2654	0.4601	
842517	0.2416	0.1860	0.2750	
84300903	0.4504	0.2430	0.3613	
84348301	0.6869	0.2575	0.6638	

84358402	0.4000	0.1625	0.2364
843786	0.5355	0.1741	0.3985
844359	0.3784	0.1932	0.3063
84458202	0.2678	0.1556	0.3196
844981	0.5390	0.2060	0.4378
84501001	1.1050	0.2210	0.4366

	fractal_dimension_worst	Unnamed: 32
id		
842302	0.11890	NaN
842517	0.08902	NaN
84300903	0.08758	NaN
84348301	0.17300	NaN
84358402	0.07678	NaN
843786	0.12440	NaN
844359	0.08368	NaN
84458202	0.11510	NaN
844981	0.10720	NaN
84501001	0.20750	NaN

[10 rows x 32 columns]

In [3]: df.iloc[:,1:].describe()

Out[3]:

	radius_mean	texture_mean	perimeter_mean	area_mean	\
count	569.000000	569.000000	569.000000	569.000000	
mean	14.127292	19.289649	91.969033	654.889104	
std	3.524049	4.301036	24.298981	351.914129	
min	6.981000	9.710000	43.790000	143.500000	
25%	11.700000	16.170000	75.170000	420.300000	
50%	13.370000	18.840000	86.240000	551.100000	
75%	15.780000	21.800000	104.100000	782.700000	
max	28.110000	39.280000	188.500000	2501.000000	

	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	\
count	569.000000	569.000000	569.000000	569.000000	
mean	0.096360	0.104341	0.088799	0.048919	
std	0.014064	0.052813	0.079720	0.038803	
min	0.052630	0.019380	0.000000	0.000000	
25%	0.086370	0.064920	0.029560	0.020310	
50%	0.095870	0.092630	0.061540	0.033500	
75%	0.105300	0.130400	0.130700	0.074000	
max	0.163400	0.345400	0.426800	0.201200	

	symmetry_mean	fractal_dimension_mean	...	texture_worst	\
count	569.000000	569.000000	...	569.000000	
mean	0.181162	0.062798	...	25.677223	
std	0.027414	0.007060	...	6.146258	
min	0.106000	0.049960	...	12.020000	
25%	0.161900	0.057700	...	21.080000	

50%	0.179200	0.061540	...	25.410000
75%	0.195700	0.066120	...	29.720000
max	0.304000	0.097440	...	49.540000

	perimeter_worst	area_worst	smoothness_worst	compactness_worst	\
count	569.000000	569.000000	569.000000	569.000000	
mean	107.261213	880.583128	0.132369	0.254265	
std	33.602542	569.356993	0.022832	0.157336	
min	50.410000	185.200000	0.071170	0.027290	
25%	84.110000	515.300000	0.116600	0.147200	
50%	97.660000	686.500000	0.131300	0.211900	
75%	125.400000	1084.000000	0.146000	0.339100	
max	251.200000	4254.000000	0.222600	1.058000	

	concavity_worst	concave points_worst	symmetry_worst	\
count	569.000000	569.000000	569.000000	
mean	0.272188	0.114606	0.290076	
std	0.208624	0.065732	0.061867	
min	0.000000	0.000000	0.156500	
25%	0.114500	0.064930	0.250400	
50%	0.226700	0.099930	0.282200	
75%	0.382900	0.161400	0.317900	
max	1.252000	0.291000	0.663800	

	fractal_dimension_worst	Unnamed: 32
count	569.000000	0.0
mean	0.083946	NaN
std	0.018061	NaN
min	0.055040	NaN
25%	0.071460	NaN
50%	0.080040	NaN
75%	0.092080	NaN
max	0.207500	NaN

[8 rows x 31 columns]

```
In [4]: df = df.replace({'B':0, 'M':1})
df
```

```
Out[4]:
```

	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	\
id						
842302	1	17.99	10.38	122.80	1001.0	
842517	1	20.57	17.77	132.90	1326.0	
84300903	1	19.69	21.25	130.00	1203.0	
84348301	1	11.42	20.38	77.58	386.1	
84358402	1	20.29	14.34	135.10	1297.0	
...	...	...	...	...	...	
926424	1	21.56	22.39	142.00	1479.0	
926682	1	20.13	28.25	131.20	1261.0	
926954	1	16.60	28.08	108.30	858.1	

