#1 - Trabajo CIMAT Gto - BoW-W2v-Concatenaci?n

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1 Parte I TF-IDF

2 TF-IDF -México

```
In [2]: import numpy as np
        import pandas as pd
        import re # lidia con expresiones regulares
        import nltk
        import matplotlib.pyplot as plt
        from bs4 import BeautifulSoup
        from nltk.corpus import stopwords
        from sklearn.feature_extraction.text import CountVectorizer
        from nltk import word_tokenize # sentencia en palabras
        from nltk.stem import SnowballStemmer # idioma steam
        from nltk.stem.porter import PorterStemmer
        from nltk.stem import WordNetLemmatizer
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.feature_extraction.text import TfidfVectorizer
        from sklearn import feature_extraction, model_selection, naive_bayes, metrics, svm



        from sklearn.model_selection import train_test_split
        from sklearn.feature_extraction.text import TfidfVectorizer
        # Any results you write to the current directory are saved as output.
        from sklearn.naive_bayes import GaussianNB
        from sklearn.metrics import accuracy_score

In [3]: # Importando los textos
        import os
```

```
# introducit path datos de entrenamiento

os.chdir('C:\\Users\\h_air\\Documents\\Diplomado Deep Learning\\Estancia\\Datos\\Datos'
train = pd.read_csv('irosva.mx.training.csv');

# introducit path datos de prueba
os.chdir('C:\\Users\\h_air\\Documents\\Diplomado Deep Learning\\Estancia\\Datos\\Datos'
test_nolabel = pd.read_csv('irosva.mx - irosva.mx.test.csv');


# introducit path etiquetas verdaderas de prueba
os.chdir('C:\\Users\\h_air\\Documents\\Diplomado Deep Learning\\Estancia\\Datos\\Datos'
test_label = pd.read_csv('irosva.mx.test.truth.csv');

test_nolabel.head()
```

```
Out[3]:                                  ID        TOPIC IS_IRONIC  \
        0  00b72ddf1bc2407aca2d894fcc15858b  divorcioEPN         ?
        1  0191f2511079cc0fdc3c9303dbdb9194    venezuela         ?
        2  01f162d9a7cc37f3954dca0b73199974    venezuela         ?
        3  022a4dc5768a616861746743e36881e5  tierraPlana         ?
        4  029041e492841a402d68988d4e07fd97  tierraPlana         ?

                                                     MESSAGE
        0  Indigna la postura de una mujer mexicana, vend...
        1                  Sip te traje un llavero! Jajajaja
        2  Siiii. Rusia, Cuba y China no quieren el petró...
        3                          ADORO LOS FINALES FELICES!
        4  RT @ElErreCuatro: Los astrónomos sentirán lo m...
```

```
In [4]: test_nolabel.head()
```

```
Out[4]:                                  ID        TOPIC IS_IRONIC  \
        0  00b72ddf1bc2407aca2d894fcc15858b  divorcioEPN         ?
        1  0191f2511079cc0fdc3c9303dbdb9194    venezuela         ?
        2  01f162d9a7cc37f3954dca0b73199974    venezuela         ?
        3  022a4dc5768a616861746743e36881e5  tierraPlana         ?
        4  029041e492841a402d68988d4e07fd97  tierraPlana         ?

                                                     MESSAGE
        0  Indigna la postura de una mujer mexicana, vend...
        1                  Sip te traje un llavero! Jajajaja
        2  Siiii. Rusia, Cuba y China no quieren el petró...
        3                          ADORO LOS FINALES FELICES!
        4  RT @ElErreCuatro: Los astrónomos sentirán lo m...
```

```
In [5]: test_label.head()
```

```
Out[5]:                                  ID           TOPIC  IS_IRONIC
        0  117e2564e8f70610a92cbcf5d667c587  asuntosConacyt          1
```

```
1  2706c1bda8f66136b97f1eb41c81eb39  asuntosConacyt          1
2  271fae76eef136ad339fa5b4b43a1300  asuntosConacyt          1
3  290853214bcd8bfc1e1d42ce91d85781  asuntosConacyt          1
4  29a72a4c42e8cacf9ca225f4834d3da1  asuntosConacyt          1
```

In [6]:
```python
# Se realiza merge para tener las etiquetas de los datos de prueba

test = pd.merge(test_nolabel, test_label, on='ID')
test.head()
```

Out[6]:
```
                                 ID      TOPIC_x IS_IRONIC_x  \
0  00b72ddf1bc2407aca2d894fcc15858b  divorcioEPN           ?
1  0191f2511079cc0fdc3c9303dbdb9194    venezuela           ?
2  01f162d9a7cc37f3954dca0b73199974    venezuela           ?
3  022a4dc5768a616861746743e36881e5  tierraPlana           ?
4  029041e492841a402d68988d4e07fd97  tierraPlana           ?

                                             MESSAGE      TOPIC_y  IS_IRONIC_y
0  Indigna la postura de una mujer mexicana, vend...  divorcioEPN            0
1                      Sip te traje un llavero! Jajajaja    venezuela            0
2  Siiii. Rusia, Cuba y China no quieren el petró...    venezuela            1
3                             ADORO LOS FINALES FELICES!  tierraPlana            0
4  RT @ElErreCuatro: Los astrónomos sentirán lo m...  tierraPlana            0
```

In [7]:
```python
entrenamiento = train["TOPIC"].astype(str).str.cat(train["MESSAGE"].astype(str), sep='
prueba = test["TOPIC_y"].astype(str).str.cat(test["MESSAGE"].astype(str), sep=' ')
```

Las siguientes funciones realiza pre-proceso de corpus

- review_to_words: con steamed
- review_to_words2: sin steamed

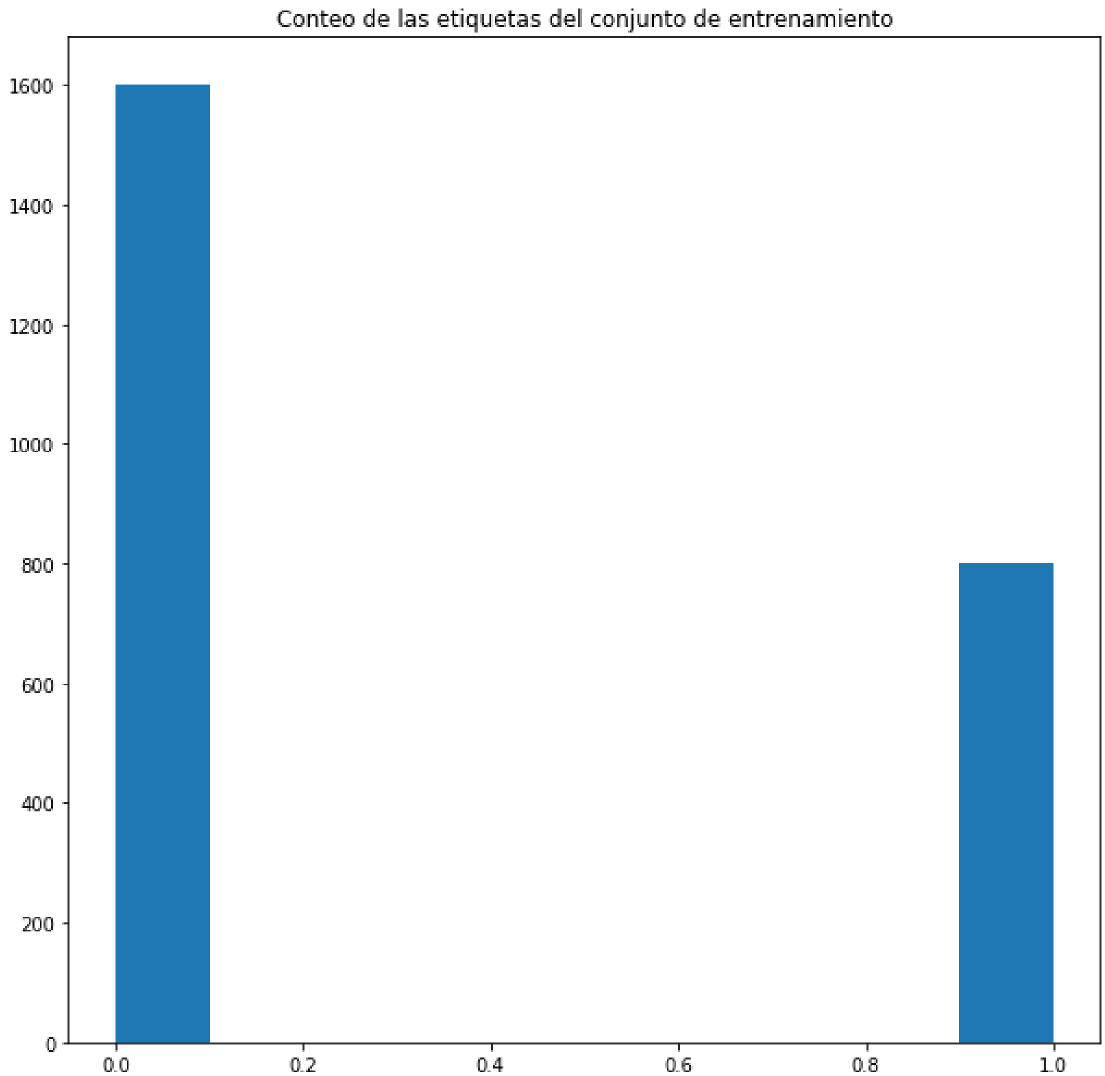
In [8]:
```python
def review_to_words( raw_review ):
    # 1. Remover todo menos letras y comas
    letters_only = re.sub('[^\w]\d*',  " ", raw_review)
    # 2. convertir a minusculas
    words = letters_only.lower().split()
    # 3. remover stopwords
    stops = set(stopwords.words("spanish"))
    # 3.1 retirando stopwords
    meaningful_words = [w for w in words if not w in stops]
    # 4 stemming en español
    stemmer = SnowballStemmer('spanish')
    stemmed_text = [stemmer.stem(i) for i in meaningful_words]
    # 5. uniendo documeto
    return( " ".join( stemmed_text ))
```

In [9]:
```python
def review_to_words2( raw_review ):
    # 1. Remover todo menos letras y comas
```

```
letters_only = re.sub('[^\w]\d*',  " ", raw_review)
# 2. convertir a mínusculas
words = letters_only.lower().split()
# 3. remover stopwords
stops = set(stopwords.words("spanish"))
# 3.1 retirando stopwords
meaningful_words = [w for w in words if not w in stops]
return( " ".join( meaningful_words ))
```

- La clases se observan desbalanceadas

In [443]:
```
plt.figure(figsize=(10,10))
plt.hist(train['IS_IRONIC'][:], bins=10)
plt. title('Conteo de las etiquetas del conjunto de entrenamiento')
plt.show()
```



- Las variables que representanBoW TF-IDF, W2vec Google y W2vec Twitter, de los twits en México.

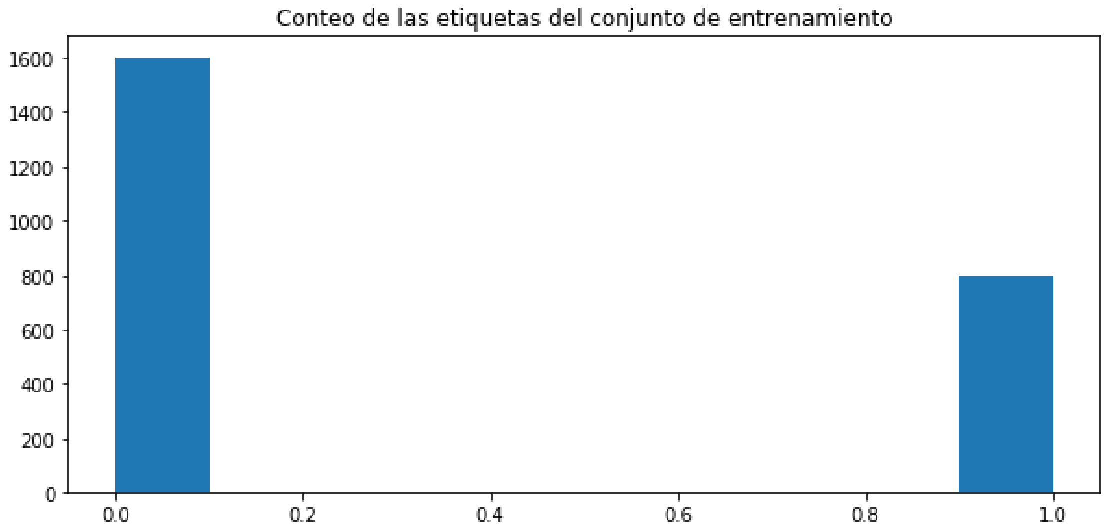
In [10]:
```
x_train = train["MESSAGE"]
x_test = test["MESSAGE"]
y_train = train['IS_IRONIC']
y_test = test['IS_IRONIC_y']
```

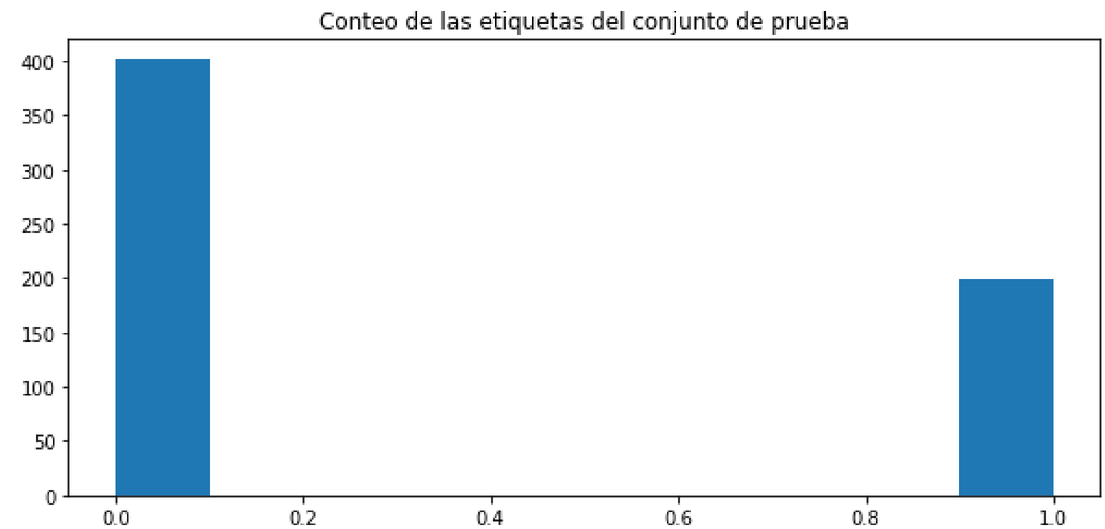
- Limpiando corpus de entrenamiento y prueba

In [11]:
```
#Limpiando datos de entrenamiento
num = x_train.size
# Lista para guardar twits limpios
clean_train = []

for i in range( 0, num):
    clean_train.append(review_to_words(x_train.values[i]))

x_train_mx = clean_train


num= x_test.size

clean_test_train = []

for i in range( 0, num):
    clean_test_train.append( review_to_words(x_test.values[i] ) )

x_test_mx = clean_test_train
```

Se observa que la proporcióin de las etiquetas se conservan

In [446]:
```
plt.figure(figsize=(10,10))
plt.subplot(211)
plt.hist(y_train, bins=10)
plt. title('Conteo de las etiquetas del conjunto de entrenamiento')
plt.subplot(212)
plt.hist(y_test, bins=10)
plt. title('Conteo de las etiquetas del conjunto de prueba')
plt.show()
```





In [12]:
```
x_train_mx = train["TOPIC"].astype(str).str.cat(x_train_mx, sep=' ')
x_test_mx = test["TOPIC_y"].astype(str).str.cat(x_test_mx, sep=' ')
```

In [28]:
```
x_test_mx# Datos de entrenamient y de prueba ya pre-procesados

x_train_mx = pd.Series(x_train_mx)
y_train = pd.Series(y_train)
x_test_mx = pd.Series(x_test_mx)
y_test = pd.Series(y_test)

print(x_train_mx.shape)
print(y_train.shape)
print(x_test_mx.shape)
print(y_test.shape)
```

```
(2400,)
(2400,)
(600,)
(600,)
```

- Representación BoW TF-IDF, datos de entrenamiento y de prueba

```
In [31]: vect_mx = TfidfVectorizer(min_df=.01)
         x_train_tf_mx = vect_mx.fit_transform(x_train_mx)
         x_test_tf_mx = vect_mx.transform(x_test_mx)

         x_train_tf_mx = x_train_tf_mx.toarray()
         x_test_tf_mx = x_test_tf_mx.toarray()

         print(x_train_tf_mx.shape)
         print(x_test_tf_mx.shape)

         #print(vect_mx.vocabulary_)
         #print(x_train_tf_mx[:5])
```

```
(2400, 186)
(600, 186)
```

3 Clasificador NN

- Se utiliza keras para estimar NN

```
In [179]: # Bibliotecas
          import itertools
          import tensorflow as tf # tensorflow

          from sklearn.preprocessing import LabelBinarizer, LabelEncoder
          from sklearn.metrics import confusion_matrix
          # keras
          from tensorflow import keras
          from keras.models import Sequential
          from keras.layers import Dense, Activation, Dropout

          from keras.utils import to_categorical
          from keras.preprocessing import text, sequence
          from keras import utils
```

```
In [180]: # targets de entrenamiento y de prueba como indicadoras

          y_train_mx = to_categorical(y_train)
          y_test_mx  = to_categorical(y_test)
```

```
num_mx, sz_mx = y_train_mx.shape

print(num_mx)
print(sz_mx)
```

```
2400
2
```

3.0.1 Selección de modelo

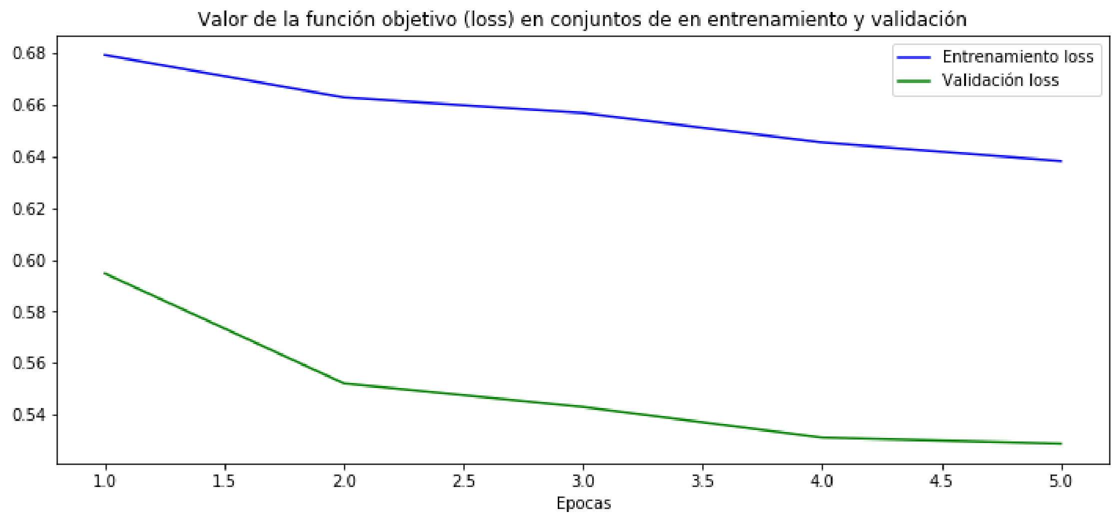
- Seleccionar el número de epocas para evitar el sobre ajuste

```
In [20]: import time
         tic=time.time()

         np.random.seed(1)

         batch_size = 100
         epochs = 5

         nn_mx = Sequential()
         nn_mx.add(Dense(12, activation='relu'))
         nn_mx.add(Dropout(0.25))
         nn_mx.add(Dense(sz_mx, activation='softmax'))
         nn_mx.compile(loss='binary_crossentropy',
                       optimizer='nadam',
                       metrics=['accuracy'])

         history_mx = nn_mx.fit(x_train_tf_mx,
                       y_train_mx,
                       validation_split=.2,
                       batch_size= batch_size,
                       shuffle   =True,
                       epochs=epochs,
                       verbose=2)

         print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

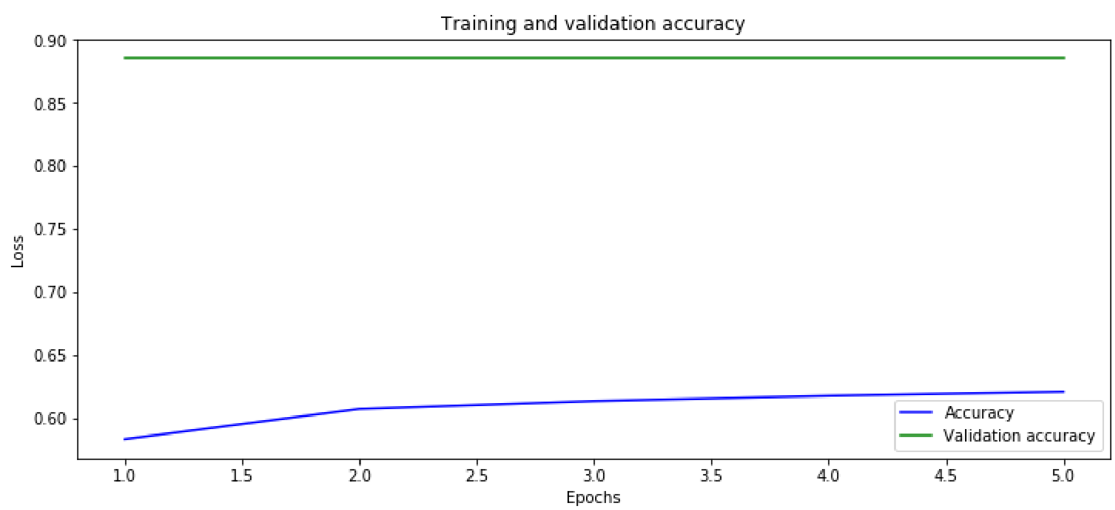
```
WARNING: Logging before flag parsing goes to stderr.
W0627 22:42:09.863517   672 deprecation_wrapper.py:119] From C:\Users\h_air\Anaconda3\envs\tens

W0627 22:42:10.631410   672 deprecation_wrapper.py:119] From C:\Users\h_air\Anaconda3\envs\tens

W0627 22:42:10.896834   672 deprecation_wrapper.py:119] From C:\Users\h_air\Anaconda3\envs\tens

W0627 22:42:10.929146   672 deprecation_wrapper.py:119] From C:\Users\h_air\Anaconda3\envs\tens
```

```
W0627 22:42:10.977183   672 deprecation_wrapper.py:119] From C:\Users\h_air\Anaconda3\envs\tens

W0627 22:42:10.989173   672 deprecation.py:506] From C:\Users\h_air\Anaconda3\envs\tensorflow-g
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep_prob`.
W0627 22:42:11.033147   672 deprecation_wrapper.py:119] From C:\Users\h_air\Anaconda3\envs\tens

W0627 22:42:11.041154   672 deprecation.py:323] From C:\Users\h_air\Anaconda3\envs\tensorflow-g
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where


Train on 1920 samples, validate on 480 samples
Epoch 1/5
 - 13s - loss: 0.6793 - acc: 0.5833 - val_loss: 0.5946 - val_acc: 0.8854
Epoch 2/5
 - 0s - loss: 0.6629 - acc: 0.6073 - val_loss: 0.5520 - val_acc: 0.8854
Epoch 3/5
 - 0s - loss: 0.6569 - acc: 0.6135 - val_loss: 0.5429 - val_acc: 0.8854
Epoch 4/5
 - 0s - loss: 0.6455 - acc: 0.6177 - val_loss: 0.5311 - val_acc: 0.8854
Epoch 5/5
 - 0s - loss: 0.6383 - acc: 0.6208 - val_loss: 0.5288 - val_acc: 0.8854
Tiempo de procesamiento (secs):  15.420767784118652
```

In [21]:
```
history_dict_mx = history_mx.history
dictkeys_mx=list(history_dict_mx.keys())

loss_values_mx = history_mx.history['loss']
val_loss_values_mx = history_mx.history['val_loss']
epochs_mx = range(1, len(loss_values_mx) + 1)


plt.figure(figsize=(12,5))
plt.plot(epochs_mx, loss_values_mx, 'b', label='Entrenamiento loss')
plt.plot(epochs_mx, val_loss_values_mx, 'g', label='Validación loss')
plt.title('Valor de la función objetivo (loss) en conjuntos de en entrenamiento y vali
plt.xlabel('Epocas')
plt.ylabel('')
plt.legend()

plt.show()
```



In [24]:
```
acc_values_mx = history_dict_mx['acc']
val_acc_values_mx = history_dict_mx['val_acc']


plt.figure(figsize=(12,5))
plt.plot(epochs_mx, acc_values_mx, 'b', label='Accuracy')
plt.plot(epochs_mx, val_acc_values_mx, 'g', label='Validation accuracy')
plt.title('Training and validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

plt.show()
```



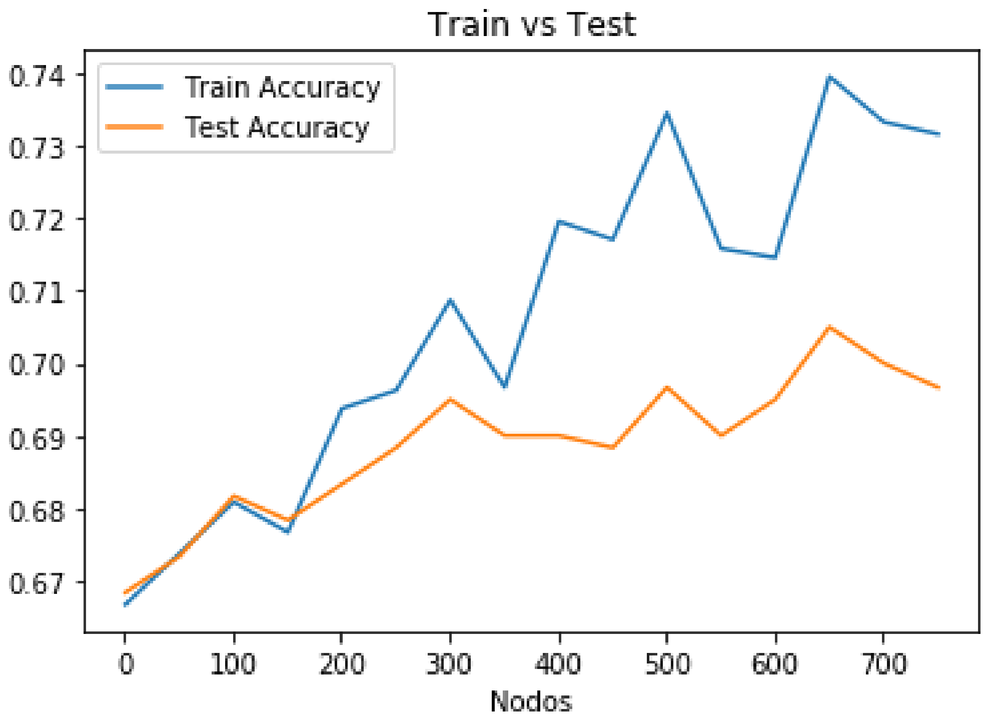
Como se pueded observar, la función de pérdida en el conjunto de validación alcanza su mínimo alrededor de las épocas 2 o 3, después incrementa su valor. A ese número de épocas, el accuracy también tienen un máximo local.

- Seleccionando el número de nodos

