In [1]:

```
%matplotlib inline
```

Tema: Support Vector Machines

En esta notebook, utilizaremos el dataset "empty.all.csv" que contiene como clase positiva, 900 artículos de Wikipedia en inglés que presentan la falla "Empty Section" y como clase negativa, contiene 900 artículos destacados. El mismo se encuentra en el subdirectorio "miscelaneos" del repositorio Github. Los datos se cargan como un DataFrame mediante un método de la biblioteca seaborn. A tal fin es necesario copiar el dataset en el home local de seaborn. Por defecto usa ~/seaborn-data/, en Windows: "C:\Users\Nbre_Usuario\seaborn-data".

Ejemplos

In [2]:

```
import seaborn as sns
empty = sns.load_dataset('empty.all',cache=True)
empty.head()
```

Out[2]:

	wordSyllables	wordLength	wordCount	weaselWordRate	triviaSectionsCount	to_be_verbRate
0	1.000000	3.021739	46	0.000000	0	0.000000
1	2.000000	7.500000	4	0.000000	0	0.000000
2	1.642857	5.714286	14	0.000000	0	0.000000
3	1.642857	5.714286	14	0.000000	0	0.000000
4	1.902256	5.393484	399	0.250627	0	3.759398

5 rows × 96 columns

In [3]:

```
list(empty.columns.values)
```

Out[3]:

```
['wordSyllables',
 'wordLength',
 'wordCount',
 'weaselWordRate',
 'triviaSectionsCount',
 'to_be_verbRate',
 'templateCount',
 'tableCount',
 'syllableCount',
 'subsubsectionLength',
 'subsubsectionCount',
 'subsectionNesting',
 'subsectionLength',
 'subsectionCount',
 'stopwordRate',
 'smogIndex',
 'shortestSubsubsectionLength',
 'shortestSubsectionLength',
 'shortestSentenceLength',
 'shortestSectionLength',
 'shortSentenceRate',
 'sentenceLength',
 'sentenceCount',
 'sentenceBeginSubordinatingConjunctionRate',
 'sentenceBeginPronounRate',
 'sentenceBeginPrepositionRate',
 'sentenceBeginInterrogativePronounRate',
 'sentenceBeginCoordinatingConjunctionRate',
 'sentenceBeginArticleRate',
 'sectionNesting',
 'sectionLength',
 'sectionCount',
 'registeredEditorRate',
 'referenceWordRate',
 'referenceSectionsCount',
 'referenceSectionRate',
 'referenceCount',
 'reciprocity',
 'questionRate',
 'questionCount',
 'pronounRate',
 'prepositionRate',
 'peacockWordRate',
 'passiveSentenceRate',
 'paragraphLength',
 'paragraphCount',
 'pageRank',
 'oneSyllableWordRate',
 'oneSyllableWordCount',
 'nominalizationRate',
 'miyazaki',
 'longestSubsubsectionLength',
 'longestSubsectionLength',
 'longestSentenceLength',
 'longestSectionLength',
```

```
 'longWordRate',
 'longSentenceRate',
 'lix',
 'listRate',
 'linkRate',
 'languageLinkCount',
 'internalLinkCount',
 'informationToNoiseRatio',
 'inLinkCount',
 'imagesPerSection',
 'imageCount',
 'headingCount',
 'gunningFogIndex',
 'forcastGradeLevel',
 'fleschReadingEase',
 'fleschKincaidGradeLevel',
 'fileCount',
 'externalLinksPerSection',
 'externalLinkCount',
 'editsPerEditor',
 'editorRate',
 'editorCount',
 'editCount',
 'easyWordRate',
 'discussionEditCount',
 'difficultWordRate',
 'daleChall',
 'currency',
 'conjunctionRate',
 'complexWordRate',
 'colemanLiauIndex',
 'characterCount',
 'categoryCount',
 'brokenLinkCount',
 'bormuth',
 'auxiliaryVerbRate',
 'ari',
 'anonymousEditorRate',
 'agePerEdit',
 'age',
 'has_flaw']
```

In [4]:

```
empty.shape
```

Out[4]:

```
(1800, 96)
```

In [5]:

```
X_empty = empty.drop('has_flaw', axis=1)
X_empty.shape
```

Out[5]:

```
(1800, 95)
```

In [6]:

```
y_empty = empty['has_flaw']
y_empty.shape
```

Out[6]:

```
(1800,)
```

In [7]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
    X_empty, y_empty, random_state=0)
```

In [8]:

```
print("X_train shape: {}".format(X_train.shape))
print("y_train shape: {}".format(y_train.shape))
```

```
X_train shape: (1350, 95)
y_train shape: (1350,)
```

In [9]:

```
print("X_test shape: {}".format(X_test.shape))
print("y_test shape: {}".format(y_test.shape))
```

```
X_test shape: (450, 95)
y_test shape: (450,)
```

```
La celda a continuación tiene como objetivo estandarizar los valores de las
características para que tengan media 0 y varianza 1. Hacemos esto pues SVM es muy
sensitivo al escalado de características. Para corroborar esto se sugiere primeramente no
ejecutar la celda de estandarización y ver la performance que tiene el clasificador.
Luego, ejecutar la misma y las que siguen a continuación para poder comparar la
diferencia existente en la calidad predictiva del clasificador.
```

In [15]:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
# fit only on training data
scaler.fit(X_train)
X_train = scaler.transform(X_train)
# apply same transformation to test data
X_test = scaler.transform(X_test)
```

In [16]:

```
from sklearn import svm
modelSVM = svm.SVC(gamma=0.001,C=256)
modelSVM.fit(X_train, y_train)
```

Out[16]:

```
SVC(C=256, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=0.001, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```

In [17]:

```
y_model = modelSVM.predict(X_test)
```

In [18]:

```
from sklearn.metrics import accuracy_score
accuracy_score(y_test, y_model)
```

Out[18]:

```
0.9866666666666669
```

In [19]:

```
from sklearn.metrics import classification_report
print(classification_report(y_test, y_model))
```

```
             precision    recall  f1-score   support

         no       1.00      0.98      0.99       220
        yes       0.98      1.00      0.99       230

avg / total       0.99      0.99      0.99       450
```

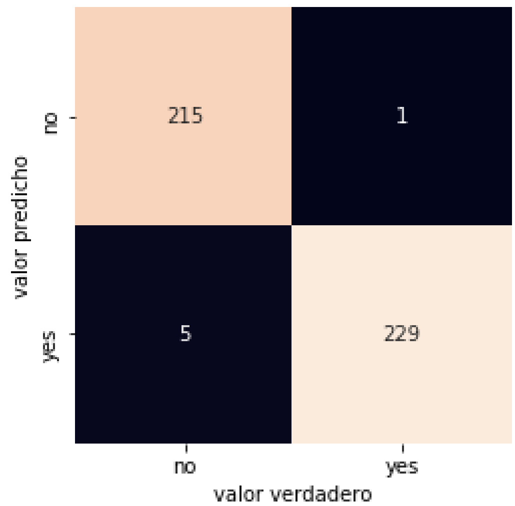
In [20]:

```
target_names = ['no', 'yes']

import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix

mat = confusion_matrix(y_test, y_model)

sns.heatmap(mat.T, square=True, annot=True, cbar=False, fmt="d", xticklabels=target_names,
plt.xlabel('valor verdadero')
plt.ylabel('valor predicho');
```



In [ ]:

```

```