927241	1	20.60	29.33	140.10	1265.0
92751	0	7.76	24.54	47.92	181.0

	smoothness_mean	compactness_mean	concavity_mean	\
id				
842302	0.11840	0.27760	0.30010	
842517	0.08474	0.07864	0.08690	
84300903	0.10960	0.15990	0.19740	
84348301	0.14250	0.28390	0.24140	
84358402	0.10030	0.13280	0.19800	
...	...	...	...	
926424	0.11100	0.11590	0.24390	
926682	0.09780	0.10340	0.14400	
926954	0.08455	0.10230	0.09251	
927241	0.11780	0.27700	0.35140	
92751	0.05263	0.04362	0.00000	

	concave points_mean	symmetry_mean	...	texture_worst	\
id					
842302	0.14710	0.2419	...	17.33	
842517	0.07017	0.1812	...	23.41	
84300903	0.12790	0.2069	...	25.53	
84348301	0.10520	0.2597	...	26.50	
84358402	0.10430	0.1809	...	16.67	
...	...	...	...	...	
926424	0.13890	0.1726	...	26.40	
926682	0.09791	0.1752	...	38.25	
926954	0.05302	0.1590	...	34.12	
927241	0.15200	0.2397	...	39.42	
92751	0.00000	0.1587	...	30.37	

	perimeter_worst	area_worst	smoothness_worst	compactness_worst	\
id					
842302	184.60	2019.0	0.16220	0.66560	
842517	158.80	1956.0	0.12380	0.18660	
84300903	152.50	1709.0	0.14440	0.42450	
84348301	98.87	567.7	0.20980	0.86630	
84358402	152.20	1575.0	0.13740	0.20500	
...	...	...	...	...	
926424	166.10	2027.0	0.14100	0.21130	
926682	155.00	1731.0	0.11660	0.19220	
926954	126.70	1124.0	0.11390	0.30940	
927241	184.60	1821.0	0.16500	0.86810	
92751	59.16	268.6	0.08996	0.06444	

	concavity_worst	concave points_worst	symmetry_worst	\
id				
842302	0.7119	0.2654	0.4601	
842517	0.2416	0.1860	0.2750	

84300903	0.4504	0.2430	0.3613
84348301	0.6869	0.2575	0.6638
84358402	0.4000	0.1625	0.2364
...	...	...	...
926424	0.4107	0.2216	0.2060
926682	0.3215	0.1628	0.2572
926954	0.3403	0.1418	0.2218
927241	0.9387	0.2650	0.4087
92751	0.0000	0.0000	0.2871

	fractal_dimension_worst	Unnamed: 32
id		
842302	0.11890	NaN
842517	0.08902	NaN
84300903	0.08758	NaN
84348301	0.17300	NaN
84358402	0.07678	NaN
...	...	...
926424	0.07115	NaN
926682	0.06637	NaN
926954	0.07820	NaN
927241	0.12400	NaN
92751	0.07039	NaN

[569 rows x 32 columns]

## Preparar datos para entrenamiento

```
In [5]: from sklearn.model_selection import train_test_split
```

```
X = df.drop('diagnosis',axis=1)
X = X.drop('Unnamed: 32',axis=1)
y = df['diagnosis']
# dividir datos
train, test, train_labels, test_labels = train_test_split(X, y,
                                                            test_size = 0.33, random_state = 42)
```

```
In [6]: train.head()
```

```
Out[6]:
```

	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	\
id						
87164	15.46	11.89	102.50	736.9	0.12570	
905190	12.85	21.37	82.63	514.5	0.07551	
857637	19.21	18.57	125.50	1152.0	0.10530	
914580	12.47	17.31	80.45	480.1	0.08928	
892604	12.46	19.89	80.43	471.3	0.08451	

	compactness_mean	concavity_mean	concave points_mean	symmetry_mean	\
id					
87164	0.15550	0.20320	0.10970	0.1966	