```
In [39]: batch_size = 100
         epochs = 3 # epocas seleccionadas

         list_nn_mx = np.arange( 1, 800, 50) # parámetro de regularización
         score_train_mx = np.zeros(len(list_nn_mx)) # almacena acurracy entrenamiento
         score_test_mx = np.zeros(len(list_nn_mx)) # almacena acurracy prueba
         count = 0
         for i in list_nn_mx:
             # Build the model
             nn_mx = Sequential()
             nn_mx.add(Dense(i, activation='relu'))
             nn_mx.add(Dropout(0.25))
             nn_mx.add(Dense(sz_mx, activation='softmax'))
             nn_mx.compile(loss='binary_crossentropy',
                           optimizer='nadam',
                           metrics=['accuracy'])

         # No se utilizan datos de validación
             nn_mx.fit(x_train_tf_mx,
                           y_train_mx,
                           batch_size= batch_size,
                           shuffle   =True,
                           epochs=epochs,
                           verbose=0)

             temp1_mx = nn_mx.evaluate(x_train_tf_mx, y_train_mx, verbose=0)
             score_train_mx[count] = temp1_mx[1]
             temp2_mx = nn_mx.evaluate(x_test_tf_mx, y_test_mx, verbose=0)
             score_test_mx[count]= temp2_mx[1]
             count = count + 1
```

Gráfica acurracy datos de entrenamiento y de prueba

```
In [40]: matriz_mx = np.matrix(np.c_[list_nn_mx, score_train_mx, score_test_mx])
         models_mx = pd.DataFrame(data = matriz_mx, columns =
                      ['Nodos', 'Train Accuracy', 'Test Accuracy'])
         plt.plot(models_mx['Nodos'],models_mx['Train Accuracy'])
         plt.plot(models_mx['Nodos'],models_mx['Test Accuracy'])
         plt.title('Train vs Test')
         plt.xlabel('Nodos')
         plt.legend()
         plt.show()
```



In [41]: models_mx

Out[41]:

	Nodos	Train Accuracy	Test Accuracy
0	1.0	0.666667	0.668333
1	51.0	0.673750	0.673333
2	101.0	0.680833	0.681667
3	151.0	0.676667	0.678333
4	201.0	0.693750	0.683333
5	251.0	0.696250	0.688333
6	301.0	0.708750	0.695000
7	351.0	0.696667	0.690000
8	401.0	0.719583	0.690000
9	451.0	0.717083	0.688333
10	501.0	0.734583	0.696667
11	551.0	0.715833	0.690000
12	601.0	0.714583	0.695000
13	651.0	0.739583	0.705000
14	701.0	0.733333	0.700000
15	751.0	0.731667	0.696667

In [336]:
```
#nodo_mx = list_nn_mx[np.argmax(np.array(models_mx['Test Accuracy']))]
nodo_mx
```

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- Diseño final

```
In [35]: import time
         tic=time.time()

         np.random.seed(1)

         batch_size = 100
         epochs = 7 # seleccionadas

         nn_mx = Sequential()
         nn_mx.add(Dense(nodo_mx, activation='relu'))
         nn_mx.add(Dropout(0.25))
         nn_mx.add(Dense(sz_mx, activation='softmax'))
         nn_mx.compile(loss='binary_crossentropy',
                       optimizer='nadam',
                       metrics=['accuracy'])

         history_mx = nn_mx.fit(x_train_tf_mx,
                       y_train_mx,
                       validation_split=.2, #20% de para validad
                       batch_size= batch_size,
                       shuffle   =True,
                       epochs=epochs,
                       verbose=2)

         print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
Train on 1920 samples, validate on 480 samples
Epoch 1/7
 - 1s - loss: 0.6634 - acc: 0.6083 - val_loss: 0.4964 - val_acc: 0.8854
Epoch 2/7
 - 0s - loss: 0.6230 - acc: 0.6417 - val_loss: 0.5153 - val_acc: 0.8771
Epoch 3/7
 - 0s - loss: 0.5875 - acc: 0.6880 - val_loss: 0.5135 - val_acc: 0.7937
Epoch 4/7
 - 0s - loss: 0.5588 - acc: 0.7089 - val_loss: 0.5101 - val_acc: 0.7688
Epoch 5/7
 - 0s - loss: 0.5366 - acc: 0.7313 - val_loss: 0.5329 - val_acc: 0.7250
Epoch 6/7
 - 0s - loss: 0.5098 - acc: 0.7536 - val_loss: 0.5435 - val_acc: 0.7208
Epoch 7/7
 - 0s - loss: 0.4860 - acc: 0.7656 - val_loss: 0.5837 - val_acc: 0.6833
Tiempo de procesamiento (secs):  1.730325698852539
```

- Se guarda el modelo seleciconado

```
In [181]: from keras.models import load_model
```

```
#nn_mx.save('nn_mexico_tfidf')  # Guardar
nn_mx = load_model('nn_mexico_tfidf') # Cargar
```

```
In [183]: results_mx = nn_mx.evaluate(x_test_tf_mx, y_test_mx)
          print('Test loss:', results_mx[0])
          print('Test accuracy:', results_mx[1])
```

```
600/600 [==============================] - 0s 53us/step
Test loss: 0.5971186947822571
Test accuracy: 0.693333334128062
```

- Visualización del desempeño matriz de confusión

```
In [184]: import numpy as np
          from sklearn.metrics import confusion_matrix, precision_score, recall_score, f1_score
          y_pred_mx = nn_mx.predict(x_test_tf_mx).squeeze()
          y_test_label_mx = np.argmax(y_test_mx,1)
          y_pred_label_mx = np.argmax(y_pred_mx,1)

          # Confusion matrix
          C=confusion_matrix(y_test_label_mx , y_pred_label_mx)
          print(C)
```

```
[[350  51]
 [133  66]]
```

3.0.2 Resultados

```
In [185]: print('Accuracy score:', results_mx[1])  # nn evaluate keras
          print("F1 score", f1_score( y_test_label_mx,  y_pred_label_mx,  average='macro'))
          print("F1 weighted", f1_score( y_test_label_mx,  y_pred_label_mx,  average='weighted
          print("Recall score", recall_score( y_test_label_mx,  y_pred_label_mx,  average='mac
          print("Precision score", precision_score( y_test_label_mx,  y_pred_label_mx, average=
```

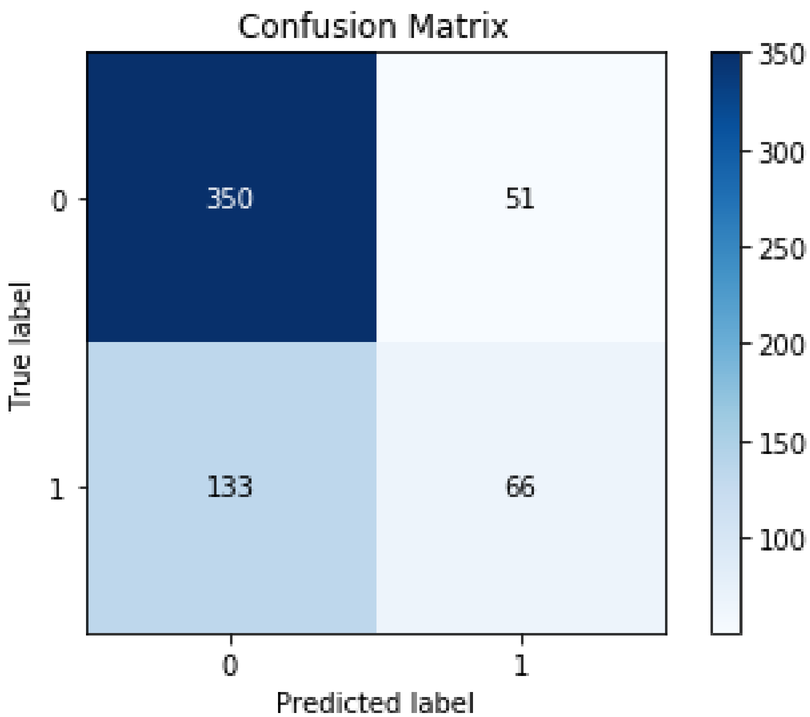
```
Accuracy score: 0.693333334128062
F1 score 0.6047883613036256
F1 weighted 0.6677675315501078
Recall score 0.6022381232847529
Precision score 0.6443701226309921
```

```
In [19]: from sklearn.metrics import classification_report
         print(classification_report(y_test_label_mx, y_pred_label_mx, target_names=['no-ironi
```

```
              precision    recall  f1-score   support

   no-ironia       0.72      0.87      0.79       401
```

```
      ironia       0.56      0.33      0.42       199

   micro avg       0.69      0.69      0.69       600
   macro avg       0.64      0.60      0.60       600
weighted avg       0.67      0.69      0.67       600
```

```
In [458]: %matplotlib inline
          import matplotlib.pyplot as plt
          import scikitplot

          scikitplot.metrics.plot_confusion_matrix(y_test_label_mx, y_pred_label_mx)

Out[458]: <matplotlib.axes._subplots.AxesSubplot at 0x15d5c8b37f0>
```



4 Clasificador SVM

- Selección de modelo, parámetro de regularización

```
In [455]: from sklearn.pipeline import Pipeline
          from sklearn.svm import LinearSVC
          from sklearn.model_selection import GridSearchCV
```

```
from sklearn.preprocessing import StandardScaler
import time
tic=time.time()

SVCpipe = Pipeline([('SVC',LinearSVC(class_weight="balanced", random_state=1,verbose=

# Gridsearch to determine the value of C
param_grid = {'SVC__C':np.arange(.01,10,.1)}
linearSVC = GridSearchCV(SVCpipe,param_grid,cv=5,return_train_score=True, verbose=0)
linearSVC.fit(x_train_tf_mx, y_train.values)
print(linearSVC.best_params_)
#linearSVC.coef_
#linearSVC.intercept_

svm_mx = linearSVC.best_estimator_
svm_mx.fit(x_train_tf_mx, y_train.values)
svm_mx.coef_ = svm_mx.named_steps['SVC'].coef_
svm_mx.score(x_train_tf_mx, y_train.values)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
{'SVC__C': 0.27}
Tiempo de procesamiento (secs):  255.94659614562988
```

- Gráfica accuracy datos de entrenamiento y de prueba

```
In [456]: prediction_mx=svm_mx.predict(x_test_tf_mx)
          print("Acurracy Test",metrics.accuracy_score(prediction_mx, y_test.values))
```

```
Acurracy Test 0.6633333333333333
```

```
In [457]: print("Confusion Metrix:\n",metrics.confusion_matrix(y_test.values, prediction_mx))
```

```
Confusion Metrix:
 [[270 131]
 [ 71 128]]
```

```
In [186]: from joblib import dump, load
          #dump(svm_mx, 'svm_mexico_tfidf.joblib') # Guarda modelos
          svm_mx = load('svm_mexico_tfidf.joblib') # Carga modelo

In [187]: #Prediction
          prediction_mx=svm_mx.predict(x_test_tf_mx)
          print("Acurracy Test",metrics.accuracy_score(prediction_mx, y_test.values))
```

```
Acurracy Test 0.6633333333333333
```

```
In [188]: print("Confusion Metrix:\n",metrics.confusion_matrix(y_test.values, prediction_mx))
```

```
Confusion Metrix:
 [[271 130]
 [ 72 127]]
```

4.0.1 Resultados

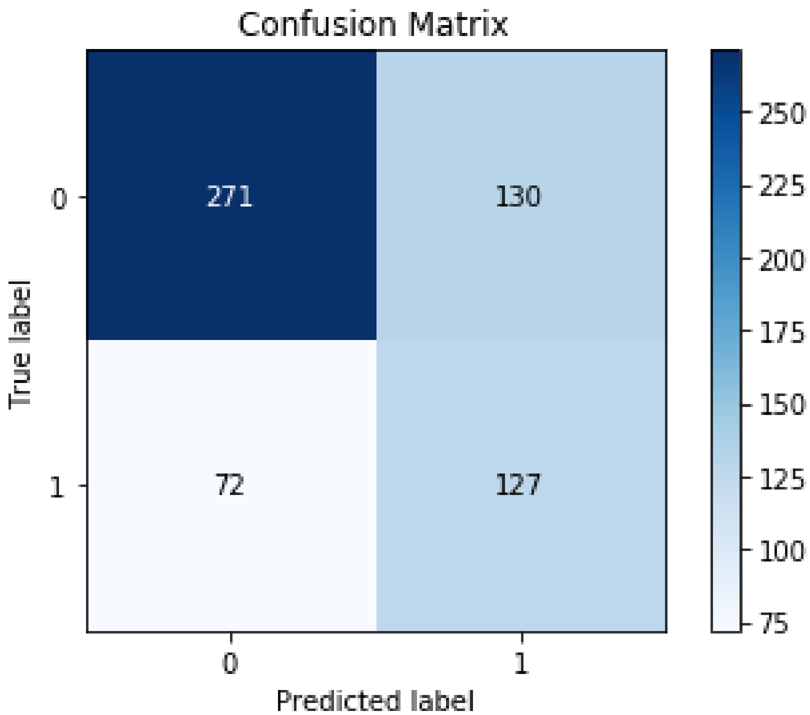
```
In [189]: import numpy as np
          from sklearn.metrics import confusion_matrix, precision_score, recall_score, f1_score

          print('Accuracy score:', metrics.accuracy_score(y_test.values,  prediction_mx, ))  #
          print("F1 score", f1_score(y_test.values,  prediction_mx,  average='macro'))
          print("F1 weighted", f1_score(y_test.values,  prediction_mx,   average='weighted'))
          print("Recall score", recall_score(y_test.values,  prediction_mx,   average='macro'))
          print("Precision score", precision_score(y_test.values,  prediction_mx,  average='ma
```

```
Accuracy score: 0.6633333333333333
F1 score 0.6427560837577816
F1 weighted 0.6716213921901528
Recall score 0.6570007142946653
Precision score 0.6421254438406825
```

```
In [463]: from sklearn.metrics import classification_report
          print(classification_report( y_test.values, prediction_mx, target_names=['no-ironia'
```

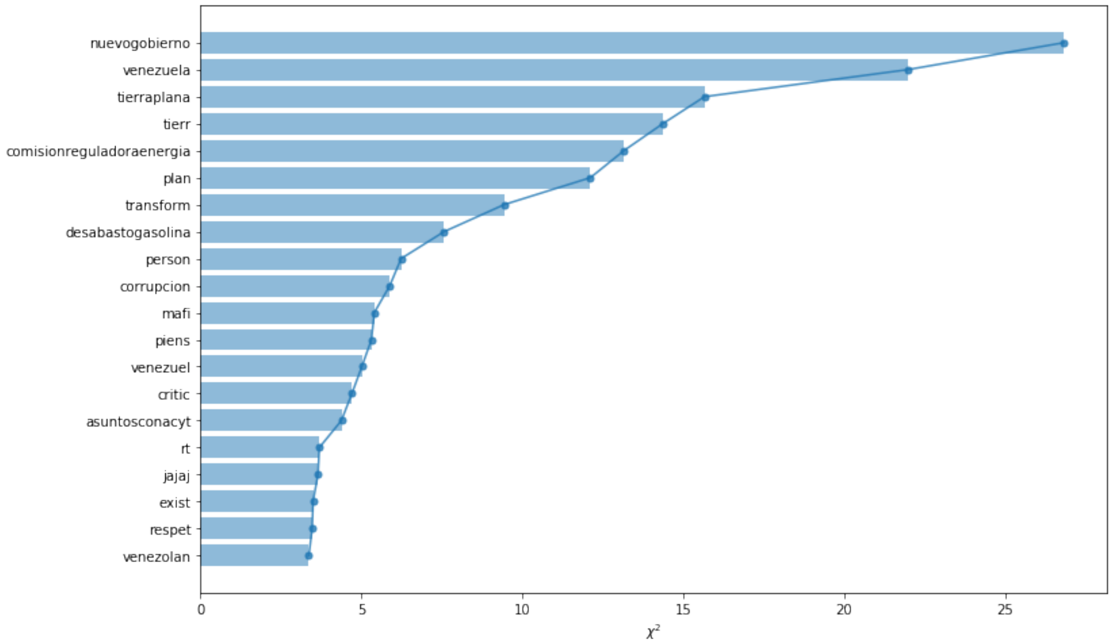
```
              precision    recall  f1-score   support

   no-ironia       0.79      0.68      0.73       401
      ironia       0.49      0.64      0.56       199

   micro avg       0.66      0.66      0.66       600
   macro avg       0.64      0.66      0.64       600
weighted avg       0.69      0.66      0.67       600
```

```
In [464]: # matriz de confusión

          %matplotlib inline
          import matplotlib.pyplot as plt
          import scikitplot

          scikitplot.metrics.plot_confusion_matrix(y_test.values, prediction_mx)

Out[464]: <matplotlib.axes._subplots.AxesSubplot at 0x15d5c931400>
```



- Chi2 importancia del término respecto target

In [48]:
```
import matplotlib.pyplot as plt
from sklearn.feature_selection import chi2
# compute chi2 for each feature
chi2score_mx = chi2(x_train_tf_mx,y_train)[0]


%matplotlib inline
plt.figure(figsize=(12,8))
scores_mx = list(zip(vect_mx.get_feature_names(), chi2score_mx))
chi2_mx = sorted(scores_mx, key=lambda x:x[1])
topchi2_mx = list(zip(*chi2_mx[-20:]))
x_mx = range(len(topchi2_mx[1]))
labels_mx = topchi2_mx[0]
plt.barh(x_mx,topchi2_mx[1], align='center', alpha=0.5)
plt.plot(topchi2_mx[1], x_mx, '-o', markersize=5, alpha=0.8)
plt.yticks(x_mx, labels_mx)
plt.xlabel('$\chi^2$')
plt.show();
```



5 TF-IDF -España

In [108]:
```
# Importando los textos
import os

# introducit path
os.chdir('C:\\Users\\h_air\\Documents\\Diplomado Deep Learning\\Estancia\\Datos\\Dat
train_es = pd.read_csv('irosva.es.training.csv');

# introducit path
os.chdir('C:\\Users\\h_air\\Documents\\Diplomado Deep Learning\\Estancia\\Datos\\Dat
test_es_nolabel = pd.read_csv('irosva.es - irosva.es.test.csv');

# introducit path
os.chdir('C:\\Users\\h_air\\Documents\\Diplomado Deep Learning\\Estancia\\Datos\\Dat
test_es_label = pd.read_csv('irosva.es.test.truth.csv');
```

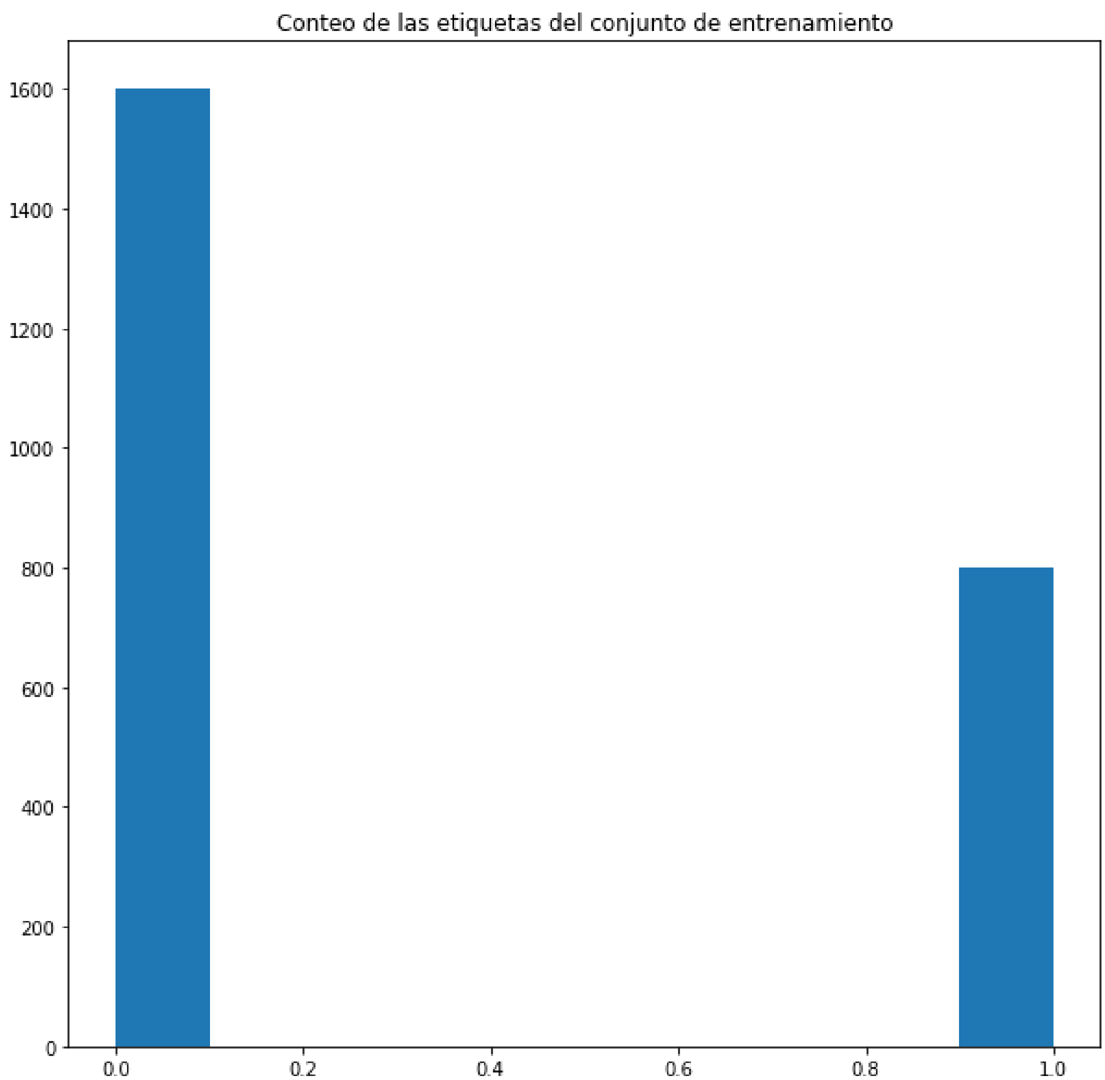
In [109]:
```
test_es = pd.merge(test_es_nolabel, test_es_label, on='ID')
test_es.head()
```

Out[109]:
```
                                 ID          TOPIC_x IS_IRONIC_x  \
0  002dec9f773cc17edcc7b02acb8e8926           FRANCO           ?
1  007342bd6eed6cca55d2587db4504a7a  TIERRAPLANISTAS           ?
2  00a96b4357a8bccbb9bef0cb72097a30          RELATOR           ?
3  00c6d1ffc0c371450d61c3d05e424934           FRANCO           ?
```

```
4  0163cd612a33f7f8cf1e9ac3a28ac80c           FRANCO           ?

                                              MESSAGE          TOPIC_y  \
0   £Suspenden exhumación de Francisco Franco? E...            FRANCO
1  @alonsokas1 Por cierto, además de tierraplanis...  TIERRAPLANISTAS
2  #ThisIsTheRealSpain\n La oposición y un sector...          RELATOR
3  El cardenal Blázquez dice que nunca apoyó dese...           FRANCO
4  Exhumación Franco: El Supremo puede impedir qu...           FRANCO

   IS_IRONIC_y
0            0
1            0
2            0
3            0
4            0
```

- Balance en las clases

In [467]:
```python
plt.figure(figsize=(10,10))
plt.hist(train_es['IS_IRONIC'][:], bins=10)
plt. title('Conteo de las etiquetas del conjunto de entrenamiento')
plt.show()
```



- Nombre de las variables que se utilizan par las tres representaciones de los twits de España

```
In [110]: x_train_españa = train_es["MESSAGE"]
          x_test_españa = test_es["MESSAGE"]
          y_train_es = train_es['IS_IRONIC']
          y_test_es = test_es['IS_IRONIC_y']
          print([y_train_es.shape, y_test_es.shape])
```

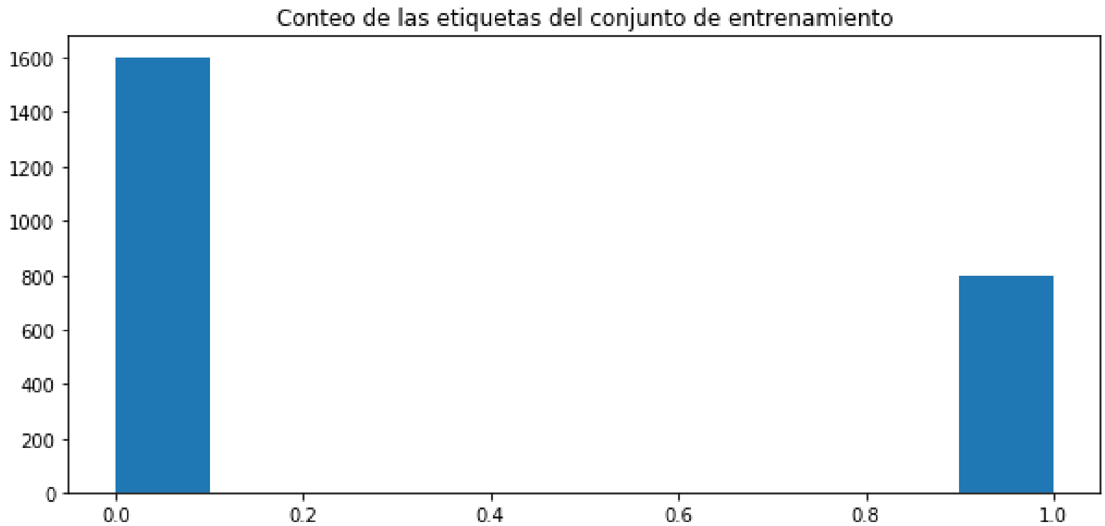
```
[(2400,), (600,)]
```

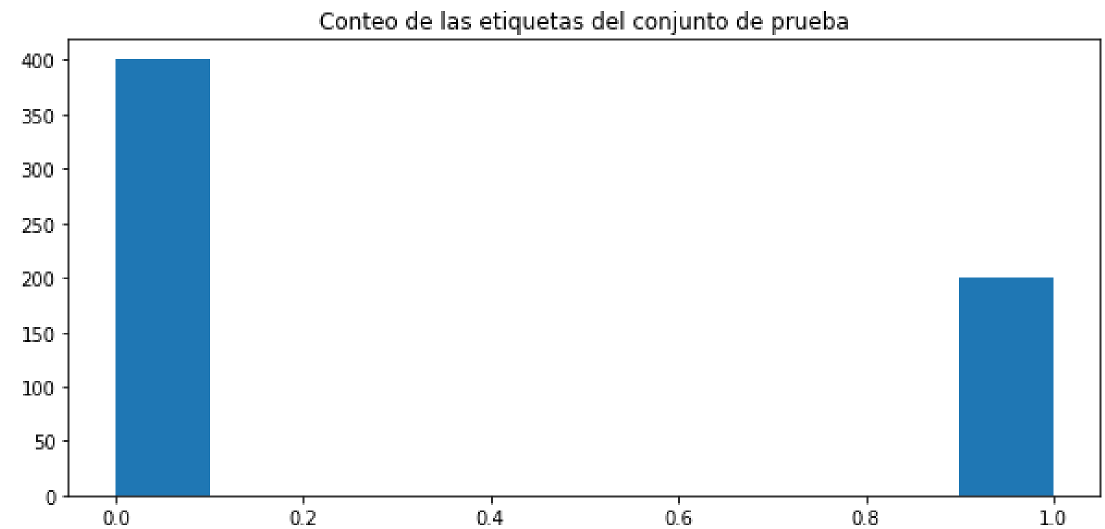
```
In [111]: #Limpiando datos de entrenamiento
          num = x_train_españa.size
```

```
clean_train = []


for i in range( 0, num):

    clean_train.append(review_to_words(x_train_españa.values[i]))

x_train_es = clean_train

#Limpiando datos de prueba
num= x_test_españa.size

clean_test_train = []


for i in range( 0, num):

    clean_test_train.append( review_to_words(x_test_españa.values[i] ) )

x_test_es = clean_test_train
```

- Conservan proporción

In [28]:
```
plt.figure(figsize=(10,10))
plt.subplot(211)
plt.hist(y_train_es, bins=10)
plt. title('Conteo de las etiquetas del conjunto de entrenamiento')
plt.subplot(212)
plt.hist(y_test_es, bins=10)
plt. title('Conteo de las etiquetas del conjunto de prueba')
plt.show()
```






```
In [112]: x_train_es = train_es["TOPIC"].astype(str).str.cat(x_train_es, sep=' ')
          x_test_es = test_es["TOPIC_y"].astype(str).str.cat(x_test_es, sep=' ')
```

```
In [113]: x_train_es = pd.Series(x_train_es)
          y_train_es = pd.Series(y_train_es)
          x_test_es = pd.Series(x_test_es)
          y_test_es = pd.Series(y_test_es)

          print(x_train_es.shape)
          print(y_train_es.shape)
          print(x_test_es.shape)
          print(y_test_es.shape)
```

```
(2400,)
(2400,)
```

```
(600,)
(600,)
```

- Representación Bow TF-IDF

```
In [114]: vect_es = TfidfVectorizer()# completo
          x_train_tf_es = vect_es.fit_transform(x_train_es)
          x_test_tf_es = vect_es.transform(x_test_es)

          x_train_tf_es = x_train_tf_es.toarray()
          x_test_tf_es = x_test_tf_es.toarray()

          print(x_train_tf_es.shape)
          print(x_test_tf_es.shape)
```

```
(2400, 6944)
(600, 6944)
```

6 Clasificador NN

```
In [197]: from keras.utils import to_categorical

          y_train_esp = to_categorical(y_train_es)
          y_test_esp = to_categorical(y_test_es)

          num_es, sz_es = y_train_esp.shape

          print(num_es)
          print(sz_es)
```

```
2400
2
```

6.0.1 Selección de modelo

- Seleccionar el número de epocas para evitar el sobre ajuste

```
In [198]: import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 100
          epochs = 10
```

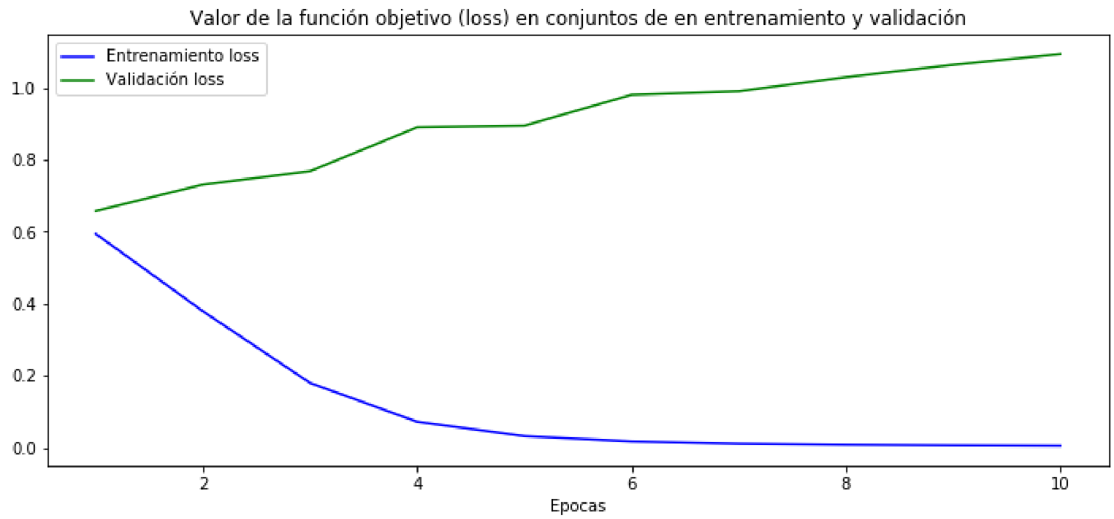
```
nn_es = Sequential()
nn_es.add(Dense(512, activation='relu'))
nn_es.add(Dropout(0.25))
nn_es.add(Dense(sz_es, activation='softmax'))
nn_es.compile(loss='binary_crossentropy',
              optimizer='nadam',
              metrics=['accuracy'])

history_es = nn_es.fit(x_train_tf_es,
              y_train_esp,
              validation_split=.2,
              batch_size= batch_size,
              shuffle   =True,
              epochs=epochs,
              verbose=2)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
Train on 1920 samples, validate on 480 samples
Epoch 1/10
 - 6s - loss: 0.5939 - acc: 0.6766 - val_loss: 0.6579 - val_acc: 0.5854
Epoch 2/10
 - 1s - loss: 0.3787 - acc: 0.8344 - val_loss: 0.7311 - val_acc: 0.5583
Epoch 3/10
 - 1s - loss: 0.1793 - acc: 0.9427 - val_loss: 0.7683 - val_acc: 0.5875
Epoch 4/10
 - 1s - loss: 0.0716 - acc: 0.9875 - val_loss: 0.8906 - val_acc: 0.5833
Epoch 5/10
 - 1s - loss: 0.0318 - acc: 0.9958 - val_loss: 0.8950 - val_acc: 0.5979
Epoch 6/10
 - 1s - loss: 0.0170 - acc: 0.9984 - val_loss: 0.9807 - val_acc: 0.5854
Epoch 7/10
 - 1s - loss: 0.0106 - acc: 0.9990 - val_loss: 0.9905 - val_acc: 0.5958
Epoch 8/10
 - 1s - loss: 0.0076 - acc: 0.9990 - val_loss: 1.0296 - val_acc: 0.5958
Epoch 9/10
 - 1s - loss: 0.0058 - acc: 0.9995 - val_loss: 1.0642 - val_acc: 0.5875
Epoch 10/10
 - 1s - loss: 0.0047 - acc: 0.9995 - val_loss: 1.0939 - val_acc: 0.5896
Tiempo de procesamiento (secs):  12.440585374832153
```

Gráfica loss values datos de entrenamiento y validación

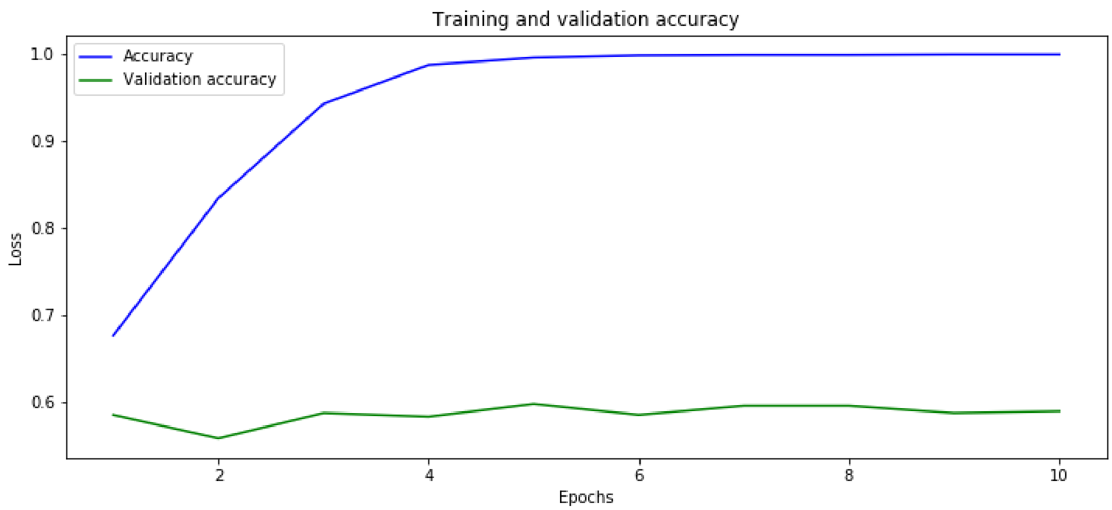
```
In [63]: history_dict_es = history_es.history
         dictkeys_es=list(history_dict_es.keys())
         loss_values_es = history_es.history['loss']
         val_loss_values_es = history_es.history['val_loss']
```

```
epochs_es = range(1, len(loss_values_es) + 1)


plt.figure(figsize=(12,5))
plt.plot(epochs_es, loss_values_es, 'b', label='Entrenamiento loss')
plt.plot(epochs_es, val_loss_values_es, 'g', label='Validación loss')
plt.title('Valor de la función objetivo (loss) en conjuntos de en entrenamiento y vali
plt.xlabel('Epocas')
plt.ylabel('')
plt.legend()

plt.show()
```



Gráfica accuracy datos de entrenamiento y validación

```
In [64]: acc_values_es = history_dict_es['acc']
         val_acc_values_es = history_dict_es['val_acc']
         plt.figure(figsize=(12,5))
         plt.plot(epochs_es, acc_values_es, 'b', label='Accuracy')
         plt.plot(epochs_es, val_acc_values_es, 'g', label='Validation accuracy')
         plt.title('Training and validation accuracy')
         plt.xlabel('Epochs')
         plt.ylabel('Loss')
         plt.legend()

         plt.show()
```



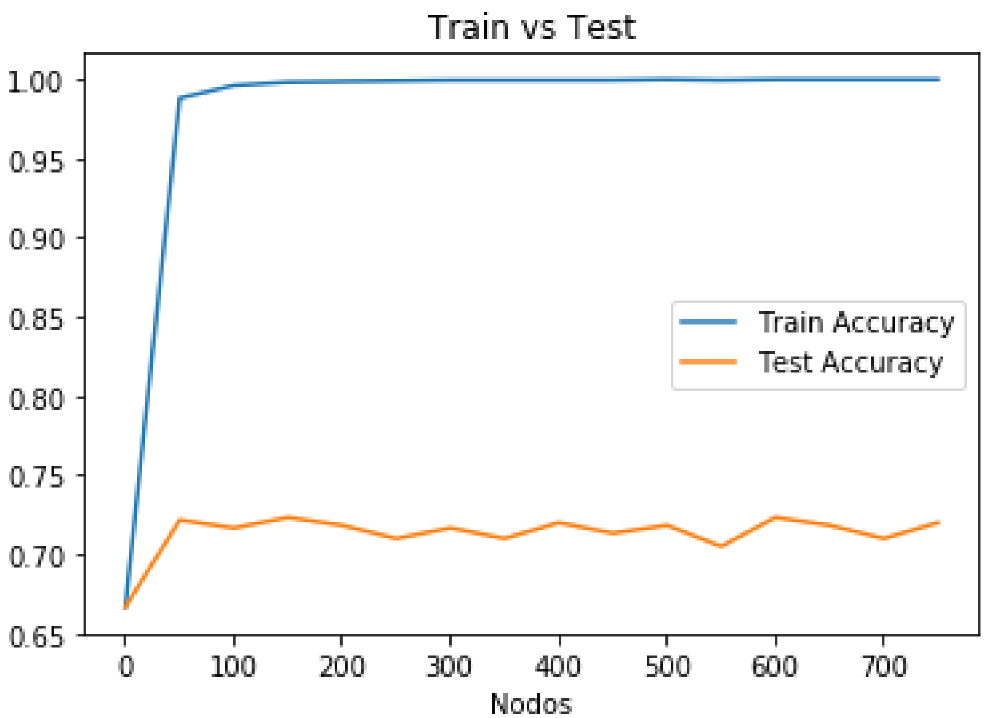
- Seleccionando el número de nodos

```
In [65]: batch_size = 100
         epochs = 6 # epocas seleccionadas

         list_nn_es = np.arange( 1, 800, 50) # parámetro de regularización
         score_train_es = np.zeros(len(list_nn_es)) # almacena acurracy entrenamiento
         score_test_es = np.zeros(len(list_nn_es)) # almacena acurracy prueba
         count = 0
         for i in list_nn_es:
             # Build the model
             nn_es = Sequential()
             nn_es.add(Dense(i, activation='relu'))
             nn_es.add(Dropout(0.25))
             nn_es.add(Dense(sz_es, activation='softmax'))
             nn_es.compile(loss='binary_crossentropy',
                           optimizer='nadam',
                           metrics=['accuracy'])

         # No se utilizan datos de validación
             nn_es.fit(x_train_tf_es,
                           y_train_esp,
                           batch_size= batch_size,
                           shuffle    =True,
                           epochs=epochs,
                           verbose=0)

             temp1_es = nn_es.evaluate(x_train_tf_es, y_train_esp, verbose=0)
             score_train_es[count] = temp1_es[1]
             temp2_es= nn_es.evaluate(x_test_tf_es, y_test_esp, verbose=0)
```

```
            score_test_es[count]= temp2_es[1]
            count = count + 1
```

Gráfico acurracy datos de entrenamiento y de prueba

```
In [66]: matriz_es = np.matrix(np.c_[list_nn_es, score_train_es, score_test_es])
         models_es = pd.DataFrame(data = matriz_es, columns =
                      ['Nodos', 'Train Accuracy', 'Test Accuracy'])
         plt.plot(models_es['Nodos'],models_es['Train Accuracy'])
         plt.plot(models_es['Nodos'],models_es['Test Accuracy'])
         plt.title('Train vs Test')
         plt.xlabel('Nodos')
         plt.legend()
         plt.show()
```




```
In [67]: models_es

Out[67]:    Nodos  Train Accuracy  Test Accuracy
         0    1.0        0.666667       0.666667
         1   51.0        0.987917       0.721667
         2  101.0        0.995833       0.716667
         3  151.0        0.997917       0.723333
         4  201.0        0.998333       0.718333
         5  251.0        0.998750       0.710000
```

```
6   301.0        0.999167       0.716667
7   351.0        0.999167       0.710000
8   401.0        0.999167       0.720000
9   451.0        0.999167       0.713333
10  501.0        0.999583       0.718333
11  551.0        0.999167       0.705000
12  601.0        0.999583       0.723333
13  651.0        0.999583       0.718333
14  701.0        0.999583       0.710000
15  751.0        0.999583       0.720000
```

```
In [68]: nodo_es = list_nn_es[np.argmax(np.array(models_es['Test Accuracy']))]
         nodo_es

         # Se seleccionan 50 nodos
         #nodo_es = 50
         #nodo_es
```

```
Out[68]: 151
```

- Diseño modelo final

```
In [73]: import time
         tic=time.time()

         np.random.seed(1)

         batch_size = 100
         epochs = 3

         nn_es = Sequential()
         nn_es.add(Dense(nodo_es, activation='relu'))
         nn_es.add(Dropout(0.25))
         nn_es.add(Dense(sz_es, activation='softmax'))
         nn_es.compile(loss='binary_crossentropy',
                       optimizer='nadam',
                       metrics=['accuracy'])

         history_es = nn_es.fit(x_train_tf_es,
                       y_train_esp,
                       validation_split=.2,
                       batch_size= batch_size,
                       shuffle   =True,
                       epochs=epochs,
                       verbose=2)

         print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
Train on 1920 samples, validate on 480 samples
Epoch 1/3
```

```
 - 2s - loss: 0.6296 - acc: 0.6573 - val_loss: 0.6463 - val_acc: 0.6542
Epoch 2/3
 - 0s - loss: 0.4678 - acc: 0.7885 - val_loss: 0.6917 - val_acc: 0.5375
Epoch 3/3
 - 0s - loss: 0.3080 - acc: 0.8875 - val_loss: 0.7302 - val_acc: 0.5562
Tiempo de procesamiento (secs):  3.2347073554992676
```

- Se guarda el modelo

```
In [199]: from keras.models import load_model
          #nn_es.save('nn_españa_tfidf')  # Guardad el modelo
          nn_es = load_model('nn_españa_tfidf') # Cargar el modelo
```

```
In [200]: results_es = nn_es.evaluate(x_test_tf_es, y_test_esp)
          print('Test loss:', results_es[0])
          print('Test accuracy:', results_es[1])
```

```
600/600 [==============================] - 1s 913us/step
Test loss: 0.5398333676656087
Test accuracy: 0.725
```

```
In [30]: import numpy as np
         from sklearn.metrics import confusion_matrix, precision_score, recall_score, f1_score

         y_pred_es = nn_es.predict(x_test_tf_es).squeeze()
         y_test_label_es = np.argmax(y_test_esp,1)
         y_pred_label_es = np.argmax(y_pred_es,1)

         # Confusion matrix
         C=confusion_matrix(y_test_label_es , y_pred_label_es)
         print(C)
```

```
[[337  63]
 [102  98]]
```

6.0.2 Resultados

```
In [201]: print('Accuracy score:', results_es[1])  # nn evaluate keras
          print("F1 score", f1_score(y_test_label_es,  y_pred_label_es,  average='macro'))
          print("F1 weighted", f1_score(y_test_label_es,  y_pred_label_es,   average='weighted
          print("Recall score", recall_score(y_test_label_es,  y_pred_label_es,  average='macro
          print("Precision score", precision_score( y_test_label_es,  y_pred_label_es, average=
```

```
Accuracy score: 0.725
F1 score 0.6731367972028435
F1 weighted 0.716536966907577
```

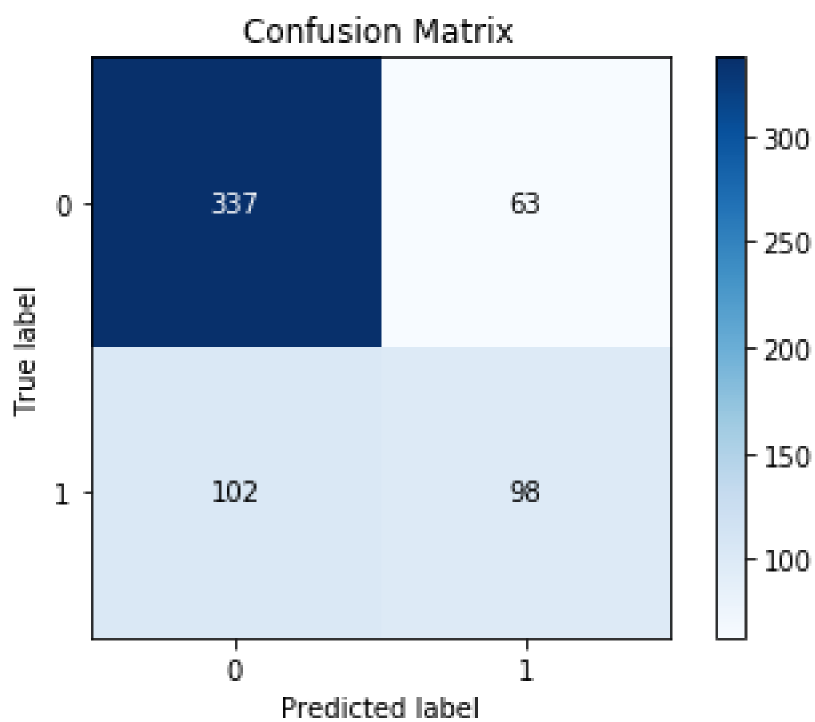
```
Recall score 0.66625
Precision score 0.6881747053580272
```

```
In [81]: from sklearn.metrics import classification_report
         print(classification_report(y_test_label_es, y_pred_label_es,target_names=['no-ironia
```

```
              precision    recall  f1-score   support

   no-ironia       0.77      0.84      0.80       400
      ironia       0.61      0.49      0.54       200

   micro avg       0.72      0.72      0.73       600
   macro avg       0.69      0.67      0.67       600
weighted avg       0.71      0.72      0.72       600
```

```
In [82]: %matplotlib inline
         import matplotlib.pyplot as plt
         import scikitplot

         scikitplot.metrics.plot_confusion_matrix(y_test_label_es, y_pred_label_es)
```

```
Out[82]: <matplotlib.axes._subplots.AxesSubplot at 0x15abaa4d5c0>
```



7 Clasificador SVM

- Selección del modelo

```
In [83]: from sklearn.pipeline import Pipeline
         from sklearn.svm import LinearSVC
         from sklearn.model_selection import GridSearchCV
         from sklearn.preprocessing import StandardScaler
         import time
         tic=time.time()

         SVCpipe = Pipeline([('SVC',LinearSVC(class_weight="balanced", random_state=1,verbose=(

         # Gridsearch to determine the value of C
         param_grid = {'SVC__C':np.arange(.001,5,1)}
         linearSVC = GridSearchCV(SVCpipe,param_grid,cv=5,return_train_score=True, verbose=0)
         linearSVC.fit(x_train_tf_es, y_train_es.values)
         print(linearSVC.best_params_)
         #linearSVC.coef_
         #linearSVC.intercept_

         svm_es = linearSVC.best_estimator_
         svm_es.fit(x_train_tf_es, y_train_es.values)
         svm_es.coef_ = svm_es.named_steps['SVC'].coef_
         svm_es.score(x_train_tf_es, y_train_es.values)
         print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
{'SVC__C': 0.001}
Tiempo de procesamiento (secs):  4.632094383239746
```

Gráfico accuracy de entrenamiento y prueba respecto al parámetro de regularización

- Guardad modelo

```
In [202]: from joblib import dump, load
          #dump(svm_es, 'svm_epaña_tfidf.joblib') # Guardad modelo
          svm_es = load('svm_epaña_tfidf.joblib') # Cargar modelo#
```

```
In [203]: #Prediction
          prediction_es=svm_es.predict(x_test_tf_es) # se vuelve a poner esto aquí dado a que 
          print("Acurracy Test",metrics.accuracy_score(prediction_es, y_test_es.values))
```

```
Acurracy Test 0.715
```

```
In [204]: print("Confusion Metrix:\n",metrics.confusion_matrix(y_test_es.values, prediction_es
```

```
Confusion Metrix:
 [[307  93]
 [ 78 122]]
```

7.0.1 Resultados

```
In [205]: print('Accuracy score:', metrics.accuracy_score(y_test_es.values, prediction_es, ))
          print("F1 score", f1_score(y_test_es.values, prediction_es,   average='macro'))
          print("F1 weighted", f1_score(y_test_es.values, prediction_es,  average='weighted'))
          print("Recall score", recall_score(y_test_es.values, prediction_es,   average='macro
          print("Precision score", precision_score(y_test_es.values, prediction_es,  average='r
```

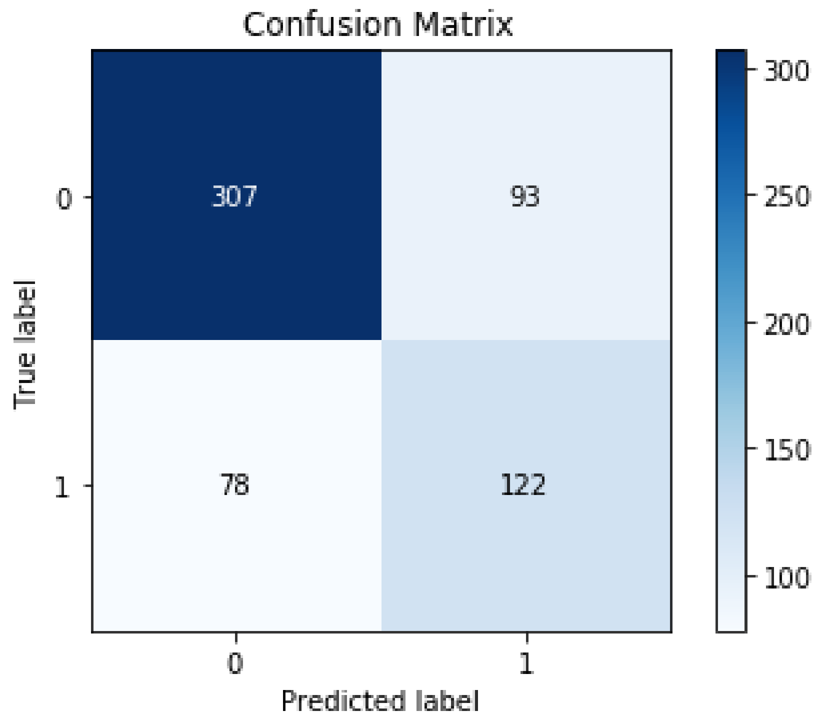
```
Accuracy score: 0.715
F1 score 0.6850587061622284
F1 weighted 0.7174276724733327
Recall score 0.68875
Precision score 0.6824222289338568
```