905190	0.08316	0.06126	0.01867	0.1580
857637	0.12670	0.13230	0.08994	0.1917
914580	0.07630	0.03609	0.02369	0.1526
892604	0.10140	0.06830	0.03099	0.1781

	fractal_dimension_mean	...	radius_worst	texture_worst	\
id		...			
87164	0.07069	...	18.79	17.04	
905190	0.06114	...	14.40	27.01	
857637	0.05961	...	26.14	28.14	
914580	0.06046	...	14.06	24.34	
892604	0.06249	...	13.46	23.07	

	perimeter_worst	area_worst	smoothness_worst	compactness_worst	\
id					
87164	125.00	1102.0	0.15310	0.3583	
905190	91.63	645.8	0.09402	0.1936	
857637	170.10	2145.0	0.16240	0.3511	
914580	92.82	607.3	0.12760	0.2506	
892604	88.13	551.3	0.10500	0.2158	

	concavity_worst	concave points_worst	symmetry_worst	\
id				
87164	0.5830	0.18270	0.3216	
905190	0.1838	0.05601	0.2488	
857637	0.3879	0.20910	0.3537	
914580	0.2028	0.10530	0.3035	
892604	0.1904	0.07625	0.2685	

	fractal_dimension_worst
id	
87164	0.10100
905190	0.08151
857637	0.08294
914580	0.07661
892604	0.07764

[5 rows x 30 columns]

## Visualizar características con matplotlib

- Obtener etiquetas

```
In [7]: import numpy as np
```

```
target_ids = np.unique(df.values[:,0])
```

```
In [8]: df['area_mean'].values.shape, df['perimeter_mean'].values.shape
```

```
Out[8]: ((569,), (569,))
```

```

In [9]: X_plot = np.concatenate((df['area_mean'].values, [df['perimeter_mean'].values]), axis=0)

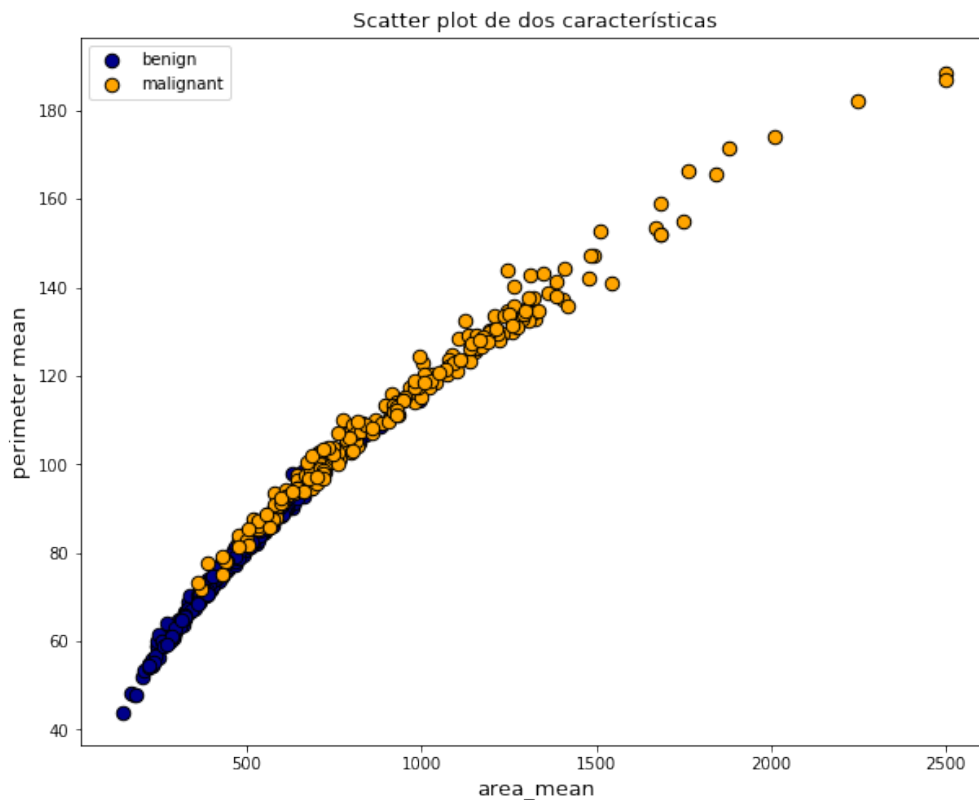
In [10]: y = df['diagnosis'].values

In [11]: X_plot.shape
Out[11]: (2, 569)

In [12]: plt.figure(figsize=(10,8))
        colors = ['darkblue','orange']
        target_names = ['benign','malignant']

        for i, c, label in zip(target_ids, colors, target_names):
            plt.scatter(X_plot[0,i == y], X_plot[1,i == y], c = c, edgecolors='black', s=285,la
        plt.legend()
        plt.title("Scatter plot de dos características",fontsize=13)
        plt.xlabel("area_mean",fontsize=13)
        plt.ylabel("perimeter mean",fontsize=13)
        plt.show()