```
In [206]: from sklearn.metrics import classification_report
          print(classification_report( y_test_es.values, prediction_es,target_names=['no-ironia
```

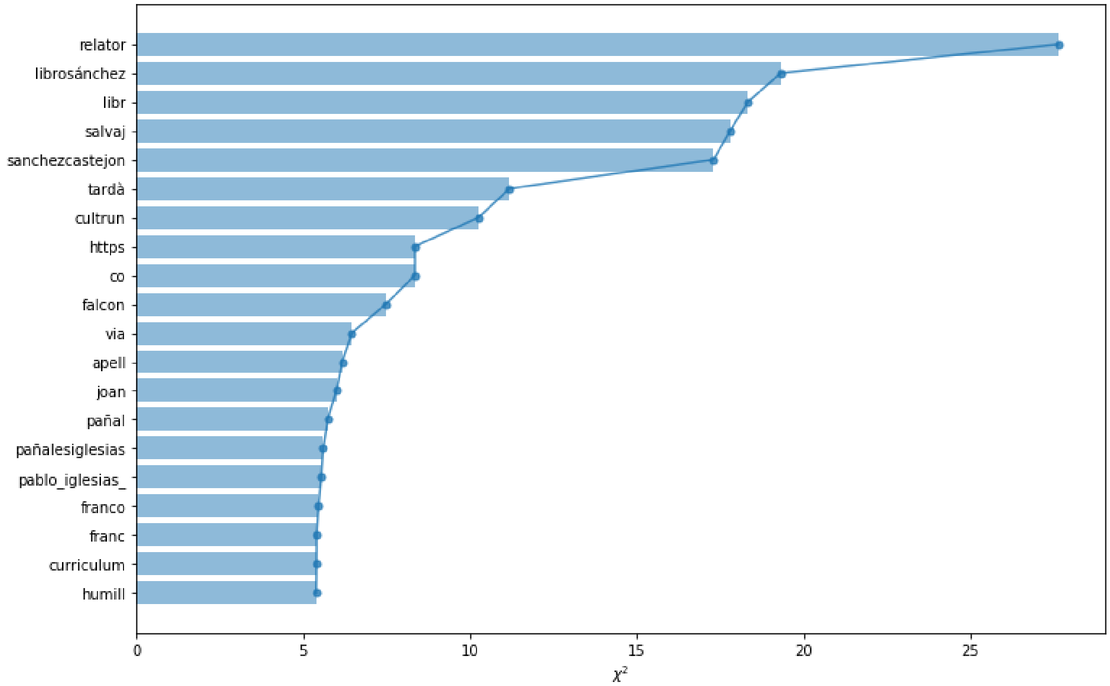
```
              precision    recall  f1-score   support

   no-ironia       0.80      0.77      0.78       400
      ironia       0.57      0.61      0.59       200

   micro avg       0.71      0.71      0.71       600
   macro avg       0.68      0.69      0.69       600
weighted avg       0.72      0.71      0.72       600
```

```
In [486]: %matplotlib inline
          import matplotlib.pyplot as plt
          import scikitplot

          scikitplot.metrics.plot_confusion_matrix(y_test_es.values, prediction_es)
```

```
Out[486]: <matplotlib.axes._subplots.AxesSubplot at 0x15d6861b748>
```




```
In [487]: from sklearn.feature_selection import chi2
          # compute chi2 for each feature
          chi2score_es = chi2(x_train_tf_es,y_train_es)[0]

In [488]: import matplotlib.pyplot as plt
          %matplotlib inline
          plt.figure(figsize=(12,8))
          scores_es = list(zip(vect_es.get_feature_names(), chi2score_es))
          chi2_es = sorted(scores_es, key=lambda x:x[1])
          topchi2_es = list(zip(*chi2_es[-20:]))
          x_es = range(len(topchi2_es[1]))
          labels_es = topchi2_es[0]
          plt.barh(x_es,topchi2_es[1], align='center', alpha=0.5)
          plt.plot(topchi2_es[1], x_es, '-o', markersize=5, alpha=0.8)
          plt.yticks(x_es, labels_es)
          plt.xlabel('$\chi^2$')
          plt.show();
```



8 TF-IDF - Cuba

In [207]:
```
# Importando los textos
import os

# introducit path
os.chdir('C:\\Users\\h_air\\Documents\\Diplomado Deep Learning\\Estancia\\Datos\\Dat
train_cu = pd.read_csv('irosva.cu.training.csv');

# introducit path
os.chdir('C:\\Users\\h_air\\Documents\\Diplomado Deep Learning\\Estancia\\Datos\\Dat
test_cu_nolabel = pd.read_csv('irosva.cu - irosva.cu.test.csv');

# introducit path
os.chdir('C:\\Users\\h_air\\Documents\\Diplomado Deep Learning\\Estancia\\Datos\\Dat
test_cu_label = pd.read_csv('irosva.cu.test.truth.csv');
```

In [490]:
```
train_cu.head()
```

Out[490]:
```
                                  ID  \
0  4fdfed6e794a4c1c1550a2996803ba6e
1  64dc97da772a5d70b62c2c124e12705d
2  d66fc3e9a7353a1495a889f34e6371af
3  7b303e9eeb0c1ca5c2ec80047dff519b
```

```
4  fd8a327fe8d642851db4b702069df1f0

                                              TOPIC  IS_IRONIC  \
0  TELEVISIÓN DIGITAL, CAJAS DECODIFICADORAS, TEL...          1
1  TELEVISIÓN DIGITAL, CAJAS DECODIFICADORAS, TEL...          1
2  TELEVISIÓN DIGITAL, CAJAS DECODIFICADORAS, TEL...          1
3  TELEVISIÓN DIGITAL, CAJAS DECODIFICADORAS, TEL...          1
4  TELEVISIÓN DIGITAL, CAJAS DECODIFICADORAS, TEL...          1

                                            MESSAGE
0                                         magnifico
1  VIVA EL PAQUETE. Mas pelis clásicas por favor...
2  gracias una y mil veces por la programación de...
3        LA TV DIGITAL ESTA SIENDO MUY EFICIENTE.
4  O sea que los trabajadores de salario medio, l...
```

In [491]: test_cu_nolabel.head()

Out[491]:
```
                                 ID  \
0  00466090f558ec4d1a4b312284aee502
1  0069480d19db6f82600e0d34501281d2
2  0097b7f8824cf7465f7963aa0b85c98c
3  00d1e2079fc31d88e7a7f5f743e321ea
4  00f2c9d7f54f25dba6d0deb88a6fe404

                                              TOPIC IS_IRONIC  \
0                          ECONOMÍA. TURISMOS, HOTELES         ?
1      TRANSPORTE, BOTEROS, CHOFERES, ÓMNIBUS, RUTAS         ?
2                          ETECSA,  CALIDAD, SERVICIOS         ?
3  NUEVAS TECNOLOGÍAS, INFORMATIZACIÓN DE LA SOCI...         ?
4                          ETECSA,  CALIDAD, SERVICIOS         ?

                                            MESSAGE
0  La oferta es 90 por persona por noche la habit...
1  Si vamos a hacer la denuncia, hacedla con todo...
2  ?Creo q es una falta d repeto los precios q ti...
3  muy buen articulo, espero que nuestra red siga...
4  Yo pagaria los 15 cuc, por algo se empieza, ah...
```

In [492]: test_cu_label.head()

Out[492]:
```
                                 ID  \
0  00466090f558ec4d1a4b312284aee502
1  0069480d19db6f82600e0d34501281d2
2  0097b7f8824cf7465f7963aa0b85c98c
3  00d1e2079fc31d88e7a7f5f743e321ea
4  00f2c9d7f54f25dba6d0deb88a6fe404

                                              TOPIC  IS_IRONIC
```

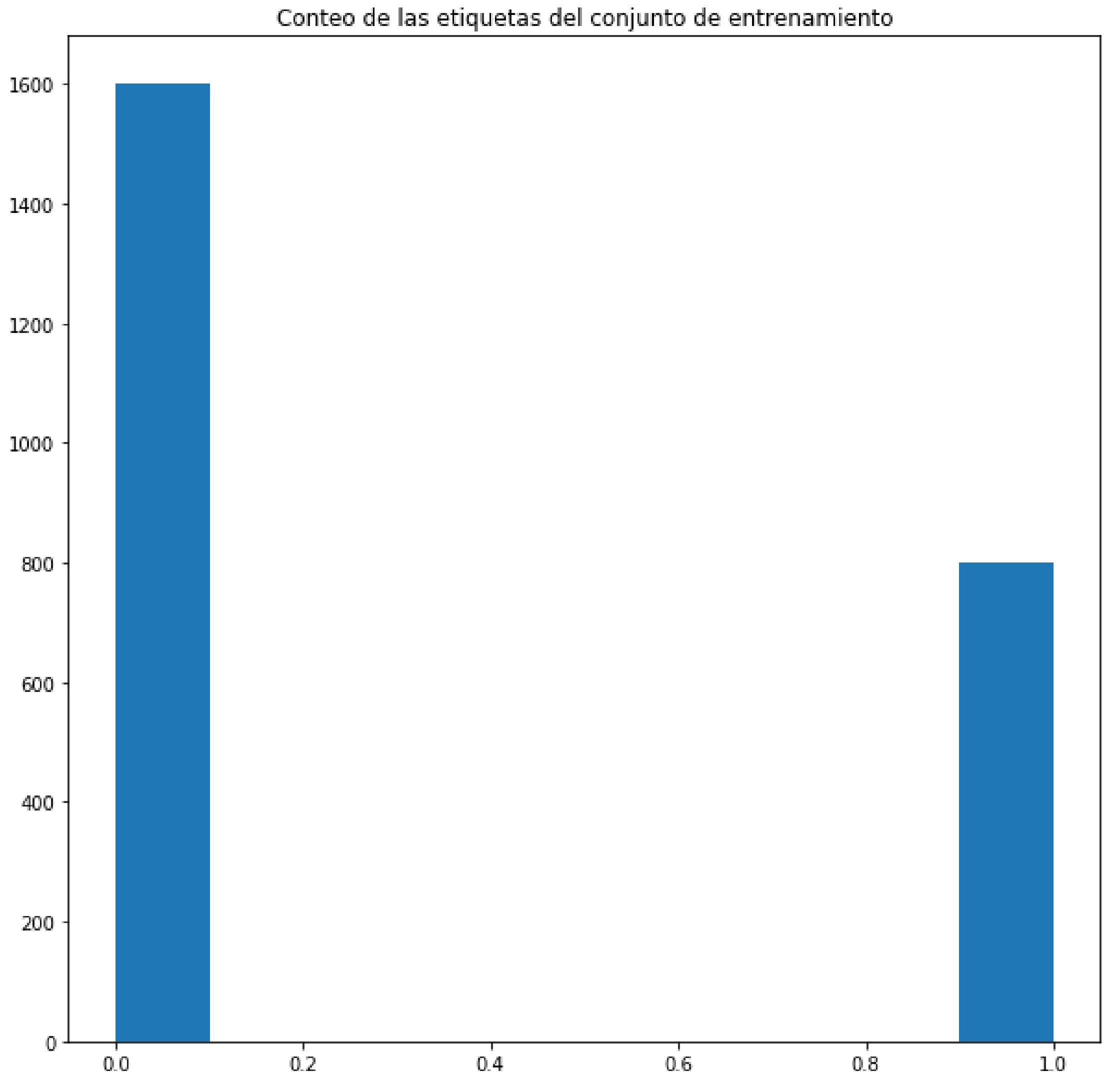
```
0                         ECONOMÍA. TURISMOS, HOTELES          0
1      TRANSPORTE, BOTEROS, CHOFERES, ÓMNIBUS, RUTAS          0
2                          ETECSA,  CALIDAD, SERVICIOS          0
3  NUEVAS TECNOLOGÍAS, INFORMATIZACIÓN DE LA SOCI...          0
4                          ETECSA,  CALIDAD, SERVICIOS          1
```

In [208]:
```
test_cu = pd.merge(test_cu_nolabel, test_cu_label, on='ID')
test_cu.head()
```

Out[208]:
```
                                  ID  \
0  00466090f558ec4d1a4b312284aee502
1  0069480d19db6f82600e0d34501281d2
2  0097b7f8824cf7465f7963aa0b85c98c
3  00d1e2079fc31d88e7a7f5f743e321ea
4  00f2c9d7f54f25dba6d0deb88a6fe404

                                             TOPIC_x IS_IRONIC_x  \
0                         ECONOMÍA. TURISMOS, HOTELES           ?
1      TRANSPORTE, BOTEROS, CHOFERES, ÓMNIBUS, RUTAS           ?
2                          ETECSA,  CALIDAD, SERVICIOS           ?
3  NUEVAS TECNOLOGÍAS, INFORMATIZACIÓN DE LA SOCI...           ?
4                          ETECSA,  CALIDAD, SERVICIOS           ?

                                             MESSAGE  \
0  La oferta es 90 por persona por noche la habit...
1  Si vamos a hacer la denuncia, hacedla con todo...
2  ?Creo q es una falta d repeto los precios q ti...
3  muy buen articulo, espero que nuestra red siga...
4  Yo pagaria los 15 cuc, por algo se empieza, ah...

                                             TOPIC_y  IS_IRONIC_y
0                         ECONOMÍA. TURISMOS, HOTELES            0
1      TRANSPORTE, BOTEROS, CHOFERES, ÓMNIBUS, RUTAS            0
2                          ETECSA,  CALIDAD, SERVICIOS            0
3  NUEVAS TECNOLOGÍAS, INFORMATIZACIÓN DE LA SOCI...            0
4                          ETECSA,  CALIDAD, SERVICIOS            1
```

- Proporción de clase

In [494]:
```
plt.figure(figsize=(10,10))
plt.hist(train_cu['IS_IRONIC'][:], bins=10)
plt. title('Conteo de las etiquetas del conjunto de entrenamiento')
plt.show()
```



Nombre de las variables que se utilizan para los datos de Cuba

```
In [209]: x_train_cuba = train_cu["MESSAGE"]
          x_test_cuba = test_cu["MESSAGE"]
          y_train_cu = train_cu['IS_IRONIC']
          y_test_cu = test_cu['IS_IRONIC_y']
          print([y_train_cu.shape, y_test_cu.shape])
```

```
[(2400,), (600,)]
```

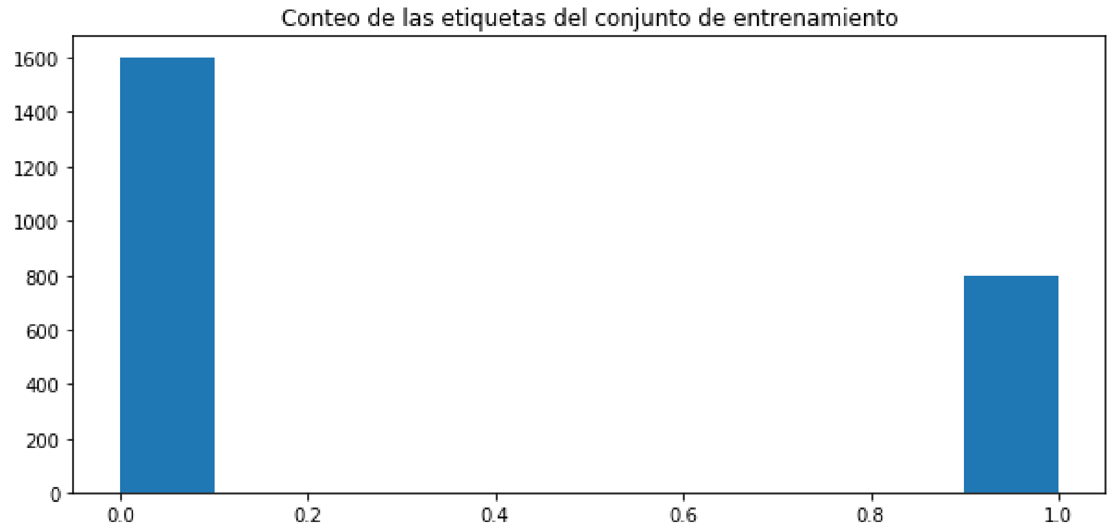
- Limpiando Corpus de entrenamiento y de prueba

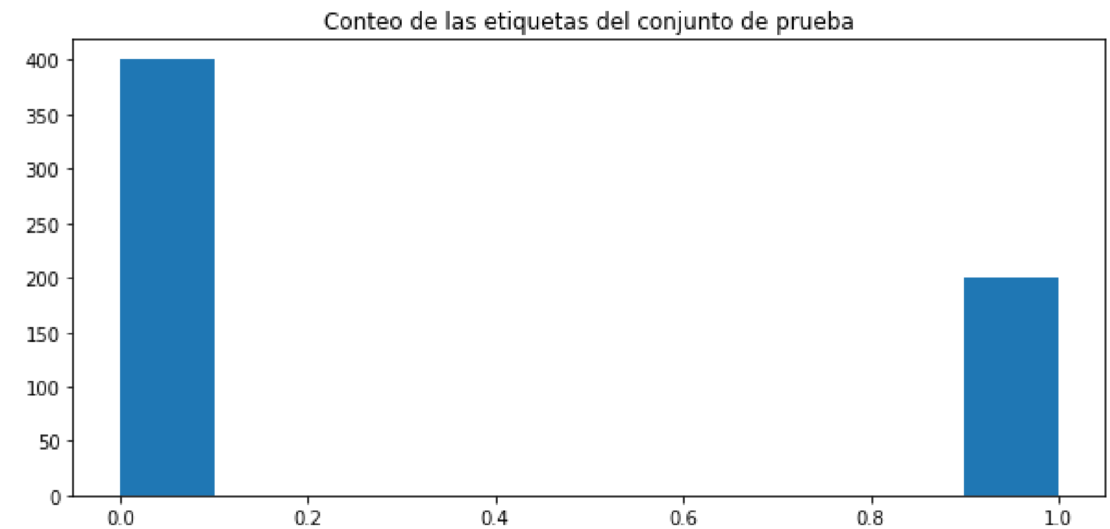
```
In [210]: #Limpiando datos de entrenamiento
          num = x_train_cuba.size
```

```
clean_train = []


for i in range( 0, num):

    clean_train.append(review_to_words(x_train_cuba.values[i]))

x_train_cu = clean_train

# limpiando datos de entrenamiento
num= x_test_cuba.size

clean_test_train = []


for i in range( 0, num):

    clean_test_train.append( review_to_words(x_test_cuba.values[i] ) )

x_test_cu = clean_test_train
```

Se conserva la proporción

```
In [497]: plt.figure(figsize=(10,10))
          plt.subplot(211)
          plt.hist(y_train_cu, bins=10)
          plt. title('Conteo de las etiquetas del conjunto de entrenamiento')
          plt.subplot(212)
          plt.hist(y_test_cu, bins=10)
          plt. title('Conteo de las etiquetas del conjunto de prueba')
          plt.show()
```






```
In [211]: x_train_cu = train_cu["TOPIC"].astype(str).str.cat(x_train_cu, sep=' ')
          x_test_cu = test_cu["TOPIC_y"].astype(str).str.cat(x_test_cu, sep=' ')
```

```
In [212]: x_train_cu = pd.Series(x_train_cu)
          y_train_cu = pd.Series(y_train_cu)
          x_test_cu = pd.Series(x_test_cu)
          y_test_cu = pd.Series(y_test_cu)

          print(x_train_cu.shape)
          print(y_train_cu.shape)
          print(x_test_cu.shape)
          print(y_test_cu.shape)
```

```
(2400,)
(2400,)
```

```
(600,)
(600,)
```

Representación BoW TF-IDF

```
In [213]: vect_cu = TfidfVectorizer(min_df=.01)
          x_train_tf_cu = vect_cu.fit_transform(x_train_cu)
          x_test_tf_cu = vect_cu.transform(x_test_cu)

          x_train_tf_cu = x_train_tf_cu.toarray()
          x_test_tf_cu = x_test_tf_cu.toarray()

          print(x_train_tf_cu.shape)
          print(x_test_tf_cu.shape)
```

```
(2400, 291)
(600, 291)
```

9 Clasificador NN

```
In [214]: from keras.utils import to_categorical

          y_train_cub = to_categorical(y_train_cu)
          y_test_cub = to_categorical(y_test_cu)

          num_cu, sz_cu = y_train_cub.shape

          print(num_cu)
          print(sz_cu)
```

```
2400
2
```

9.0.1 Selección de modelo

- Número de epocas

```
In [212]: import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 50
          epochs = 10
```

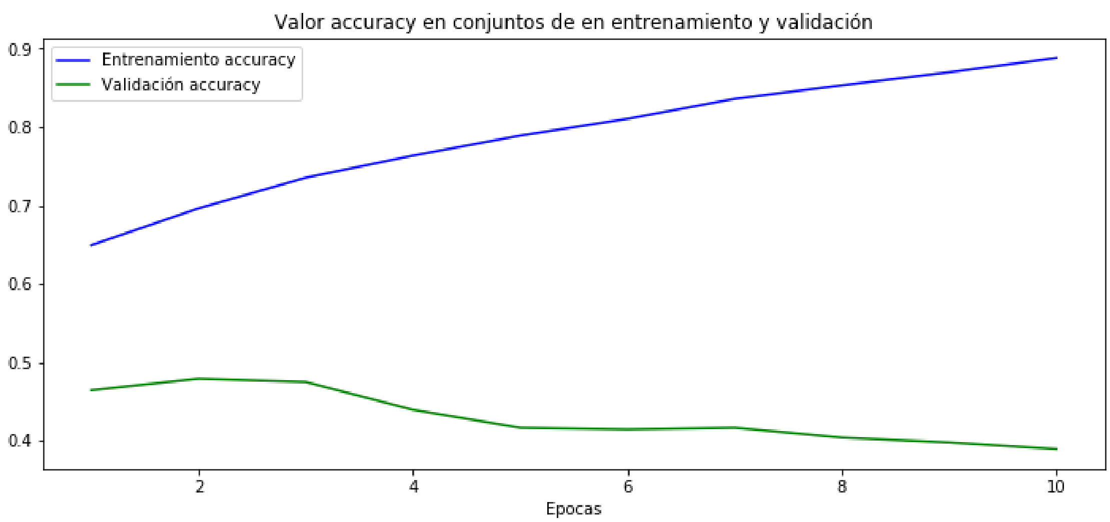
```
nn_cu = Sequential()
nn_cu.add(Dense(200, activation='relu'))
nn_cu.add(Dropout(0.25))
nn_cu.add(Dense(sz_cu, activation='softmax'))
nn_cu.compile(loss='binary_crossentropy',
              optimizer='nadam',
              metrics=['accuracy'])

history_cu = nn_cu.fit(x_train_tf_cu,
              y_train_cub,
              validation_split=.2,
              batch_size= batch_size,
              shuffle   =True,
              epochs=epochs,
              verbose=2)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
Train on 1920 samples, validate on 480 samples
Epoch 1/10
 - 10s - loss: 0.6446 - acc: 0.6495 - val_loss: 0.7582 - val_acc: 0.4646
Epoch 2/10
 - 0s - loss: 0.5731 - acc: 0.6964 - val_loss: 1.1202 - val_acc: 0.4792
Epoch 3/10
 - 0s - loss: 0.5240 - acc: 0.7354 - val_loss: 1.4802 - val_acc: 0.4750
Epoch 4/10
 - 0s - loss: 0.4787 - acc: 0.7635 - val_loss: 1.9527 - val_acc: 0.4396
Epoch 5/10
 - 0s - loss: 0.4506 - acc: 0.7891 - val_loss: 2.2928 - val_acc: 0.4167
Epoch 6/10
 - 0s - loss: 0.4198 - acc: 0.8104 - val_loss: 2.5929 - val_acc: 0.4146
Epoch 7/10
 - 0s - loss: 0.3922 - acc: 0.8359 - val_loss: 2.9269 - val_acc: 0.4167
Epoch 8/10
 - 0s - loss: 0.3653 - acc: 0.8531 - val_loss: 3.2588 - val_acc: 0.4042
Epoch 9/10
 - 0s - loss: 0.3358 - acc: 0.8698 - val_loss: 3.6312 - val_acc: 0.3979
Epoch 10/10
 - 0s - loss: 0.3051 - acc: 0.8880 - val_loss: 3.9124 - val_acc: 0.3896
Tiempo de procesamiento (secs):  13.789531230926514
```

Gráfico loss values entrenamiento y prueba respecto al número de epocas

```
In [213]: history_dict_cu = history_cu.history
          dictkeys_cu=list(history_dict_cu.keys())
          loss_values_cu = history_cu.history['acc']
          val_loss_values_cu = history_cu.history['val_acc']
```

```
epochs_cu = range(1, len(loss_values_cu) + 1)


plt.figure(figsize=(12,5))
plt.plot(epochs_cu, loss_values_cu, 'b', label='Entrenamiento accuracy')
plt.plot(epochs_cu, val_loss_values_cu, 'g', label='Validación accuracy')
plt.title('Valor accuracy en conjuntos de en entrenamiento y validación')
plt.xlabel('Epocas')
plt.ylabel('')
plt.legend()

plt.show()
```



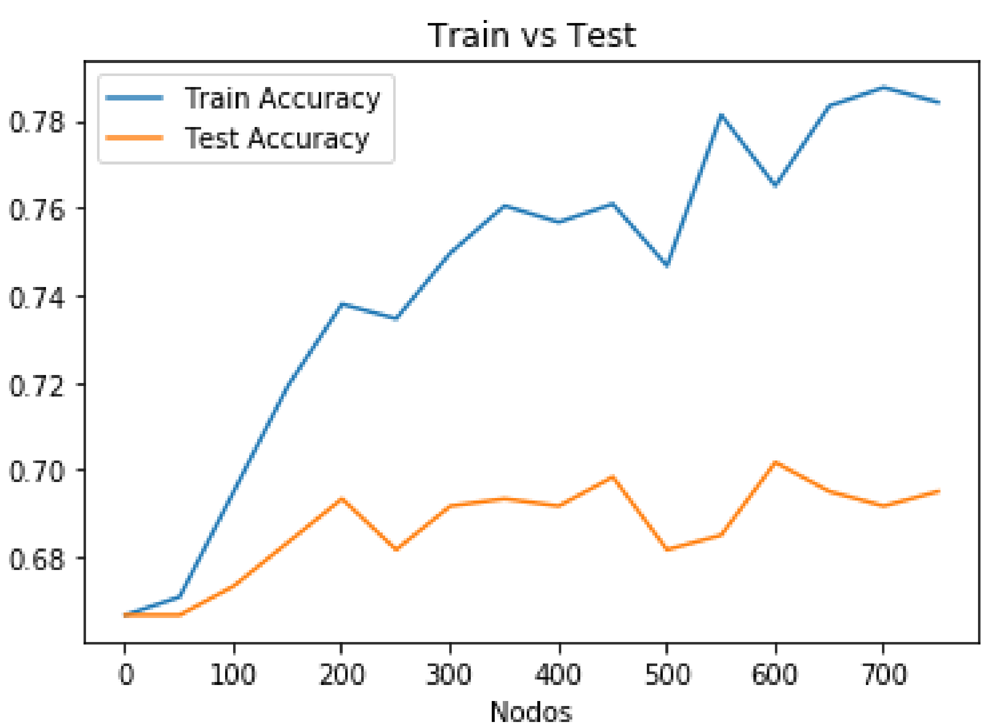
Selección de nodos dado las epocas

```
In [226]: batch_size = 100
          epochs = 3  # epocas seleccionadas

          list_nn_cu = np.arange( 1, 800, 50) # parámetro de regularización
          score_train_cu = np.zeros(len(list_nn_cu)) # almacena acurracy entrenamiento
          score_test_cu = np.zeros(len(list_nn_cu)) # almacena acurracy prueba
          count = 0
          for i in list_nn_cu:
              # Build the model
              nn_cu = Sequential()
              nn_cu.add(Dense(i, activation='relu'))
              nn_cu.add(Dropout(0.25))
              nn_cu.add(Dense(sz_cu, activation='softmax'))
              nn_cu.compile(loss='binary_crossentropy',
                         optimizer='nadam',
                         metrics=['accuracy'])
```

```
# No se utilizan datos de validación
    nn_cu.fit(x_train_tf_cu,
              y_train_cub,
              batch_size= batch_size,
              shuffle   =True,
              epochs=epochs,
              verbose=0)

    temp1_cu = nn_cu.evaluate(x_train_tf_cu, y_train_cub, verbose=0)
    score_train_cu[count] = temp1_cu[1]
    temp2_cu= nn_cu.evaluate(x_test_tf_cu, y_test_cub, verbose=0)
    score_test_cu[count]= temp2_cu[1]
    count = count + 1
```

Gráfico accuracy entrenamiento y prueba respecto al número de nodos

```
In [227]: matriz_cu = np.matrix(np.c_[list_nn_cu, score_train_cu, score_test_cu])
          models_cu = pd.DataFrame(data = matriz_cu, columns =
                       ['Nodos', 'Train Accuracy', 'Test Accuracy'])
          plt.plot(models_cu['Nodos'],models_cu['Train Accuracy'])
          plt.plot(models_cu['Nodos'],models_cu['Test Accuracy'])
          plt.title('Train vs Test')
          plt.xlabel('Nodos')
          plt.legend()
          plt.show()
```



In [228]: models_cu

Out[228]:

	Nodos	Train Accuracy	Test Accuracy
0	1.0	0.666667	0.666667
1	51.0	0.670833	0.666667
2	101.0	0.695000	0.673333
3	151.0	0.719167	0.683333
4	201.0	0.737917	0.693333
5	251.0	0.734583	0.681667
6	301.0	0.749583	0.691667
7	351.0	0.760417	0.693333
8	401.0	0.756667	0.691667
9	451.0	0.760833	0.698333
10	501.0	0.746667	0.681667
11	551.0	0.781250	0.685000
12	601.0	0.765000	0.701667
13	651.0	0.783333	0.695000
14	701.0	0.787500	0.691667
15	751.0	0.784167	0.695000

In [371]:
```
nodo_cu = list_nn_cu[np.argmax(np.array(models_cu['Test Accuracy']))]
nodo_cu
```

Out[371]: 601

- Diseño del modelo

In [108]:
```
import time
tic=time.time()

np.random.seed(1)

batch_size = 100
epochs = 5

nn_cu = Sequential()
nn_cu.add(Dense(nodo_cu, activation='relu'))
nn_cu.add(Dropout(0.25))
nn_cu.add(Dense(sz_cu, activation='softmax'))
nn_cu.compile(loss='binary_crossentropy',
              optimizer='nadam',
              metrics=['accuracy'])

history_cu = nn_cu.fit(x_train_tf_cu,
              y_train_cub,
              validation_split=.2,
```

```
                        batch_size= batch_size,
                        shuffle   =True,
                        epochs=epochs,
                        verbose=2)

          print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
Train on 1920 samples, validate on 480 samples
Epoch 1/5
 - 2s - loss: 0.6387 - acc: 0.6583 - val_loss: 0.7554 - val_acc: 0.4604
Epoch 2/5
 - 0s - loss: 0.5678 - acc: 0.6911 - val_loss: 1.1478 - val_acc: 0.4750
Epoch 3/5
 - 0s - loss: 0.5081 - acc: 0.7474 - val_loss: 1.5150 - val_acc: 0.4854
Epoch 4/5
 - 0s - loss: 0.4684 - acc: 0.7729 - val_loss: 2.0142 - val_acc: 0.4208
Epoch 5/5
 - 0s - loss: 0.4319 - acc: 0.8047 - val_loss: 2.3807 - val_acc: 0.4042
Tiempo de procesamiento (secs):  3.1972484588623047
```

- Guardar el modelo

```
In [215]: from keras.models import load_model
          #nn_cu.save('nn_cuba_tfidf')  # Guarda modelo
          nn_cu = load_model('nn_cuba_tfidf') # Carga modelo
```

```
In [216]: results_cu = nn_cu.evaluate(x_test_tf_cu, y_test_cub)
          print('Test loss:', results_cu[0])
          print('Test accuracy:', results_cu[1])
```

```
600/600 [==============================] - 1s 1ms/step
Test loss: 0.9913563903172811
Test accuracy: 0.6116666674613953
```

```
In [217]: import numpy as np
          from sklearn.metrics import confusion_matrix, precision_score, recall_score, f1_scor
          y_pred_cu = nn_cu.predict(x_test_tf_cu).squeeze()
          y_test_label_cu = np.argmax(y_test_cub,1)
          y_pred_label_cu = np.argmax(y_pred_cu,1)

          # Confusion matrix
          C=confusion_matrix(y_test_label_cu , y_pred_label_cu)
          print(C)
```

```
[[267 133]
 [100 100]]
```

9.0.2 Resultados

In [218]:
```
print('Accuracy score:', results_cu[1])  # nn evaluate keras
print("F1 score", f1_score(y_test_label_cu,  y_pred_label_cu,   average='macro'))
print("F1 weighted", f1_score(y_test_label_cu,  y_pred_label_cu,    average='weighted
print("Recall score", recall_score(y_test_label_cu,  y_pred_label_cu,  average='macro
print("Precision score", precision_score(y_test_label_cu,  y_pred_label_cu,  average=
```

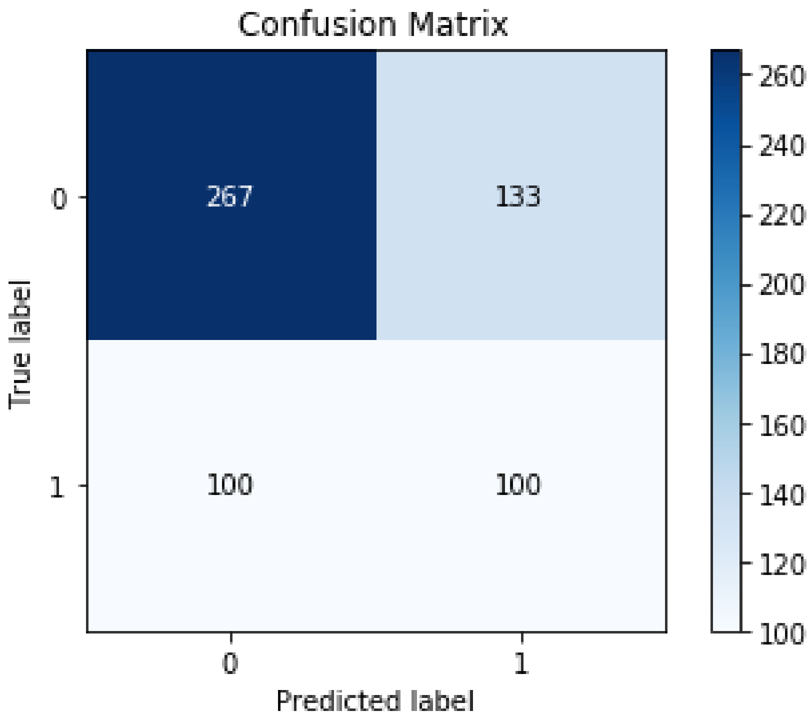
```
Accuracy score: 0.6116666674613953
F1 score 0.5790563998181331
F1 weighted 0.618110611612784
Recall score 0.58375
Precision score 0.5783524926617628
```

In [55]:
```
from sklearn.metrics import classification_report
print(classification_report(y_test_label_cu, y_pred_label_cu,  target_names=['no-ironi
```

```
              precision    recall  f1-score   support

   no-ironia       0.73      0.67      0.70       400
      ironia       0.43      0.50      0.46       200

   micro avg       0.61      0.61      0.61       600
   macro avg       0.58      0.58      0.58       600
weighted avg       0.63      0.61      0.62       600
```

In [56]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import scikitplot

scikitplot.metrics.plot_confusion_matrix(y_test_label_cu, y_pred_label_cu)
```

Out[56]: <matplotlib.axes._subplots.AxesSubplot at 0x21924181748>



10 Clasificador SVM

- Selección de modelo

```
In [219]: from sklearn.pipeline import Pipeline
          from sklearn.svm import LinearSVC
          from sklearn.model_selection import GridSearchCV
          from sklearn.preprocessing import StandardScaler
          import time
          tic=time.time()

          SVCpipe = Pipeline([('SVC',LinearSVC(class_weight="balanced", random_state=1,verbose=

          # Gridsearch to determine the value of C
          param_grid = {'SVC__C':np.arange(.1,10,.1)}
          linearSVC = GridSearchCV(SVCpipe,param_grid,cv=5,return_train_score=True, verbose=0)
          linearSVC.fit(x_train_tf_cu, y_train_cu.values)
          print(linearSVC.best_params_)
          #linearSVC.coef_
          #linearSVC.intercept_

          svm_cu = linearSVC.best_estimator_
          svm_cu.fit(x_train_tf_cu, y_train_cu.values)
```

```
        svm_cu.coef_ = svm_cu.named_steps['SVC'].coef_
        svm_cu.score(x_train_tf_cu, y_train_cu.values)
        print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
{'SVC__C': 0.1}
Tiempo de procesamiento (secs):  37.55752992630005
```

- Guardad modelo

```
In [220]: from joblib import dump, load
          #dump(svm_cu, 'svm_cuba_tfidf.joblib') # Guardad modelo
          svm_cu = load('svm_cuba_tfidf.joblib') # Cargar modelo
```

```
In [221]: prediction_cu=svm_cu.predict(x_test_tf_cu)
          print("Acurracy Test",metrics.accuracy_score(prediction_es, y_test_es.values))
```

```
Acurracy Test 0.715
```

```
In [49]: print("Confusion Metrix:\n",metrics.confusion_matrix(y_test_cu.values, prediction_cu)
```

```
Confusion Metrix:
 [[261 139]
 [ 86 114]]
```

10.0.1 Resultados

```
In [222]: print('Accuracy score:',metrics.accuracy_score(y_test_cu.values, prediction_cu ))  #
          print("F1 score", f1_score(y_test_cu.values, prediction_cu ,  average='macro'))
          print("F1 weighted", f1_score(y_test_cu.values, prediction_cu ,  average='weighted')
          print("Recall score", recall_score(y_test_cu.values, prediction_cu ,  average='macro
          print("Precision score", precision_score(y_test_cu.values, prediction_cu ,  average=
```

```
Accuracy score: 0.625
F1 score 0.6010532195005187
F1 weighted 0.6336338732413096
Recall score 0.61125
Precision score 0.6013771343303983
```

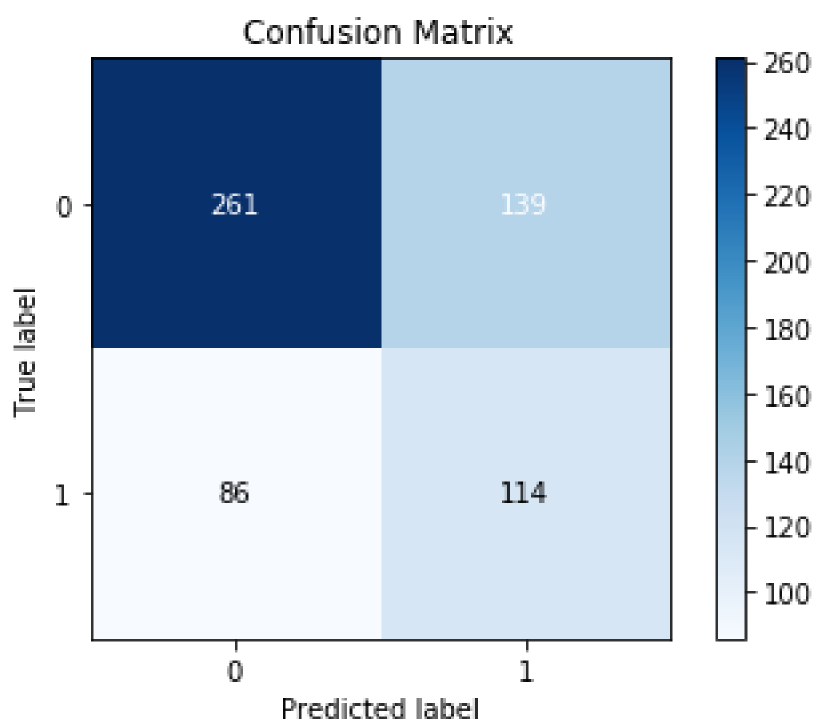
```
In [62]: from sklearn.metrics import classification_report
         print(classification_report( y_test_cu.values, prediction_cu, target_names=['no-ironia
```

```
              precision    recall  f1-score   support

   no-ironia       0.75      0.65      0.70       400
      ironia       0.45      0.57      0.50       200
```

```
   micro avg       0.62      0.62      0.62       600
   macro avg       0.60      0.61      0.60       600
weighted avg       0.65      0.62      0.63       600
```

```
In [65]: %matplotlib inline
         import matplotlib.pyplot as plt
         import scikitplot

         scikitplot.metrics.plot_confusion_matrix(y_test_cu.values, prediction_cu)
```

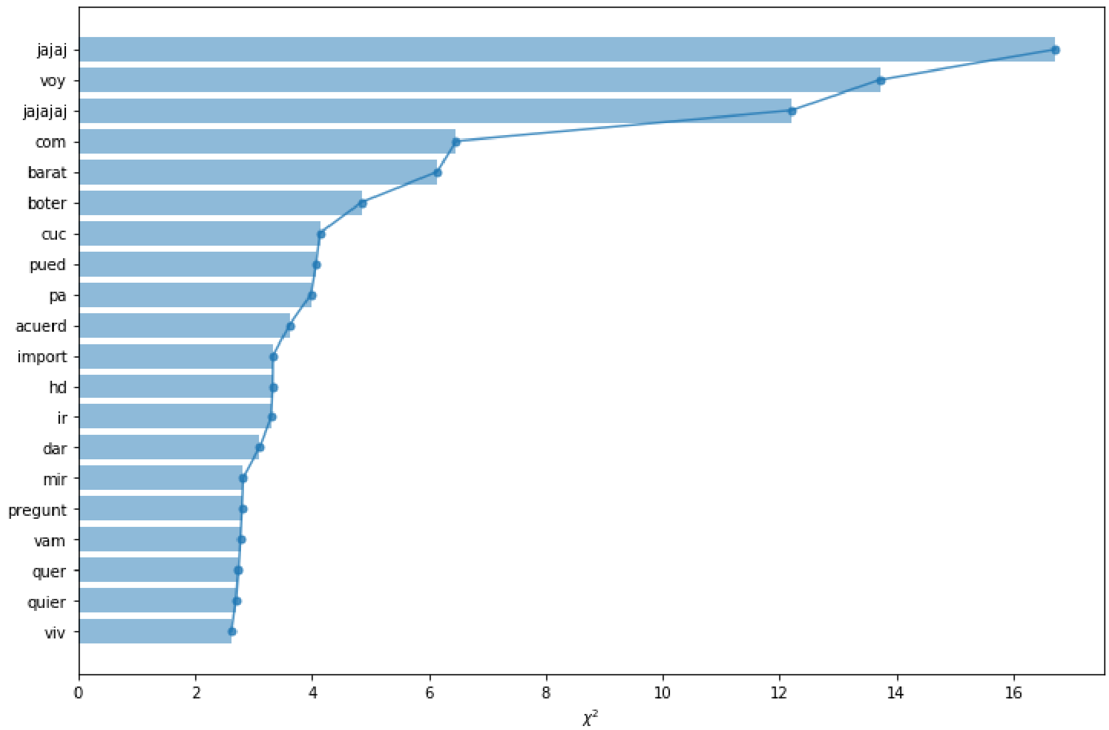
```
Out[65]: <matplotlib.axes._subplots.AxesSubplot at 0x2192525bcc0>
```



Selección de tperminos χ^2

```
In [245]: import matplotlib.pyplot as plt
          from sklearn.feature_selection import chi2
          # compute chi2 for each feature
          chi2score_cu = chi2(x_train_tf_cu,y_train_cu)[0]


          %matplotlib inline
          plt.figure(figsize=(12,8))
          scores_cu = list(zip(vect_cu.get_feature_names(), chi2score_cu))
```

```
chi2_cu = sorted(scores_cu, key=lambda x:x[1])
topchi2_cu = list(zip(*chi2_cu[-20:]))
x_cu = range(len(topchi2_cu[1]))
labels_cu = topchi2_cu[0]
plt.barh(x_es,topchi2_cu[1], align='center', alpha=0.5)
plt.plot(topchi2_cu[1], x_cu, '-o', markersize=5, alpha=0.8)
plt.yticks(x_cu, labels_cu)
plt.xlabel('$\chi^2$')
plt.show();
```



11 Parte II Word2Vec

12 Word2vec Google

```
In [223]: # Bibliotecas
          import numpy as np
          import pandas as pd
          import re # lidia con expresiones regulares
          import nltk
          from bs4 import BeautifulSoup
          from nltk.corpus import stopwords
          from sklearn.feature_extraction.text import CountVectorizer
```

```
from nltk import word_tokenize # sentencia en palabras
from nltk.stem import SnowballStemmer # idioma steam
from nltk.stem.porter import PorterStemmer
from nltk.stem import WordNetLemmatizer
from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn import feature_extraction, model_selection, naive_bayes, metrics, svm
import os
import gensim
from gensim.test.utils import common_texts, get_tmpfile
from gensim.models import Word2Vec
#path = get_tmpfile("word2vec.model")
#import gensim
from time import time
import multiprocessing
#cores = multiprocessing.cpu_count()
#import gensim
#from gensim.models import Word2Vec
from gensim.test.utils import get_tmpfile
from gensim.models import KeyedVectors
```

- Cargar modelo word2vec google

```
In [224]: # Load Google's pre-trained Word2Vec model.
          os.chdir('C:\\Users\\h_air\\Documents\\Diplomado Deep Learning\\Estancia\\Datos\\Dat
          modelo_google = gensim.models.KeyedVectors.load_word2vec_format('GoogleNews-vectors-n
```

```
C:\Users\h_air\Anaconda3\envs\tensorflow-gpu\lib\site-packages\smart_open\smart_open_lib.py:398
  'See the migration notes for details: %s' % _MIGRATION_NOTES_URL
```

- Función que tokeniza datos de entrenamiento y prueba, extra sus caracteristicas y toma la respectiva media

```
In [225]: class MyTokenizer:
              def __init__(self):
                  pass

              def fit(self, X, y=None):
                  return self

              def transform(self, X):
                  transformed_X = []
                  for document in X:
                      tokenized_doc = []
                      for sent in nltk.sent_tokenize(document):
                          tokenized_doc += nltk.word_tokenize(sent)
                      transformed_X.append(np.array(tokenized_doc))
                  return np.array(transformed_X)
```

```
    def fit_transform(self, X, y=None):
        return self.transform(X)

class MeanEmbeddingVectorizer(object):
    def __init__(self, word2vec):
        self.word2vec = word2vec
        # i si el vector está vacio introdicir ceros de la dimensión necesaria
        self.dim = len(word2vec.syn0[0])

    def fit(self, X, y=None):
        return self

    def transform(self, X):
        X = MyTokenizer().fit_transform(X)

        return np.array([
            np.mean([self.word2vec[w] for w in words if w in self.word2vec]
                    or [np.zeros(self.dim)], axis=0)
            for words in X
        ])

    def fit_transform(self, X, y=None):
        return self.transform(X)
```

12.0.1 Word2vec google México

```
In [69]: x_train.head()
         print(x_train.shape)
```

```
(2400,)
```

```
In [70]: x_test.head()
         print(x_test.shape)
```

```
(600,)
```

- Limpiar corpus de entrenamiento y de prueba.

Nota: bajo esta representación no se utiliza stemmead

```
In [226]:  #Limpiando datos de entrenamiento
          num= x_train.size

          clean_train = []

          for i in range( 0, num):
```

```
        clean_train.append( review_to_words(x_train.values[i] ) )

    x_train_w2vgoogle_mx = clean_train
```

In [72]:
```
x_train_w2vgoogle_mx[0]
```

Out[72]:
```
'ric econom pobr objet'
```

In [227]:
```
#Limpiando datos de prueba
num= x_test.size

clean_test = []

for i in range( 0, num):

    clean_test.append( review_to_words(x_test.values[i] ) )

x_test_w2vgoogle_mx = clean_test
```

In [74]:
```
x_test_w2vgoogle_mx[0]
```

Out[74]:
```
'indign postur muj mexican vend años ser espos telenovel llam espos presid cambi ser
```

In [228]:
```
x_train_w2vgoogle_mx = train["TOPIC"].astype(str).str.cat(x_train_w2vgoogle_mx, sep=
x_test_w2vgoogle_mx = test["TOPIC_y"].astype(str).str.cat(x_test_w2vgoogle_mx, sep='
```

In [76]:
```
x_train_w2vgoogle_mx[0]
```

Out[76]:
```
'asuntosConacyt ric econom pobr objet'
```

- Word2Vec Google caracteristicas media (w2v avg)

In [229]:
```
mean_embedding_vectorizer_google_mx = MeanEmbeddingVectorizer(modelo_google)
mean_emb_train_w2vgoogle_mx = mean_embedding_vectorizer_google_mx.fit_transform(x_tra

mean_emb_test_w2vgoogle_mx = mean_embedding_vectorizer_google_mx.fit_transform(x_test
```

```
C:\Users\h_air\Anaconda3\envs\tensorflow-gpu\lib\site-packages\ipykernel_launcher.py:24: Depre
```

12.0.2 Clasificador NN

In [230]:
```
from keras.utils import to_categorical

y_train_w2vgoogle_mx = to_categorical(y_train)
y_test_w2vgoogle_mx  = to_categorical(y_test)

num_mx, sz_mx = y_train_w2vgoogle_mx.shape

print(num_mx)
print(sz_mx)
```

```
2400
2
```