```

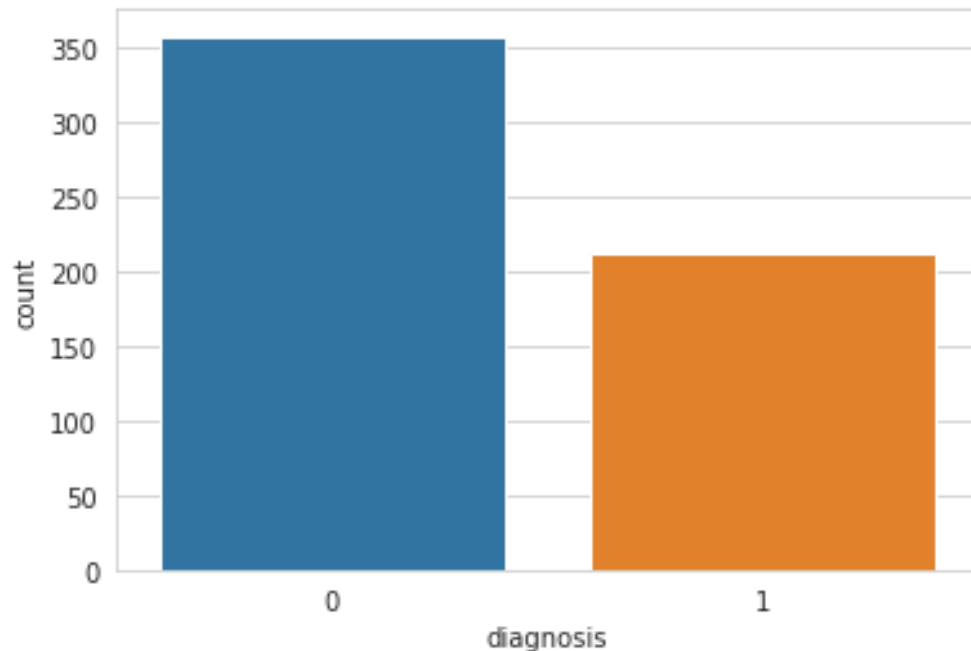


- Equilibrio de etiquetas



```
In [13]: sns.set_style('whitegrid')
sns.countplot(x='diagnosis', data=df)
```

```
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8a2c9c7790>
```



## Evaluación del modelo

- Se obtienen las predicciones, informe de clasificación y matriz de confusión.

```
In [14]: from sklearn.tree import DecisionTreeClassifier
```

```
In [15]: dtc = DecisionTreeClassifier()
dtc.fit(train, train_labels)
```

```
Out[15]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
max_features=None, max_leaf_nodes=None,
min_impurity_decrease=0.0, min_impurity_split=None,
min_samples_leaf=1, min_samples_split=2,
min_weight_fraction_leaf=0.0, presort=False,
random_state=None, splitter='best')
```

```
In [16]: predictions = dtc.predict(test)
print(predictions)
```

```
[0 1 1 0 0 1 1 1 1 1 1 0 1 0 1 0 0 0 1 0 0 1 0 0 0 0 0 0 1 0 0 1 0 0 0 1
 0 1 0 0 1 0 0 1 0 1 1 0 0 1 1 0 0 0 0 0 1 1 0 0 1 1 0 0 0 1 1 0 0 1 1 0 1
```

```

0 0 0 1 0 1 1 0 0 1 1 1 1 0 0 0 0 0 0 0 1 1 0 1 1 0 1 1 0 0 0 1 1 0 1
0 0 1 0 1 0 0 0 1 0 0 0 1 0 1 1 0 0 1 1 1 0 0 0 1 1 0 1 1 0 1 0 0 1 0 1 1
1 0 1 0 0 0 1 1 1 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0 0 1 0 0 0 0 0 0 1 1
1 0 0]

```

```

In [17]: from sklearn.metrics import accuracy_score

print(accuracy_score(test_labels, predictions))

0.9202127659574468