12.0.3 Selección de modelos

- Número de epocas

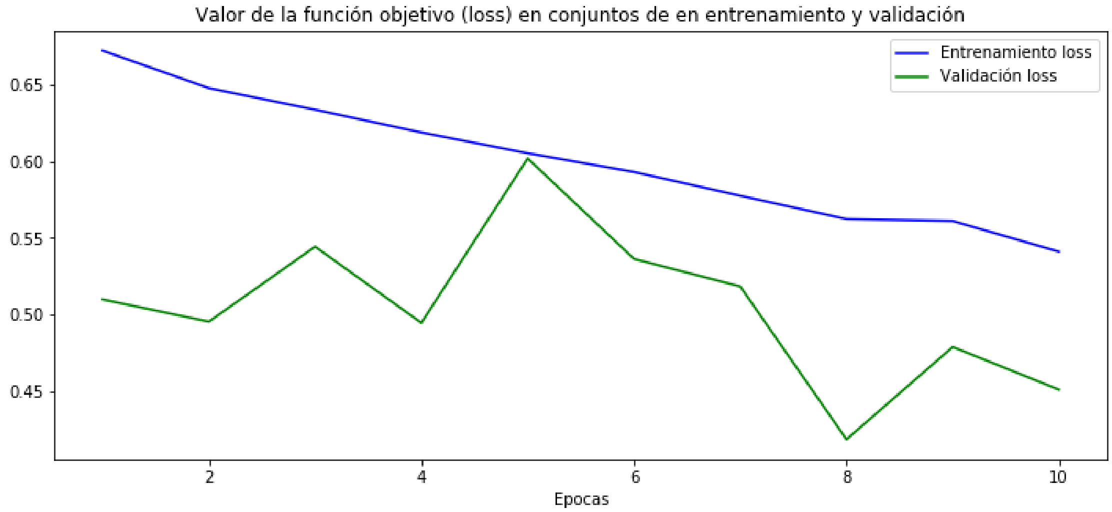
```
In [285]: import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 100
          epochs = 10

          nn_w2vgoogle_mx = Sequential()
          nn_w2vgoogle_mx.add(Dense(100, activation='relu'))
          nn_w2vgoogle_mx.add(Dropout(0.25))
          nn_w2vgoogle_mx.add(Dense(sz_mx, activation='softmax'))
          nn_w2vgoogle_mx.compile(loss='binary_crossentropy',
                        optimizer='nadam',
                        metrics=['accuracy'])

          history_w2vgoogle_mx = nn_w2vgoogle_mx.fit(mean_emb_train_w2vgoogle_mx,
                        y_train_w2vgoogle_mx,
                        validation_split=.2,
                        batch_size= batch_size,
                        shuffle   =True,
                        epochs=epochs,
                        verbose=2)

          print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
Train on 1920 samples, validate on 480 samples
Epoch 1/10
 - 11s - loss: 0.6722 - acc: 0.6096 - val_loss: 0.5098 - val_acc: 0.8854
Epoch 2/10
 - 0s - loss: 0.6478 - acc: 0.6359 - val_loss: 0.4954 - val_acc: 0.8854
Epoch 3/10
 - 0s - loss: 0.6337 - acc: 0.6469 - val_loss: 0.5443 - val_acc: 0.8604
Epoch 4/10
 - 0s - loss: 0.6188 - acc: 0.6656 - val_loss: 0.4945 - val_acc: 0.8646
Epoch 5/10
 - 0s - loss: 0.6053 - acc: 0.6766 - val_loss: 0.6019 - val_acc: 0.7687
Epoch 6/10
 - 0s - loss: 0.5930 - acc: 0.6865 - val_loss: 0.5363 - val_acc: 0.8208
Epoch 7/10
```

```
 - 0s - loss: 0.5775 - acc: 0.6953 - val_loss: 0.5183 - val_acc: 0.8333
Epoch 8/10
 - 0s - loss: 0.5623 - acc: 0.7156 - val_loss: 0.4184 - val_acc: 0.8708
Epoch 9/10
 - 0s - loss: 0.5610 - acc: 0.7073 - val_loss: 0.4788 - val_acc: 0.8604
Epoch 10/10
 - 0s - loss: 0.5410 - acc: 0.7328 - val_loss: 0.4509 - val_acc: 0.8625
Tiempo de procesamiento (secs):  13.271068811416626
```

Gráfico loss values de entrenamiento y validación respecto a las epocas

```
In [286]: history_dict_w2vgoogle_mx = history_w2vgoogle_mx.history
          dictkeys_w2vgoogle_mx=list(history_dict_w2vgoogle_mx.keys())
          dictkeys_w2vgoogle_mx
          loss_values_w2vgoogle_mx = history_w2vgoogle_mx.history['loss']
          val_loss_values_w2vgoogle_mx = history_w2vgoogle_mx.history['val_loss']
          epochs_w2vgoogle_mx = range(1, len(loss_values_w2vgoogle_mx) + 1)


          plt.figure(figsize=(12,5))
          plt.plot(epochs_w2vgoogle_mx, loss_values_w2vgoogle_mx, 'b', label='Entrenamiento los
          plt.plot(epochs_w2vgoogle_mx, val_loss_values_w2vgoogle_mx, 'g', label='Validación lo
          plt.title('Valor de la función objetivo (loss) en conjuntos de en entrenamiento y val
          plt.xlabel('Epocas')
          plt.ylabel('')
          plt.legend()

          plt.show()
```

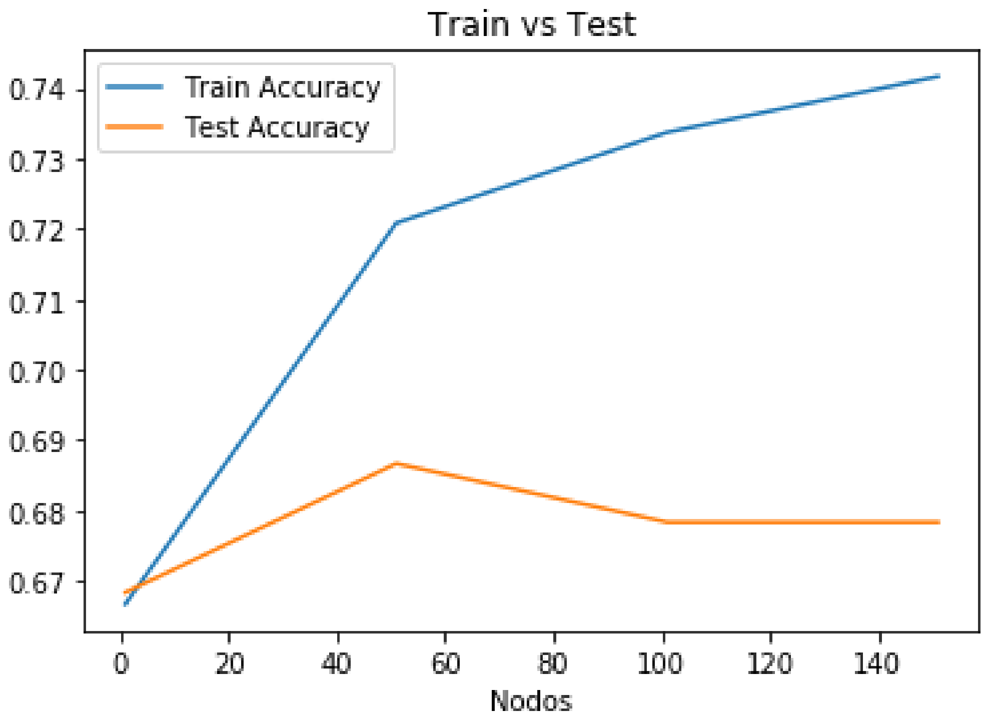


Seleccionando el número de nodos

```
In [287]: batch_size = 100
          epochs = 5 # epocas seleccionadas

          list_nn_w2vgoogle_mx = np.arange( 1, 200, 50) # parámetro de regularización
          score_train_w2vgoogle_mx = np.zeros(len(list_nn_w2vgoogle_mx)) # almacena acurr_w2vg
          score_test_w2vgoogle_mx = np.zeros(len(list_nn_w2vgoogle_mx)) # almacena acurracy pr
          count = 0
          for i in list_nn_w2vgoogle_mx:
              # Build the model
              nn_w2vgoogle_mx = Sequential()
              nn_w2vgoogle_mx.add(Dense(i, activation='relu'))
              nn_w2vgoogle_mx.add(Dropout(0.25))
              nn_w2vgoogle_mx.add(Dense(sz_mx, activation='softmax'))
              nn_w2vgoogle_mx.compile(loss='binary_crossentropy',
                        optimizer='nadam',
                        metrics=['accuracy'])

          # No se utilizan datos de validación
              nn_w2vgoogle_mx.fit(mean_emb_train_w2vgoogle_mx,
                        y_train_w2vgoogle_mx,
                        batch_size= batch_size,
                        shuffle   =True,
                        epochs=epochs,
                        verbose=0)

              temp1_w2vgoogle_mx = nn_w2vgoogle_mx.evaluate(mean_emb_train_w2vgoogle_mx, y_trai
              score_train_w2vgoogle_mx[count] = temp1_w2vgoogle_mx[1]
              temp2_w2vgoogle_mx = nn_w2vgoogle_mx.evaluate(mean_emb_test_w2vgoogle_mx, y_test_
              score_test_w2vgoogle_mx[count]= temp2_w2vgoogle_mx[1]
              count = count + 1
```

Gráfico accuracy datos de entrenamiento y prueba respecto al número de nodos

```
In [288]: matriz_w2vgoogle_mx = np.matrix(np.c_[list_nn_w2vgoogle_mx, score_train_w2vgoogle_mx
          models_w2vgoogle_mx = pd.DataFrame(data = matriz_w2vgoogle_mx, columns =
                       ['Nodos', 'Train Accuracy', 'Test Accuracy'])
          plt.plot(models_w2vgoogle_mx['Nodos'],models_w2vgoogle_mx['Train Accuracy'])
          plt.plot(models_w2vgoogle_mx['Nodos'],models_w2vgoogle_mx['Test Accuracy'])
          plt.title('Train vs Test')
          plt.xlabel('Nodos')
          plt.legend()
          plt.show()
```



In [289]: models_w2vgoogle_mx

Out[289]:

	Nodos	Train Accuracy	Test Accuracy
0	1.0	0.666667	0.668333
1	51.0	0.720833	0.686667
2	101.0	0.733750	0.678333
3	151.0	0.741667	0.678333

In [143]:
```
# Número de nodos seleccionados
nodo_w2vgoogle_mx=51
```

- Diseño final

In [144]:
```
import time
tic=time.time()

np.random.seed(1)

batch_size = 100
epochs = 5

nn_w2vgoogle_mx = Sequential()
nn_w2vgoogle_mx.add(Dense(nodo_w2vgoogle_mx, activation='relu'))
nn_w2vgoogle_mx.add(Dropout(0.25))
```

```
nn_w2vgoogle_mx.add(Dense(sz_mx, activation='softmax'))
nn_w2vgoogle_mx.compile(loss='binary_crossentropy',
              optimizer='nadam',
              metrics=['accuracy'])

history_w2vgoogle_mx = nn_w2vgoogle_mx.fit(mean_emb_train_w2vgoogle_mx,
              y_train_w2vgoogle_mx,
              validation_split=.2,
              batch_size= batch_size,
              shuffle   =True,
              epochs=epochs,
              verbose=2)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
Train on 1920 samples, validate on 480 samples
Epoch 1/5
 - 4s - loss: 0.6711 - acc: 0.6107 - val_loss: 0.5061 - val_acc: 0.8854
Epoch 2/5
 - 0s - loss: 0.6498 - acc: 0.6255 - val_loss: 0.4891 - val_acc: 0.8854
Epoch 3/5
 - 0s - loss: 0.6383 - acc: 0.6432 - val_loss: 0.5238 - val_acc: 0.8688
Epoch 4/5
 - 0s - loss: 0.6251 - acc: 0.6578 - val_loss: 0.4817 - val_acc: 0.8771
Epoch 5/5
 - 1s - loss: 0.6157 - acc: 0.6656 - val_loss: 0.5610 - val_acc: 0.8000
Tiempo de procesamiento (secs):  6.839789867401123
```

- Guardar de modelo

```
In [231]: from keras.models import load_model
          #nn_w2vgoogle_mx.save('nn_mexico_w2vgoogle')  # Guardar modelo
          nn_w2vgoogle_mx = load_model('nn_mexico_w2vgoogle') # Cargar modelo

In [232]: results_w2vgoogle_mx = nn_w2vgoogle_mx.evaluate(mean_emb_test_w2vgoogle_mx, y_test_w2
          print('Test loss:', results_w2vgoogle_mx[0])
          print('Test accuracy:', results_w2vgoogle_mx[1])
```

```
600/600 [==============================] - 0s 821us/step
Test loss: 0.6330192804336547
Test accuracy: 0.676666665871938
```

```
In [233]: y_pred_w2vgoogle_mx = nn_w2vgoogle_mx.predict(mean_emb_test_w2vgoogle_mx).squeeze()

          import numpy as np
          from sklearn.metrics import confusion_matrix, precision_score, recall_score, f1_score
```

```
y_test_label_w2vgoogle_mx = np.argmax(y_test_w2vgoogle_mx,1)
y_pred_label_w2vgoogle_mx = np.argmax(y_pred_w2vgoogle_mx,1)

# Confusion matrix
C=confusion_matrix(y_test_label_w2vgoogle_mx , y_pred_label_w2vgoogle_mx)
print(C)
```

```
[[336  65]
 [129  70]]
```

12.0.4 Resultados

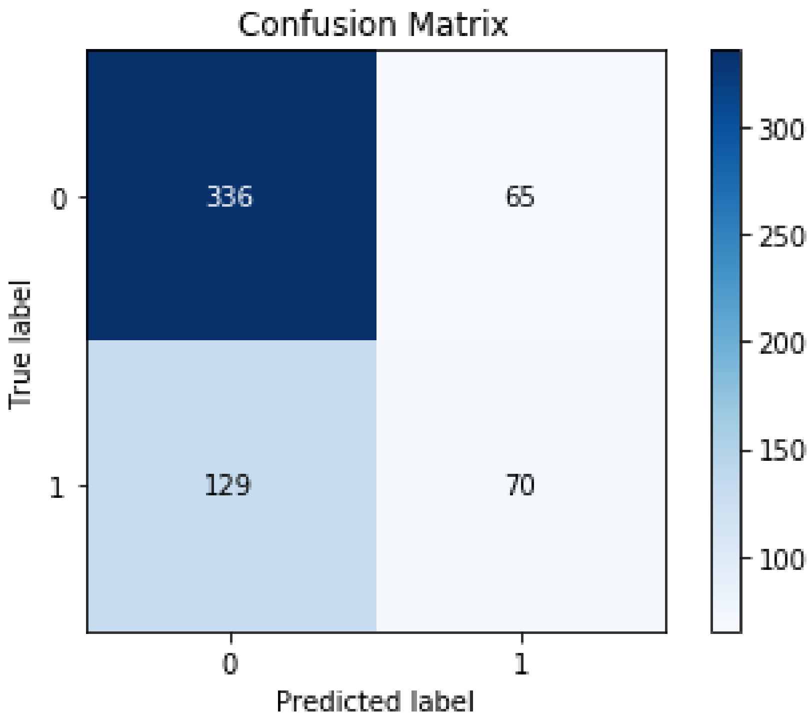
```
In [234]: print('Accuracy score:', results_w2vgoogle_mx[1])  # nn evaluate keras
          print("F1 score", f1_score( y_test_label_w2vgoogle_mx,  y_pred_label_w2vgoogle_mx, av
          print("F1 weighted", f1_score( y_test_label_w2vgoogle_mx,  y_pred_label_w2vgoogle_mx
          print("Recall score", recall_score( y_test_label_w2vgoogle_mx,  y_pred_label_w2vgoogl
          print("Precision score", precision_score( y_test_label_w2vgoogle_mx,  y_pred_label_w2
```

```
Accuracy score: 0.676666665871938
F1 score 0.5975716004480647
F1 weighted 0.6576362747945219
Recall score 0.5948320154387899
Precision score 0.6205495818399044
```

```
In [235]: from sklearn.metrics import classification_report
          print(classification_report(y_test_label_w2vgoogle_mx, y_pred_label_w2vgoogle_mx, ta
```

```
              precision    recall  f1-score   support

   no-ironia       0.72      0.84      0.78       401
      ironia       0.52      0.35      0.42       199

   micro avg       0.68      0.68      0.68       600
   macro avg       0.62      0.59      0.60       600
weighted avg       0.65      0.68      0.66       600
```

```
In [85]: %matplotlib inline
         import matplotlib.pyplot as plt
         import scikitplot

         scikitplot.metrics.plot_confusion_matrix(y_test_label_w2vgoogle_mx, y_pred_label_w2vg

Out[85]: <matplotlib.axes._subplots.AxesSubplot at 0x219252d7da0>
```



13 Clasificador SVM

- Selección de modelo

```
In [466]: from sklearn.pipeline import Pipeline
          from sklearn.svm import LinearSVC
          from sklearn.model_selection import GridSearchCV
          from sklearn.preprocessing import StandardScaler
          import time
          tic=time.time()

          SVCpipe = Pipeline([('SVC',LinearSVC(class_weight="balanced", random_state=1,verbose=

          # Gridsearch to determine the value of C
          param_grid = {'SVC__C':np.arange(.1,2,.1)}
          linearSVC = GridSearchCV(SVCpipe,param_grid,cv=5,return_train_score=True, verbose=0)
          linearSVC.fit(mean_emb_train_w2vgoogle_mx, y_train.values)
          print(linearSVC.best_params_)
          #linearSVC.coef_
          #linearSVC.intercept_

          svc_w2vgoogle_mx = linearSVC.best_estimator_
          svc_w2vgoogle_mx.fit(mean_emb_train_w2vgoogle_mx, y_train.values)
```

```
        svc_w2vgoogle_mx.coef_ = svc_w2vgoogle_mx.named_steps['SVC'].coef_
        svc_w2vgoogle_mx.score(mean_emb_train_w2vgoogle_mx, y_train.values)

        print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
{'SVC__C': 1.4000000000000001}
Tiempo de procesamiento (secs):  132.83149933815002
```

Gráfico acurracy datos de entrenamiento y de prueba respecto al parámetro de rugularización

- Guardar modelo

```
In [236]: from joblib import dump, load
          #dump(svc_w2vgoogle_mx, 'svc_w2vgoogle_mx.joblib')
          svc_w2vgoogle_mx = load('svc_w2vgoogle_mx.joblib')
```

```
In [64]: prediction_w2vgoogle_mx=svc_w2vgoogle_mx.predict(mean_emb_test_w2vgoogle_mx)
         print("Confusion Metrix:\n",metrics.confusion_matrix(y_test.values, prediction_w2vgoog
```

```
Confusion Metrix:
 [[278 123]
 [ 85 114]]
```

13.0.1 Resultados

```
In [237]: print('Accuracy score:', metrics.accuracy_score( y_test.values, prediction_w2vgoogle_
          print("F1 score", f1_score(y_test.values, prediction_w2vgoogle_mx,  average='macro'))
          print("F1 weighted", f1_score(y_test.values, prediction_w2vgoogle_mx, average='weigh
          print("Recall score", recall_score(y_test.values, prediction_w2vgoogle_mx,  average=
          print("Precision score", precision_score(y_test.values, prediction_w2vgoogle_mx, ave
```

```
Accuracy score: 0.6533333333333333
F1 score 0.6253422354579952
F1 weighted 0.6598190755239606
Recall score 0.633065577262873
Precision score 0.6234264393067614
```

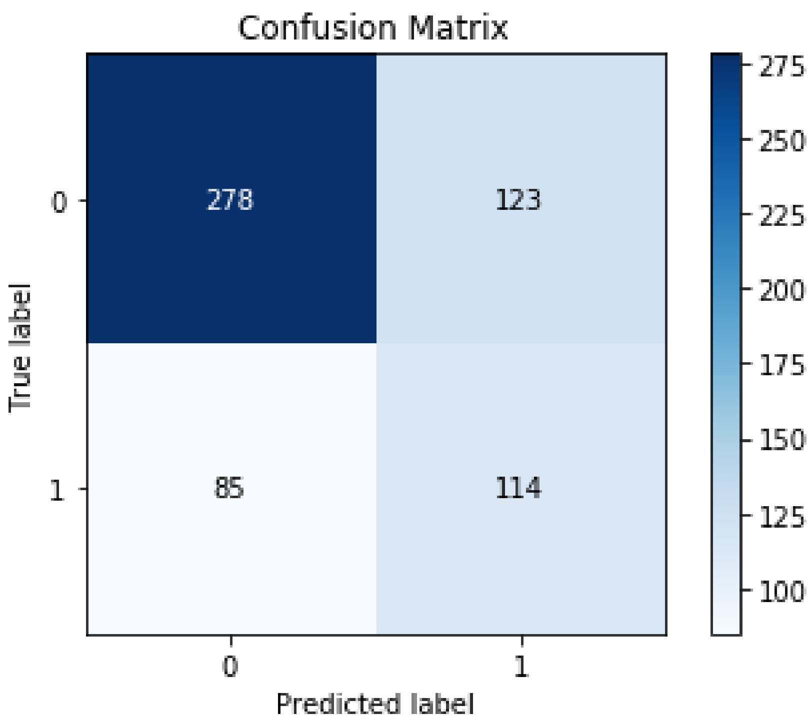
```
In [238]: from sklearn.metrics import classification_report
          print(classification_report(y_test.values, prediction_w2vgoogle_mx,  target_names=['
```

```
              precision    recall  f1-score   support

   no-ironia       0.77      0.69      0.73       401
      ironia       0.48      0.57      0.52       199

   micro avg       0.65      0.65      0.65       600
```

```
   macro avg       0.62      0.63      0.63       600
weighted avg       0.67      0.65      0.66       600
```

```
In [90]: %matplotlib inline
         import matplotlib.pyplot as plt
         import scikitplot

         scikitplot.metrics.plot_confusion_matrix(y_test.values, prediction_w2vgoogle_mx)
```

```
Out[90]: <matplotlib.axes._subplots.AxesSubplot at 0x21a1c8e1f98>
```



14 Word2vec google España

```
In [91]: x_train_españa.head()
         print(x_train_españa.shape)
```

```
(2400,)
```

```
In [92]: x_test_españa.head()
         print(x_test_españa.shape)
```

```
(600,)
```

- Limpiando corpus de entrenamiento y de prueba

```
In [239]: #Limpiando datos de entrenamiento
          num= x_train_españa.size

          clean_train_es = []


          for i in range( 0, num):

              clean_train_es.append( review_to_words2(x_train_españa.values[i] ) )

          x_train_w2vgoogle_es = clean_train_es

In [240]: #Limpiando datos de prueba
          num= x_test_españa.size
          # Lista para guardar twits limpios
          clean_test_es = []


          for i in range( 0, num):

              clean_test_es.append( review_to_words2(x_test_españa.values[i] ) )

          x_test_w2vgoogle_es = clean_test_es

In [241]: x_train_w2vgoogle_es = train_es["TOPIC"].astype(str).str.cat(x_train_w2vgoogle_es, se
          x_test_w2vgoogle_es = test_es["TOPIC_y"].astype(str).str.cat(x_test_w2vgoogle_es, sep

In [96]: x_train_w2vgoogle_es[10]

Out[96]: 'TARDÀ escuchando joan tardà carnecrudaradio febrero sé preguntarse haría psoe si pedi

In [97]: x_test_w2vgoogle_es[10]

Out[97]: 'FRANCO decisión conoce día después auto paralizara permiso urbanístico exhumación di
```

- Representación Word2vec average

```
In [242]: mean_embedding_vectorizer_google_es = MeanEmbeddingVectorizer(modelo_google)
          mean_emb_train_w2vgoogle_es = mean_embedding_vectorizer_google_es.fit_transform(x_tra

          mean_emb_test_w2vgoogle_es = mean_embedding_vectorizer_google_es.fit_transform(x_test

C:\Users\h_air\Anaconda3\envs\tensorflow-gpu\lib\site-packages\ipykernel_launcher.py:24: Depre
```

14.0.1 Clasificador NN

```
In [243]: from keras.utils import to_categorical

          y_train_w2vgoogle_es = to_categorical(y_train_es)
          y_test_w2vgoogle_es  = to_categorical(y_test_es)

          num_es, sz_es = y_train_w2vgoogle_es.shape

          print(num_es)
          print(sz_es)
```

```
2400
2
```

14.0.2 Selección de modelo

- Número de epocas

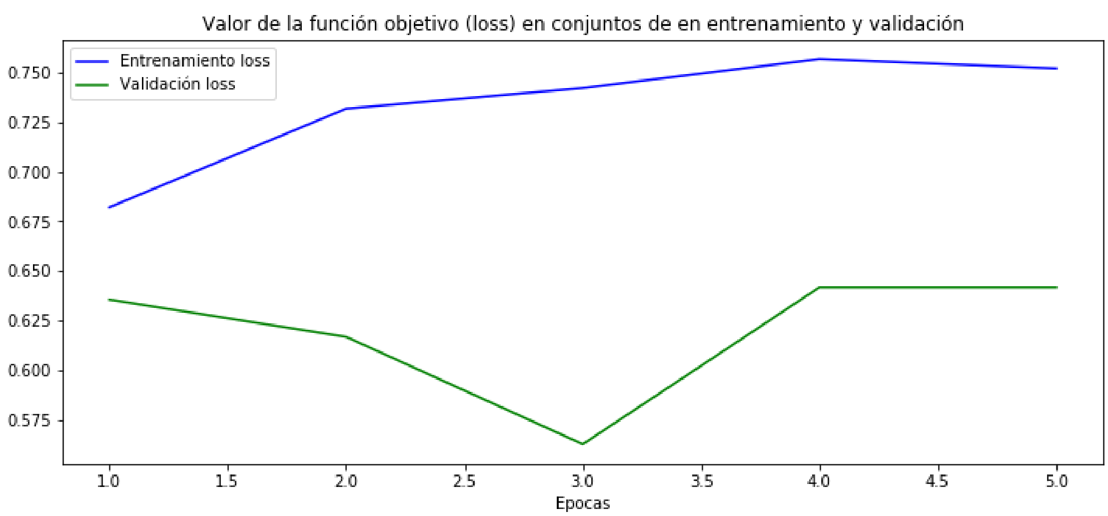
```
In [313]: import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 100
          epochs = 5

          nn_w2vgoogle_es = Sequential()
          nn_w2vgoogle_es.add(Dense(512, activation='relu'))
          nn_w2vgoogle_es.add(Dropout(0.25))
          nn_w2vgoogle_es.add(Dense(sz_es, activation='softmax'))
          nn_w2vgoogle_es.compile(loss='binary_crossentropy',
                        optimizer='nadam',
                        metrics=['accuracy'])

          history_w2vgoogle_es = nn_w2vgoogle_es.fit(mean_emb_train_w2vgoogle_es,
                        y_train_w2vgoogle_es,
                        validation_split=.2,
                        batch_size= batch_size,
                        shuffle   =True,
                        epochs=epochs,
                        verbose=2)

          print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
Train on 1920 samples, validate on 480 samples
Epoch 1/5
 - 15s - loss: 0.5929 - acc: 0.6820 - val_loss: 0.6702 - val_acc: 0.6354
```

```
Epoch 2/5
 - 0s - loss: 0.5595 - acc: 0.7318 - val_loss: 0.6631 - val_acc: 0.6167
Epoch 3/5
 - 0s - loss: 0.5362 - acc: 0.7422 - val_loss: 0.7379 - val_acc: 0.5625
Epoch 4/5
 - 0s - loss: 0.5126 - acc: 0.7568 - val_loss: 0.6844 - val_acc: 0.6417
Epoch 5/5
 - 0s - loss: 0.5170 - acc: 0.7521 - val_loss: 0.7277 - val_acc: 0.6417
Tiempo de procesamiento (secs):  15.89423394203186
```

Gráfico datos de entrenamiento y validación loss values respecto epocas

In [315]:
```
history_dict_w2vgoogle_es = history_w2vgoogle_es.history
dictkeys_w2vgoogle_es=list(history_dict_w2vgoogle_es.keys())
dictkeys_w2vgoogle_es

loss_values_w2vgoogle_es = history_w2vgoogle_es.history['acc']
val_loss_values_w2vgoogle_es = history_w2vgoogle_es.history['val_acc']
epochs_w2vgoogle_es = range(1, len(loss_values_w2vgoogle_es) + 1)


plt.figure(figsize=(12,5))
plt.plot(epochs_w2vgoogle_es, loss_values_w2vgoogle_es, 'b', label='Entrenamiento los
plt.plot(epochs_w2vgoogle_es, val_loss_values_w2vgoogle_es, 'g', label='Validación lo
plt.title('Valor de la función objetivo (loss) en conjuntos de en entrenamiento y val
plt.xlabel('Epocas')
plt.ylabel('')
plt.legend()

plt.show()
```

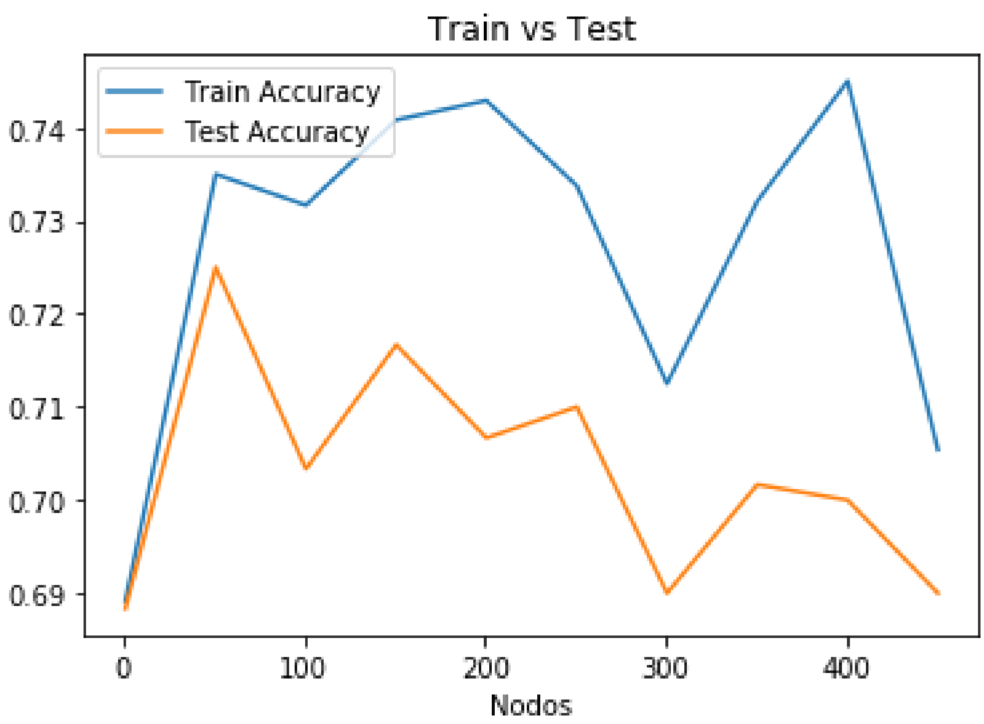


- Selección del número de nodos

```
In [316]: batch_size = 100
          epochs = 2 # epocas seleccionadas

          list_nn_w2vgoogle_es= np.arange( 1, 500, 50) # parámetro de regularización
          score_train_w2vgoogle_es = np.zeros(len(list_nn_w2vgoogle_es)) # almacena acurr_w2vg
          score_test_w2vgoogle_es = np.zeros(len(list_nn_w2vgoogle_es)) # almacena acurracy pr
          count = 0
          for i in list_nn_w2vgoogle_es:
              # Build the model
              nn_w2vgoogle_es = Sequential()
              nn_w2vgoogle_es.add(Dense(i, activation='relu'))
              nn_w2vgoogle_es.add(Dropout(0.25))
              nn_w2vgoogle_es.add(Dense(sz_es, activation='softmax'))
              nn_w2vgoogle_es.compile(loss='binary_crossentropy',
                          optimizer='nadam',
                          metrics=['accuracy'])

          # No se utilizan datos de validación
              nn_w2vgoogle_es.fit(mean_emb_train_w2vgoogle_es,
                          y_train_w2vgoogle_es,
                          batch_size= batch_size,
                          shuffle   =True,
                          epochs=epochs,
                          verbose=0)

              temp1_w2vgoogle_es = nn_w2vgoogle_es.evaluate(mean_emb_train_w2vgoogle_es, y_trai
              score_train_w2vgoogle_es[count] = temp1_w2vgoogle_es[1]
              temp2_w2vgoogle_es = nn_w2vgoogle_es.evaluate(mean_emb_test_w2vgoogle_es, y_test_
              score_test_w2vgoogle_es[count]= temp2_w2vgoogle_es[1]
              count = count + 1
```

Gráfica accuracy entrenameinto y prueba respecto número de nodos

```
In [317]: matriz_w2vgoogle_es = np.matrix(np.c_[list_nn_w2vgoogle_es, score_train_w2vgoogle_es
          models_w2vgoogle_es = pd.DataFrame(data = matriz_w2vgoogle_es, columns =
                       ['Nodos', 'Train Accuracy', 'Test Accuracy'])
          plt.plot(models_w2vgoogle_es['Nodos'],models_w2vgoogle_es['Train Accuracy'])
          plt.plot(models_w2vgoogle_es['Nodos'],models_w2vgoogle_es['Test Accuracy'])
          plt.title('Train vs Test')
          plt.xlabel('Nodos')
          plt.legend()
          plt.show()
```



In [318]:
```
models_w2vgoogle_es
```

Out[318]:

	Nodos	Train Accuracy	Test Accuracy
0	1.0	0.689167	0.688333
1	51.0	0.735000	0.725000
2	101.0	0.731667	0.703333
3	151.0	0.740833	0.716667
4	201.0	0.742917	0.706667
5	251.0	0.733750	0.710000
6	301.0	0.712500	0.690000
7	351.0	0.732083	0.701667
8	401.0	0.745000	0.700000
9	451.0	0.705417	0.690000

In [319]:
```
# número de nodos seleccionados
nodo_w2vgoogle_es=151
```

- Diseño final

In [320]:
```
import time
tic=time.time()

np.random.seed(1)
```

```
batch_size = 100
epochs = 2

nn_w2vgoogle_es = Sequential()
nn_w2vgoogle_es.add(Dense(nodo_w2vgoogle_es, activation='relu'))
nn_w2vgoogle_es.add(Dropout(0.25))
nn_w2vgoogle_es.add(Dense(sz_es, activation='softmax'))
nn_w2vgoogle_es.compile(loss='binary_crossentropy',
              optimizer='nadam',
              metrics=['accuracy'])

history_w2vgoogle_es = nn_w2vgoogle_es.fit(mean_emb_train_w2vgoogle_es,
              y_train_w2vgoogle_es,
              validation_split=.2,
              batch_size= batch_size,
              shuffle   =True,
              epochs=epochs,
              verbose=2)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
Train on 1920 samples, validate on 480 samples
Epoch 1/2
 - 13s - loss: 0.6030 - acc: 0.6716 - val_loss: 0.6699 - val_acc: 0.6062
Epoch 2/2
 - 0s - loss: 0.5621 - acc: 0.7302 - val_loss: 0.6676 - val_acc: 0.6167
Tiempo de procesamiento (secs):  13.689913272857666
```

- Guardar modelo seleccionado

```
In [244]: from keras.models import load_model
          #nn_w2vgoogle_es.save('nn_españa_w2vgoogle')  # Guardar modelo
          nn_w2vgoogle_es = load_model('nn_españa_w2vgoogle') # Cargar modelo
```

```
In [245]: results_w2vgoogle_es = nn_w2vgoogle_es.evaluate(mean_emb_test_w2vgoogle_es, y_test_w2
          print('Test loss:', results_w2vgoogle_es[0])
          print('Test accuracy:', results_w2vgoogle_es[1])
```

```
600/600 [==============================] - 0s 632us/step
Test loss: 0.5817617440223694
Test accuracy: 0.698333334128062
```

```
In [246]: y_pred_w2vgoogle_es = nn_w2vgoogle_es.predict(mean_emb_test_w2vgoogle_es).squeeze()

          import numpy as np
          from sklearn.metrics import confusion_matrix, precision_score, recall_score, f1_score
```

```
y_test_label_w2vgoogle_es = np.argmax(y_test_w2vgoogle_es,1)
y_pred_label_w2vgoogle_es = np.argmax(y_pred_w2vgoogle_es,1)

# Confusion matrix
C=confusion_matrix(y_test_label_w2vgoogle_es , y_pred_label_w2vgoogle_es)
print(C)
```

```
[[350  50]
 [131  69]]
```

14.0.3 Resultados

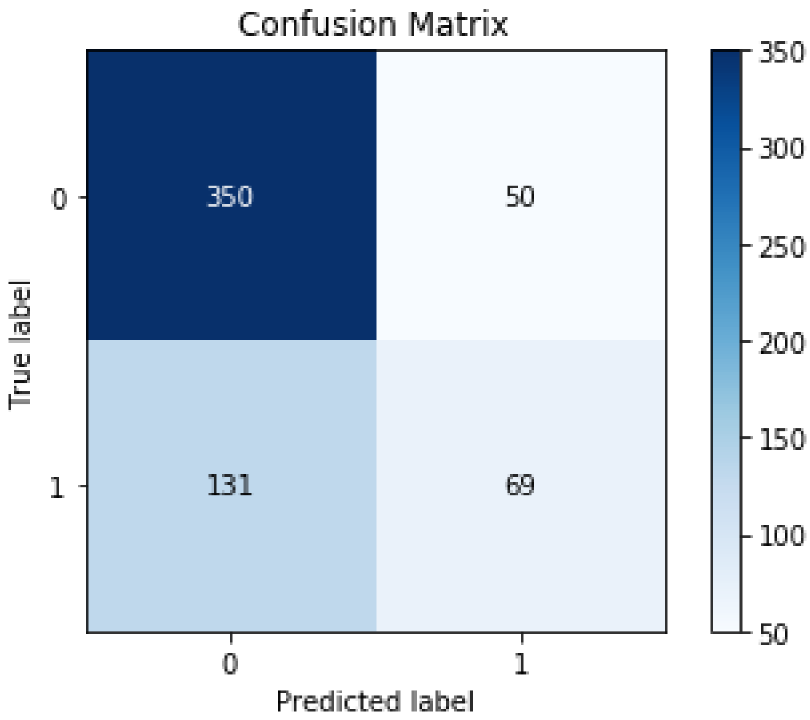
```
In [247]: print('Accuracy score:', results_w2vgoogle_es[1])  # nn evaluate keras
          print("F1 score", f1_score(y_test_label_w2vgoogle_es,  y_pred_label_w2vgoogle_es,  av
          print("F1 weighted", f1_score(y_test_label_w2vgoogle_es,  y_pred_label_w2vgoogle_es,
          print("Recall score", recall_score(y_test_label_w2vgoogle_es,  y_pred_label_w2vgoogle
          print("Precision score", precision_score(y_test_label_w2vgoogle_es,  y_pred_label_w2v
```

```
Accuracy score: 0.698333334128062
F1 score 0.6135767633673618
F1 weighted 0.6739017241972347
Recall score 0.61
Precision score 0.6537413302119185
```

```
In [248]: from sklearn.metrics import classification_report
          print(classification_report(y_test_label_w2vgoogle_es, y_pred_label_w2vgoogle_es,targ
```

```
              precision    recall  f1-score   support

   no-ironia       0.73      0.88      0.79       400
      ironia       0.58      0.34      0.43       200

   micro avg       0.70      0.70      0.70       600
   macro avg       0.65      0.61      0.61       600
weighted avg       0.68      0.70      0.67       600
```

```
In [105]: %matplotlib inline
          import matplotlib.pyplot as plt
          import scikitplot

          scikitplot.metrics.plot_confusion_matrix(y_test_label_w2vgoogle_es, y_pred_label_w2vg

Out[105]: <matplotlib.axes._subplots.AxesSubplot at 0x21a3051ea90>
```



15 Clasificador SVM

- Selección del modelo

In [191]:
```
from sklearn.pipeline import Pipeline
from sklearn.svm import LinearSVC
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
import time
tic=time.time()

SVCpipe = Pipeline([('SVC',LinearSVC(class_weight="balanced", random_state=1,verbose=

# Gridsearch to determine the value of C
param_grid = {'SVC__C':np.arange(.1,2,.1)}
linearSVC = GridSearchCV(SVCpipe,param_grid,cv=5,return_train_score=True, verbose=0)
linearSVC.fit(mean_emb_train_w2vgoogle_es, y_train_es.values)
print(linearSVC.best_params_)
#linearSVC.coef_
#linearSVC.intercept_

svc_w2vgoogle_es = linearSVC.best_estimator_
svc_w2vgoogle_es.fit(mean_emb_train_w2vgoogle_es, y_train_es.values)
```

```
svc_w2vgoogle_es.coef_ = svc_w2vgoogle_es.named_steps['SVC'].coef_
svc_w2vgoogle_es.score(mean_emb_train_w2vgoogle_es, y_train_es.values)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
{'SVC__C': 0.1}
Tiempo de procesamiento (secs):  28.22266721725464
```

- Gráfica accuracy datos de entrenamiento y de prueba respecto al parámetro de regularización

- Guardar el modelo

```
In [249]: from joblib import dump, load
          #dump(svc_w2vgoogle_es, 'svc_w2vgoogle_es.joblib') # Guardar modelo
          svc_w2vgoogle_es = load('svc_w2vgoogle_es.joblib') # Cargar modelo
```

```
In [250]: prediction_w2vgoogle_es=svc_w2vgoogle_es.predict(mean_emb_test_w2vgoogle_es)
          print("Acurracy Test",metrics.accuracy_score(prediction_w2vgoogle_es, y_test_es.valu
```

```
Acurracy Test 0.6916666666666667
```

```
In [251]: print("Confusion Metrix:\n",metrics.confusion_matrix(y_test_es.values, prediction_w2v
```

```
Confusion Metrix:
 [[299 101]
 [ 84 116]]
```

15.0.1 Resultados

```
In [252]: print('Accuracy score:', metrics.accuracy_score(y_test_es.values, prediction_w2vgoogl
          print("F1 score", f1_score(y_test_es.values, prediction_w2vgoogle_es,  average='macro
          print("F1 weighted", f1_score(y_test_es.values, prediction_w2vgoogle_es,  average='we
          print("Recall score", recall_score(y_test_es.values, prediction_w2vgoogle_es,  averag
          print("Precision score", precision_score(y_test_es.values, prediction_w2vgoogle_es,
```

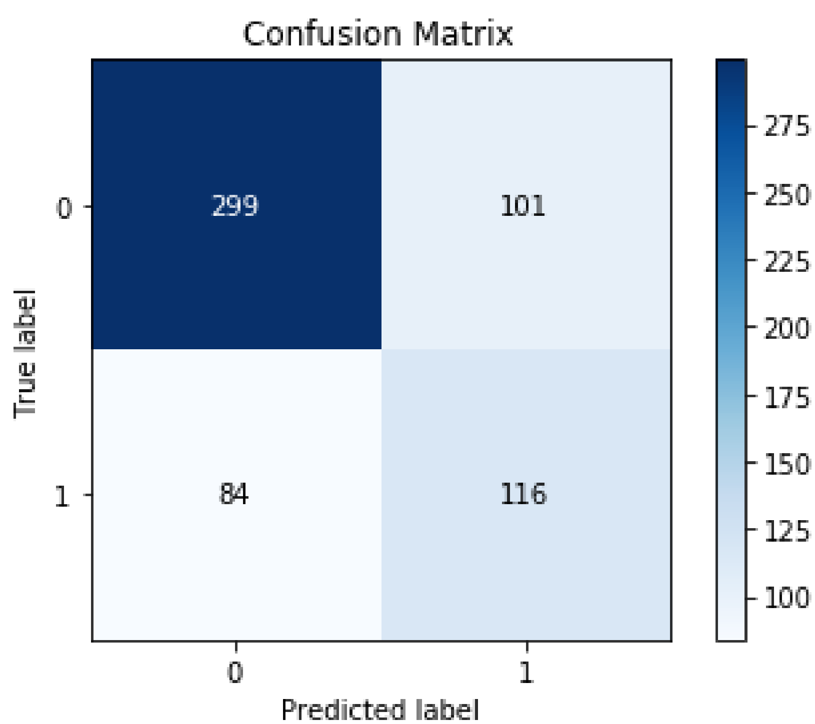
```
Accuracy score: 0.6916666666666667
F1 score 0.6600420812775067
F1 weighted 0.6946044696809603
Recall score 0.6637500000000001
Precision score 0.6576205315782508
```

```
In [253]: from sklearn.metrics import classification_report
          print(classification_report( y_test_es.values, prediction_w2vgoogle_es, target_names=
```

```
              precision    recall  f1-score   support

   no-ironia       0.78      0.75      0.76       400
      ironia       0.53      0.58      0.56       200

   micro avg       0.69      0.69      0.69       600
   macro avg       0.66      0.66      0.66       600
weighted avg       0.70      0.69      0.69       600
```

In [111]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import scikitplot

scikitplot.metrics.plot_confusion_matrix(y_test_es.values, prediction_w2vgoogle_es)
```

Out[111]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x21a305a9048>
```



16 Word2vec google Cuba

In [112]:
```
x_train_cuba.head()
print(x_train_cuba.shape)
```

```
(2400,)
```

```
In [113]: x_test_cuba.head()
          print(x_test_cuba.shape)
```

```
(600,)
```

- Limpieza de datos

```
In [254]: #Limpiando datos de entrenamiento
          num= x_train_cuba.size

          clean_train_cu = []

          for i in range( 0, num):

              clean_train_cu.append( review_to_words2(x_train_cuba.values[i] ) )
          x_train_w2vgoogle_cu = clean_train_cu
```

```
In [255]: #Limpiando datos de prueba
          num= x_test_cuba.size

          clean_test_cu = []

          for i in range( 0, num):
              clean_test_cu.append( review_to_words2(x_test_cuba.values[i] ) )

          x_test_w2vgoogle_cu = clean_test_cu
```

```
In [256]: x_train_w2vgoogle_cu = train_cu["TOPIC"].astype(str).str.cat(x_train_w2vgoogle_cu, se
          x_test_w2vgoogle_cu = test_cu["TOPIC_y"].astype(str).str.cat(x_test_w2vgoogle_cu, sep
```

```
In [117]: x_train_w2vgoogle_cu[0]
```

```
Out[117]: 'TELEVISIÓN DIGITAL, CAJAS DECODIFICADORAS, TELEVISIÓN CUBANA, AUDIOVISUALES magnific
```

```
In [118]: x_test_w2vgoogle_cu[0]
```

```
Out[118]: 'ECONOMÍA. TURISMOS, HOTELES oferta persona noche habitación doble hoy febrero precio
```

- Representación W2vec Google average

```
In [257]: mean_embedding_vectorizer_google_cu = MeanEmbeddingVectorizer(modelo_google)
          mean_emb_train_w2vgoogle_cu = mean_embedding_vectorizer_google_cu.fit_transform(x_tra
          mean_emb_test_w2vgoogle_cu = mean_embedding_vectorizer_google_cu.fit_transform(x_test
```

```
C:\Users\h_air\Anaconda3\envs\tensorflow-gpu\lib\site-packages\ipykernel_launcher.py:24: Deprec
```

Clasificador NN

```
In [258]: from keras.utils import to_categorical

          y_train_w2vgoogle_cu = to_categorical(y_train_cu)
          y_test_w2vgoogle_cu  = to_categorical(y_test_cu)

          num_cu, sz_cu = y_train_w2vgoogle_cu.shape

          print(num_cu)
          print(sz_cu)
```

```
2400
2
```

16.0.1 Selección de modelos

- Número de nodos

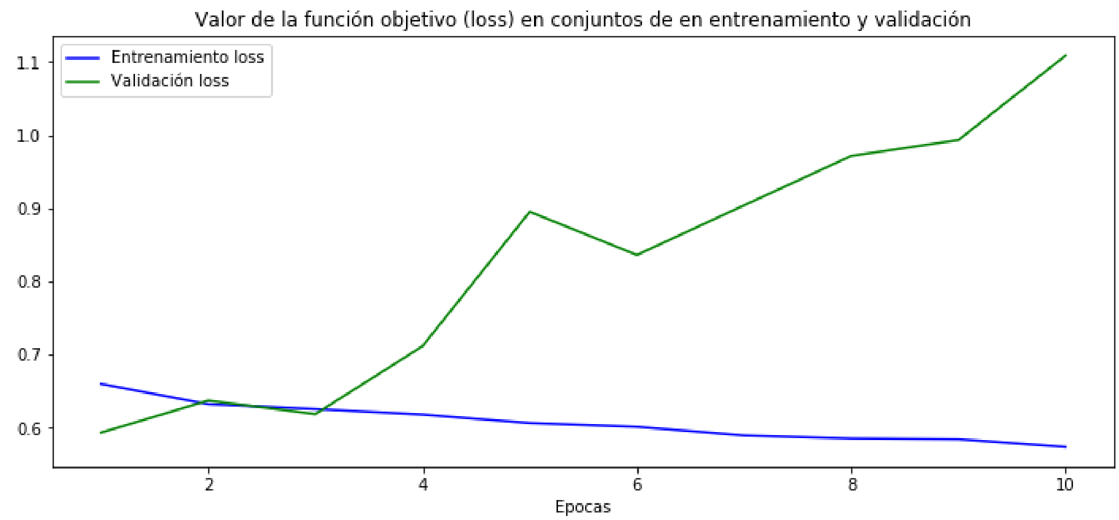
```
In [166]: import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 100
          epochs = 10

          nn_w2vgoogle_cu = Sequential()
          nn_w2vgoogle_cu.add(Dense(100, activation='relu'))
          nn_w2vgoogle_cu.add(Dropout(0.25))
          nn_w2vgoogle_cu.add(Dense(sz_cu, activation='softmax'))
          nn_w2vgoogle_cu.compile(loss='binary_crossentropy',
                        optimizer='nadam',
                        metrics=['accuracy'])

          history_w2vgoogle_cu = nn_w2vgoogle_cu.fit(mean_emb_train_w2vgoogle_cu,
                        y_train_w2vgoogle_cu,
                        validation_split=.2,
                        batch_size= batch_size,
                        shuffle   =True,
                        epochs=epochs,
                        verbose=2)

          print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
Train on 1920 samples, validate on 480 samples
Epoch 1/10
 - 1s - loss: 0.6600 - acc: 0.6286 - val_loss: 0.5935 - val_acc: 0.7521
```

```
Epoch 2/10
 - 0s - loss: 0.6323 - acc: 0.6609 - val_loss: 0.6373 - val_acc: 0.6833
Epoch 3/10
 - 0s - loss: 0.6257 - acc: 0.6589 - val_loss: 0.6188 - val_acc: 0.7104
Epoch 4/10
 - 0s - loss: 0.6182 - acc: 0.6719 - val_loss: 0.7117 - val_acc: 0.5938
Epoch 5/10
 - 0s - loss: 0.6066 - acc: 0.6812 - val_loss: 0.8953 - val_acc: 0.4250
Epoch 6/10
 - 0s - loss: 0.6015 - acc: 0.6880 - val_loss: 0.8363 - val_acc: 0.4646
Epoch 7/10
 - 0s - loss: 0.5896 - acc: 0.6969 - val_loss: 0.9041 - val_acc: 0.4417
Epoch 8/10
 - 0s - loss: 0.5855 - acc: 0.7036 - val_loss: 0.9716 - val_acc: 0.4479
Epoch 9/10
 - 0s - loss: 0.5844 - acc: 0.6948 - val_loss: 0.9933 - val_acc: 0.4542
Epoch 10/10
 - 0s - loss: 0.5740 - acc: 0.7042 - val_loss: 1.1088 - val_acc: 0.4438
Tiempo de procesamiento (secs):  2.8403916358947754
```

Gráfica accuracy datos de entrebamiento y de validación respecto al número de epocas

```
In [167]: history_dict_w2vgoogle_cu = history_w2vgoogle_cu.history
          dictkeys_w2vgoogle_cu=list(history_dict_w2vgoogle_cu.keys())
          loss_values_w2vgoogle_cu = history_w2vgoogle_cu.history['loss']
          val_loss_values_w2vgoogle_cu = history_w2vgoogle_cu.history['val_loss']
          epochs_w2vgoogle_cu = range(1, len(loss_values_w2vgoogle_cu) + 1)


          plt.figure(figsize=(12,5))
          plt.plot(epochs_w2vgoogle_cu, loss_values_w2vgoogle_cu, 'b', label='Entrenamiento los
          plt.plot(epochs_w2vgoogle_cu, val_loss_values_w2vgoogle_cu, 'g', label='Validación lo
          plt.title('Valor de la función objetivo (loss) en conjuntos de en entrenamiento y val
          plt.xlabel('Epocas')
          plt.ylabel('')
          plt.legend()

          plt.show()
```



- selección del número de nodos

```
In [184]: batch_size = 100
          epochs = 3 # epocas seleccionadas

          list_nn_w2vgoogle_cu= np.arange( 1, 800, 50) # parámetro de regularización
          score_train_w2vgoogle_cu = np.zeros(len(list_nn_w2vgoogle_cu)) # almacena acurr_w2vg
          score_test_w2vgoogle_cu = np.zeros(len(list_nn_w2vgoogle_cu)) # almacena acurracy pr
          count = 0
          for i in list_nn_w2vgoogle_cu:
              # Build the model
              nn_w2vgoogle_cu = Sequential()
              nn_w2vgoogle_cu.add(Dense(i, activation='relu'))
              nn_w2vgoogle_cu.add(Dropout(0.25))
              nn_w2vgoogle_cu.add(Dense(sz_cu, activation='softmax'))
              nn_w2vgoogle_cu.compile(loss='binary_crossentropy',
                          optimizer='nadam',
                          metrics=['accuracy'])

          # No se utilizan datos de validación
              nn_w2vgoogle_cu.fit(mean_emb_train_w2vgoogle_cu,
                          y_train_w2vgoogle_cu,
                          batch_size= batch_size,
                          shuffle   =True,
                          epochs=epochs,
                          verbose=0)

              temp1_w2vgoogle_cu = nn_w2vgoogle_cu.evaluate(mean_emb_train_w2vgoogle_cu, y_trai
              score_train_w2vgoogle_cu[count] = temp1_w2vgoogle_cu[1]
              temp2_w2vgoogle_cu = nn_w2vgoogle_cu.evaluate(mean_emb_test_w2vgoogle_cu, y_test_
```

```
        score_test_w2vgoogle_cu[count]= temp2_w2vgoogle_cu[1]
        count = count + 1
```