```

```

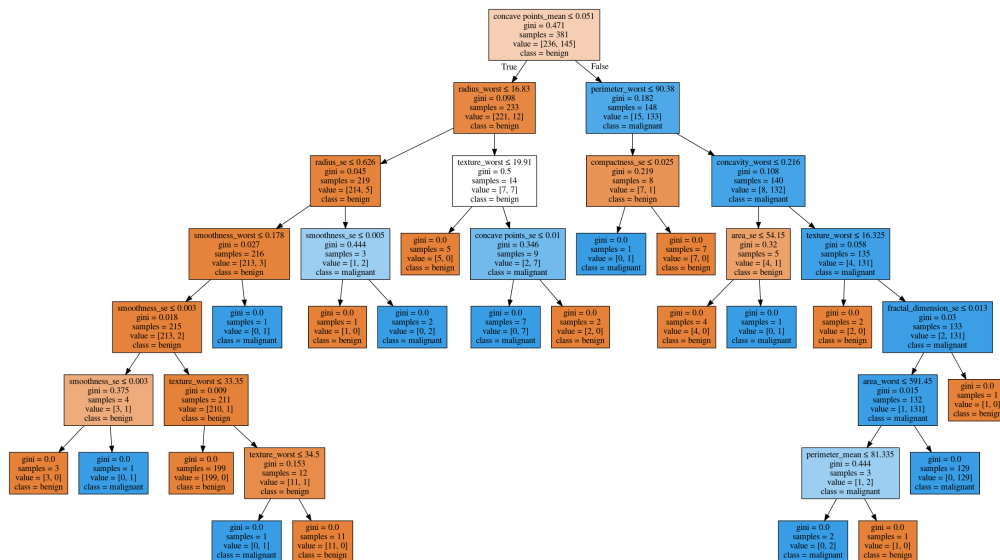
In [18]: from sklearn.externals.six import StringIO
from IPython.display import Image
from sklearn.tree import export_graphviz
import pydotplus

dot_data = StringIO()
export_graphviz(dtc, out_file=dot_data,
                filled=True, rounded=False,
                special_characters=True,
                feature_names = X.columns, class_names=target_names)
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
Image(graph.create_png())

```

/home/emam/.conda/envs/tf2/lib/python3.7/site-packages/sklearn/externals/six.py:31: DeprecationWarning: "(https://pypi.org/project/six/).", DeprecationWarning)

Out[18]:



- Guardar árbol en .png

```
In [19]: graph.write_png('cancer.png')
```

```
Out[19]: True
```

```
In [20]: from sklearn.metrics import classification_report, confusion_matrix
```

```
print("Predicciones:\n")
print(predictions)
print("\nReporte de clasificación:\n")
print(classification_report(predictions, test_labels))
```

Predicciones:

```
[0 1 1 0 0 1 1 1 1 1 1 1 0 1 0 1 0 0 0 1 0 0 1 0 0 0 0 0 0 1 0 0 1 0 0 0 1
 0 1 0 0 1 0 0 1 0 1 1 0 0 1 1 0 0 0 0 0 1 1 0 0 1 1 0 0 0 1 1 0 0 1 1 0 1
 0 0 0 1 0 1 1 0 0 1 1 1 1 1 0 0 0 0 0 0 0 0 1 1 0 1 1 0 1 1 0 0 0 1 1 0 1
 0 0 1 0 1 0 0 0 1 0 0 0 1 0 1 1 0 0 1 1 1 0 0 0 1 1 0 1 1 0 1 0 0 1 0 1 1
 1 0 1 0 0 0 1 1 1 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0 1 0 0 1 0 0 0 0 0 0 1 1
 1 0 0]
```

Reporte de clasificación:

	precision	recall	f1-score	support
0	0.89	0.98	0.94	110
1	0.97	0.83	0.90	78
accuracy			0.92	188
macro avg	0.93	0.91	0.92	188
weighted avg	0.92	0.92	0.92	188

```
In [21]: print("Confusion matrix")
conf_mat=confusion_matrix(predictions, test_labels)
print(conf_mat)
```

Confusion matrix

```
[[108  2]
 [ 13 65]]
```

```
In [22]: from sklearn.metrics import accuracy_score
```

```
print(accuracy_score(test_labels, predictions))
```

0.9202127659574468

- Probar ID3 con otro dataset