Gráfico accuracy datos de entrenamiento y de prueba respecto al número de nodos

```
In [185]: matriz_w2vgoogle_cu = np.matrix(np.c_[list_nn_w2vgoogle_cu, score_train_w2vgoogle_cu
          models_w2vgoogle_cu = pd.DataFrame(data = matriz_w2vgoogle_cu, columns =
                       ['Nodos', 'Train Accuracy', 'Test Accuracy'])
          plt.plot(models_w2vgoogle_cu['Nodos'],models_w2vgoogle_cu['Train Accuracy'])
          plt.plot(models_w2vgoogle_cu['Nodos'],models_w2vgoogle_cu['Test Accuracy'])
          plt.title('Train vs Test')
          plt.xlabel('Nodos')
          plt.legend()
          plt.show()
```


```
In [186]: models_w2vgoogle_cu
```

Out[186]:

	Nodos	Train Accuracy	Test Accuracy
0	1.0	0.666667	0.666667
1	51.0	0.672083	0.663333
2	101.0	0.676667	0.668333
3	151.0	0.683750	0.678333
4	201.0	0.671250	0.673333
5	251.0	0.697917	0.678333

```
6   301.0        0.687500       0.680000
7   351.0        0.686667       0.671667
8   401.0        0.686667       0.666667
9   451.0        0.615833       0.595000
10  501.0        0.682083       0.666667
11  551.0        0.695417       0.673333
12  601.0        0.677500       0.666667
13  651.0        0.687083       0.671667
14  701.0        0.684167       0.670000
15  751.0        0.679583       0.670000
```

- Diseño final

```
In [183]: nodo_w2vgoogle_cu=351#Número de nodos seleccionados
```

```
In [184]: import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 100
          epochs = 5

          nn_w2vgoogle_cu = Sequential()
          nn_w2vgoogle_cu.add(Dense(nodo_w2vgoogle_cu, activation='relu'))
          nn_w2vgoogle_cu.add(Dropout(0.25))
          nn_w2vgoogle_cu.add(Dense(sz_cu, activation='softmax'))
          nn_w2vgoogle_cu.compile(loss='binary_crossentropy',
                        optimizer='nadam',
                        metrics=['accuracy'])

          history_w2vgoogle_cu = nn_w2vgoogle_cu.fit(mean_emb_train_w2vgoogle_cu,
                        y_train_w2vgoogle_cu,
                        validation_split=.2,
                        batch_size= batch_size,
                        shuffle   =True,
                        epochs=epochs,
                        verbose=2)

          print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
Train on 1920 samples, validate on 480 samples
Epoch 1/5
 - 3s - loss: 0.6486 - acc: 0.6422 - val_loss: 0.6183 - val_acc: 0.7063
Epoch 2/5
 - 0s - loss: 0.6229 - acc: 0.6719 - val_loss: 0.7912 - val_acc: 0.4313
Epoch 3/5
 - 0s - loss: 0.6159 - acc: 0.6646 - val_loss: 0.6464 - val_acc: 0.7104
Epoch 4/5
```

```
 - 0s - loss: 0.6070 - acc: 0.6885 - val_loss: 0.8108 - val_acc: 0.4792
Epoch 5/5
 - 0s - loss: 0.6019 - acc: 0.6786 - val_loss: 1.0152 - val_acc: 0.4271
Tiempo de procesamiento (secs):  3.7814528942108154
```

- Guardando modelo

```
In [259]: from keras.models import load_model
          #nn_w2vgoogle_cu.save('nn_cuba_w2vgoogle')  # Guardar modelo
          nn_w2vgoogle_cu = load_model('nn_cuba_w2vgoogle') # Cargar modelo
```

```
In [260]: results_w2vgoogle_cu = nn_w2vgoogle_cu.evaluate(mean_emb_test_w2vgoogle_cu, y_test_w2
          print('Test loss:', results_w2vgoogle_cu[0])
          print('Test accuracy:', results_w2vgoogle_cu[1])
```

```
600/600 [==============================] - 0s 688us/step
Test loss: 0.7300734051068624
Test accuracy: 0.5749999992052715
```

```
In [87]: y_pred_w2vgoogle_cu = nn_w2vgoogle_cu.predict(mean_emb_test_w2vgoogle_cu).squeeze()

         import numpy as np
         from sklearn.metrics import confusion_matrix, precision_score, recall_score, f1_score

         y_test_label_w2vgoogle_cu = np.argmax(y_test_w2vgoogle_cu,1)
         y_pred_label_w2vgoogle_cu = np.argmax(y_pred_w2vgoogle_cu,1)

         # Confusion matrix
         C=confusion_matrix(y_test_label_w2vgoogle_cu , y_pred_label_w2vgoogle_cu)
         print(C)
```

```
[[235 165]
 [ 90 110]]
```

16.0.2 Reusltados

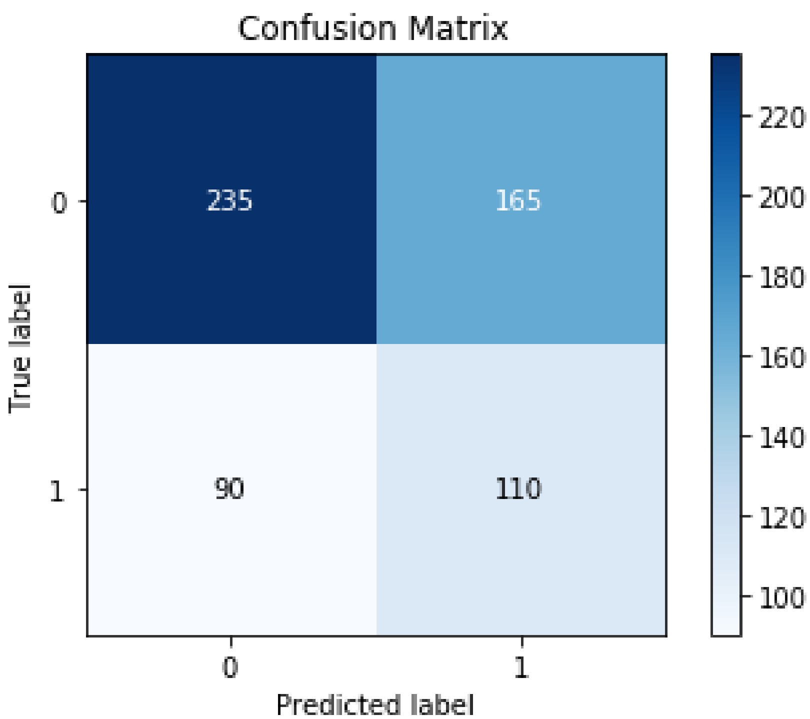
```
In [261]: print('Accuracy score:', results_w2vgoogle_cu[1])  # nn evaluate keras
          print("F1 score", f1_score(y_test_label_w2vgoogle_cu, y_pred_label_w2vgoogle_cu,  ave
          print("F1 weighted", f1_score(y_test_label_w2vgoogle_cu, y_pred_label_w2vgoogle_cu,
          print("Recall score", recall_score(y_test_label_w2vgoogle_cu, y_pred_label_w2vgoogle_
          print("Precision score", precision_score(y_test_label_w2vgoogle_cu, y_pred_label_w2vg

          from sklearn.metrics import classification_report
          print(classification_report(y_test_label_w2vgoogle_es, y_pred_label_w2vgoogle_es, ta
```

```
Accuracy score: 0.5749999992052715
F1 score 0.5557168784029038
```

```
F1 weighted 0.5865698729582578
Recall score 0.5687500000000001
Precision score 0.5615384615384615
              precision    recall  f1-score   support

   no-ironia       0.73      0.88      0.79       400
      ironia       0.58      0.34      0.43       200

   micro avg       0.70      0.70      0.70       600
   macro avg       0.65      0.61      0.61       600
weighted avg       0.68      0.70      0.67       600
```

```
In [125]: %matplotlib inline
          import matplotlib.pyplot as plt
          import scikitplot

          scikitplot.metrics.plot_confusion_matrix(  y_test_label_w2vgoogle_cu, y_pred_label_w2
```

```
Out[125]: <matplotlib.axes._subplots.AxesSubplot at 0x21a4284e518>
```



17 Clasificador SVM

- Selección de modelo

In [213]:
```
from sklearn.pipeline import Pipeline
from sklearn.svm import LinearSVC
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
import time
tic=time.time()

SVCpipe = Pipeline([('SVC',LinearSVC(class_weight="balanced", random_state=1,verbose=

# Gridsearch to determine the value of C
param_grid = {'SVC__C':np.arange(.01,.2,.01)}
linearSVC = GridSearchCV(SVCpipe,param_grid,cv=5,return_train_score=True, verbose=0)
linearSVC.fit(mean_emb_train_w2vgoogle_cu, y_train_cu.values)
print(linearSVC.best_params_)
#linearSVC.coef_
#linearSVC.intercept_

svc_w2vgoogle_cu = linearSVC.best_estimator_
svc_w2vgoogle_cu.fit(mean_emb_train_w2vgoogle_cu, y_train_cu.values)
svc_w2vgoogle_cu.coef_ = svc_w2vgoogle_cu.named_steps['SVC'].coef_
svc_w2vgoogle_cu.score(mean_emb_train_w2vgoogle_cu, y_train_cu.values)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
{'SVC__C': 0.04}
Tiempo de procesamiento (secs):  6.082455396652222
```

Gráfica ccuracy datos de entrenamiento y de prueba respecto al parámetro de regularización

- modelo seleccionado

In [262]:
```
from joblib import dump, load
#dump(svc_w2vgoogle_cu, 'svc_w2vgoogle_cu.joblib')
svc_w2vgoogle_cu = load('svc_w2vgoogle_cu.joblib')
prediction_w2vgoogle_cu=svc_w2vgoogle_cu.predict(mean_emb_test_w2vgoogle_cu)
```

In [90]:
```
print("Confusion Metrix:\n",metrics.confusion_matrix(y_test_cu.values, prediction_w2vg
```

```
Confusion Metrix:
 [[256 144]
 [ 80 120]]
```

17.0.1 Resultados

In [263]:
```
print('Accuracy score:', metrics.accuracy_score(y_test_cu.values, prediction_w2vgoogl
print("F1 score", f1_score(y_test_cu.values, prediction_w2vgoogle_cu,  average='macro
print("F1 weighted", f1_score(y_test_cu.values, prediction_w2vgoogle_cu,  average='we
print("Recall score", recall_score(y_test_cu.values, prediction_w2vgoogle_cu,  averag
print("Precision score", precision_score(y_test_cu.values, prediction_w2vgoogle_cu,
```

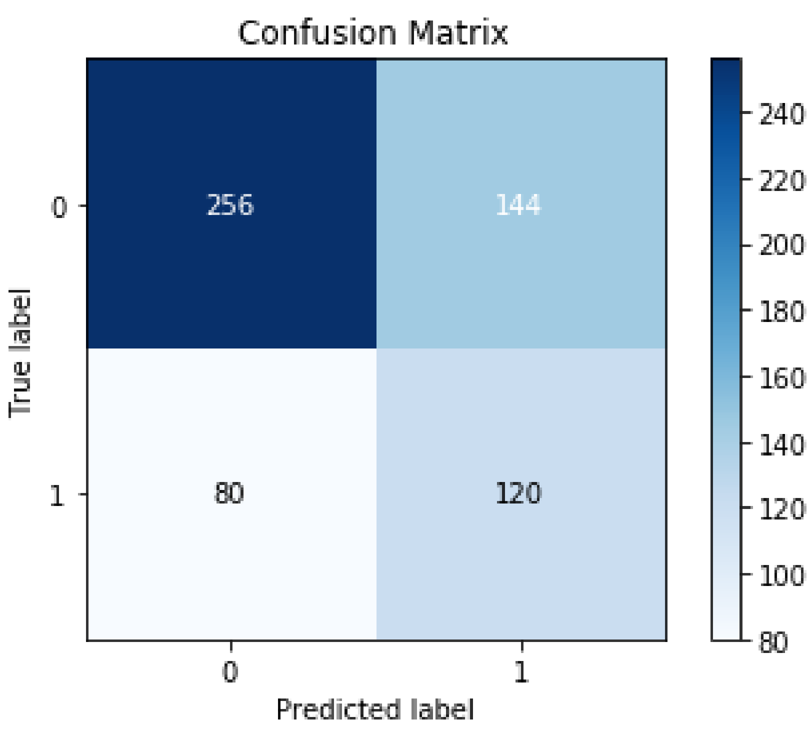
```
Accuracy score: 0.6266666666666667
F1 score 0.6064467766116941
F1 weighted 0.6361819090454772
Recall score 0.62
Precision score 0.6082251082251082
```

In [129]:
```python
from sklearn.metrics import classification_report
print(classification_report( y_test_cu.values, prediction_w2vgoogle_cu, target_names=
```

```
              precision    recall  f1-score   support

   no-ironia       0.76      0.64      0.70       400
      ironia       0.45      0.60      0.52       200

   micro avg       0.63      0.63      0.63       600
   macro avg       0.61      0.62      0.61       600
weighted avg       0.66      0.63      0.64       600
```

In [131]:
```python
%matplotlib inline
import matplotlib.pyplot as plt
import scikitplot

scikitplot.metrics.plot_confusion_matrix(y_test_cu.values, prediction_w2vgoogle_cu)
```

Out[131]: <matplotlib.axes._subplots.AxesSubplot at 0x21a4392b9e8>



```
In [264]: del modelo_google
```

Word2vec Twitter

- Cargar modelo entrenado

```
In [265]: import os
          os.chdir('C:\\Users\\h_air\\Documents\\Diplomado Deep Learning\\Estancia\\Datos\\Dat
```

```
In [158]: #pip install virtualenv
```

```
In [159]: #pip install -r requirements.txt
```

```
In [160]: #pip install word2vecReaderUtils
```

- La intalación y procedimiento se relaiza en base a Word2Vec 400M Tweets Embedding model based on https://www.fredericgodin.com/software/ y loretoparisi: Word2Vec 400M Tweets Embedding model based on https://www.fredericgodin.com/software/

- La siguientes dos funciones cargan el modelo pr-entreado " Word2Vec 400M Tweets Embedding model"

```
In [266]: # %load word2vecReaderUtils.py
          #!/usr/bin/env python
          #
          # Copyright (C) 2010 Radim Rehurek <radimrehurek@seznam.cz>
          # Licensed under the GNU LGPL v2.1 - http://www.gnu.org/licenses/lgpl.html

          """
          This module contains various general utility functions.
          """

          from __future__ import with_statement

          import logging
          logger = logging.getLogger('gensim.utils')

          try:
              from html.entities import name2codepoint as n2cp
          except ImportError:
              from htmlentitydefs import name2codepoint as n2cp
          try:
              import cPickle as _pickle
          except ImportError:
              import pickle as _pickle
```

```
import re
import unicodedata
import os
import random
import itertools
import tempfile
from functools import wraps # for `synchronous` function lock
import multiprocessing
import shutil
import sys
import traceback
from contextlib import contextmanager

import numpy
import scipy.sparse

if sys.version_info[0] >= 3:
    unicode = str

from six import iteritems, u, string_types
from six.moves import xrange

try:
    from pattern.en import parse
    logger.info("'pattern' package found; utils.lemmatize() is available for English'
    HAS_PATTERN = True
except ImportError:
    HAS_PATTERN = False


PAT_ALPHABETIC = re.compile('(((?![\d])\w)+)', re.UNICODE)
RE_HTML_ENTITY = re.compile(r'&(#?)(x?)(\w+);', re.UNICODE)



def synchronous(tlockname):
    """
    A decorator to place an instance-based lock around a method.

    Adapted from http://code.activestate.com/recipes/577105-synchronization-decorato
    """
    def _synched(func):
        @wraps(func)
        def _synchronizer(self, *args, **kwargs):
            tlock = getattr(self, tlockname)
            logger.debug("acquiring lock %r for %s" % (tlockname, func.func_name))

            with tlock: # use lock as a context manager to perform safe acquire/rele
```

```
                logger.debug("acquired lock %r for %s" % (tlockname, func.func_name))
                result = func(self, *args, **kwargs)
                logger.debug("releasing lock %r for %s" % (tlockname, func.func_name))
                return result
        return _synchronizer
    return _synched


class NoCM(object):
    def acquire(self):
        pass
    def release(self):
        pass
    def __enter__(self):
        pass
    def __exit__(self, type, value, traceback):
        pass
nocm = NoCM()


@contextmanager
def file_or_filename(input):
    """
    Return a file-like object ready to be read from the beginning. `input` is either
    a filename (gz/bz2 also supported) or a file-like object supporting seek.

    """
    if isinstance(input, string_types):
        # input was a filename: open as text file
        with smart_open(input) as fin:
            yield fin
    else:
        input.seek(0)
        yield input


def deaccent(text):
    """
    Remove accentuation from the given string. Input text is either a unicode string

    Return input string with accents removed, as unicode.

    >>> deaccent("éf chomutovských komunist dostal potou bílý práek")
    u'Sef chomutovskych komunistu dostal postou bily prasek'

    """
    if not isinstance(text, unicode):
        # assume utf8 for byte strings, use default (strict) error handling
```

```python
        text = text.decode('utf8')
    norm = unicodedata.normalize("NFD", text)
    result = u('').join(ch for ch in norm if unicodedata.category(ch) != 'Mn')
    return unicodedata.normalize("NFC", result)


def copytree_hardlink(source, dest):
    """
    Recursively copy a directory ala shutils.copytree, but hardlink files
    instead of copying. Available on UNIX systems only.
    """
    copy2 = shutil.copy2
    try:
        shutil.copy2 = os.link
        shutil.copytree(source, dest)
    finally:
        shutil.copy2 = copy2


def tokenize(text, lowercase=False, deacc=False, errors="strict", to_lower=False, lo
    """
    Iteratively yield tokens as unicode strings, optionally also lowercasing them
    and removing accent marks.

    Input text may be either unicode or utf8-encoded byte string.

    The tokens on output are maximal contiguous sequences of alphabetic
    characters (no digits!).

    >>> list(tokenize('Nic neme lett rychlostí vyí, ne 300 tisíc kilometr za sekundu
    [u'Nic', u'nemuze', u'letet', u'rychlosti', u'vyssi', u'nez', u'tisic', u'kilome

    """
    lowercase = lowercase or to_lower or lower
    text = to_unicode(text, errors=errors)
    if lowercase:
        text = text.lower()
    if deacc:
        text = deaccent(text)
    for match in PAT_ALPHABETIC.finditer(text):
        yield match.group()


def simple_preprocess(doc, deacc=False, min_len=2, max_len=15):
    """
    Convert a document into a list of tokens.

    This lowercases, tokenizes, stems, normalizes etc. -- the output are final
```

```python
    tokens = unicode strings, that won't be processed any further.

    """
    tokens = [token for token in tokenize(doc, lower=True, deacc=deacc, errors='igno
              if min_len <= len(token) <= max_len and not token.startswith('_')]
    return tokens


def any2utf8(text, errors='strict', encoding='utf8'):
    """Convert a string (unicode or bytestring in `encoding`), to bytestring in utf8
    if isinstance(text, unicode):
        return text.encode('utf8')
    # do bytestring -> unicode -> utf8 full circle, to ensure valid utf8
    return unicode(text, encoding, errors=errors).encode('utf8')
to_utf8 = any2utf8


def any2unicode(text, encoding='utf8', errors='strict'):
    """Convert a string (bytestring in `encoding` or unicode), to unicode."""
    if isinstance(text, unicode):
        return text
    return unicode(text, encoding, errors=errors)
to_unicode = any2unicode


class SaveLoad(object):
    """
    Objects which inherit from this class have save/load functions, which un/pickle
    them to disk.

    This uses pickle for de/serializing, so objects must not contain
    unpicklable attributes, such as lambda functions etc.

    """
    @classmethod
    def load(cls, fname, mmap=None):
        """
        Load a previously saved object from file (also see `save`).

        If the object was saved with large arrays stored separately, you can load
        these arrays via mmap (shared memory) using `mmap='r'`. Default: don't use
        mmap, load large arrays as normal objects.

        """
        logger.info("loading %s object from %s" % (cls.__name__, fname))
        subname = lambda suffix: fname + '.' + suffix + '.npy'
        obj = unpickle(fname)
        for attrib in getattr(obj, '__numpys', []):
```

```python
            logger.info("loading %s from %s with mmap=%s" % (attrib, subname(attrib)
            setattr(obj, attrib, numpy.load(subname(attrib), mmap_mode=mmap))
        for attrib in getattr(obj, '__scipys', []):
            logger.info("loading %s from %s with mmap=%s" % (attrib, subname(attrib)
            sparse = unpickle(subname(attrib))
            sparse.data = numpy.load(subname(attrib) + '.data.npy', mmap_mode=mmap)
            sparse.indptr = numpy.load(subname(attrib) + '.indptr.npy', mmap_mode=mma
            sparse.indices = numpy.load(subname(attrib) + '.indices.npy', mmap_mode=m
            setattr(obj, attrib, sparse)
        for attrib in getattr(obj, '__ignoreds', []):
            logger.info("setting ignored attribute %s to None" % (attrib))
            setattr(obj, attrib, None)
        return obj

    def save(self, fname, separately=None, sep_limit=10 * 1024**2, ignore=frozenset()
        """
        Save the object to file (also see `load`).

        If `separately` is None, automatically detect large numpy/scipy.sparse array
        in the object being stored, and store them into separate files. This avoids
        pickle memory errors and allows mmap'ing large arrays back on load efficient

        You can also set `separately` manually, in which case it must be a list of a
        names to be stored in separate files. The automatic check is not performed i

        `ignore` is a set of attribute names to *not* serialize (file handles, cache
        subsequent load() these attributes will be set to None.

        """
        logger.info("saving %s object under %s, separately %s" % (self.__class__.__na
        subname = lambda suffix: fname + '.' + suffix + '.npy'
        tmp = {}
        if separately is None:
            separately = []
            for attrib, val in iteritems(self.__dict__):
                if isinstance(val, numpy.ndarray) and val.size >= sep_limit:
                    separately.append(attrib)
                elif isinstance(val, (scipy.sparse.csr_matrix, scipy.sparse.csc_matri
                    separately.append(attrib)

        # whatever's in `separately` or `ignore` at this point won't get pickled any
        for attrib in separately + list(ignore):
            if hasattr(self, attrib):
                tmp[attrib] = getattr(self, attrib)
                delattr(self, attrib)

        try:
            numpys, scipys, ignoreds = [], [], []
```

```
                for attrib, val in iteritems(tmp):
                    if isinstance(val, numpy.ndarray) and attrib not in ignore:
                        numpys.append(attrib)
                        logger.info("storing numpy array '%s' to %s" % (attrib, subname(a
                        numpy.save(subname(attrib), numpy.ascontiguousarray(val))
                    elif isinstance(val, (scipy.sparse.csr_matrix, scipy.sparse.csc_matri
                        scipys.append(attrib)
                        logger.info("storing scipy.sparse array '%s' under %s" % (attrib
                        numpy.save(subname(attrib) + '.data.npy', val.data)
                        numpy.save(subname(attrib) + '.indptr.npy', val.indptr)
                        numpy.save(subname(attrib) + '.indices.npy', val.indices)
                        data, indptr, indices = val.data, val.indptr, val.indices
                        val.data, val.indptr, val.indices = None, None, None
                        try:
                            pickle(val, subname(attrib)) # store array-less object
                        finally:
                            val.data, val.indptr, val.indices = data, indptr, indices
                    else:
                        logger.info("not storing attribute %s" % (attrib))
                        ignoreds.append(attrib)
                self.__dict__['__numpys'] = numpys
                self.__dict__['__scipys'] = scipys
                self.__dict__['__ignoreds'] = ignoreds
                pickle(self, fname)
            finally:
                # restore the attributes
                for attrib, val in iteritems(tmp):
                    setattr(self, attrib, val)
#endclass SaveLoad


def identity(p):
    """Identity fnc, for flows that don't accept lambda (picking etc)."""
    return p


def get_max_id(corpus):
    """
    Return the highest feature id that appears in the corpus.

    For empty corpora (no features at all), return -1.

    """
    maxid = -1
    for document in corpus:
        maxid = max(maxid, max([-1] + [fieldid for fieldid, _ in document])) # [-1]
    return maxid
```

```
class FakeDict(object):
    """
    Objects of this class act as dictionaries that map integer->str(integer), for
    a specified range of integers <0, num_terms).

    This is meant to avoid allocating real dictionaries when `num_terms` is huge, wh
    is a waste of memory.

    """
    def __init__(self, num_terms):
        self.num_terms = num_terms


    def __str__(self):
        return "FakeDict(num_terms=%s)" % self.num_terms


    def __getitem__(self, val):
        if 0 <= val < self.num_terms:
            return str(val)
        raise ValueError("internal id out of bounds (%s, expected <0..%s))" %
                         (val, self.num_terms))

    def iteritems(self):
        for i in xrange(self.num_terms):
            yield i, str(i)

    def keys(self):
        """
        Override the dict.keys() function, which is used to determine the maximum
        internal id of a corpus = the vocabulary dimensionality.

        HACK: To avoid materializing the whole `range(0, self.num_terms)`, this retu
        the highest id = `[self.num_terms - 1]` only.

        """
        return [self.num_terms - 1]

    def __len__(self):
        return self.num_terms

    def get(self, val, default=None):
        if 0 <= val < self.num_terms:
            return str(val)
        return default
```

```python
def dict_from_corpus(corpus):
    """
    Scan corpus for all word ids that appear in it, then construct and return a mapp
    which maps each ``wordId -> str(wordId)``.

    This function is used whenever *words* need to be displayed (as opposed to just
    their ids) but no wordId->word mapping was provided. The resulting mapping
    only covers words actually used in the corpus, up to the highest wordId found.

    """
    num_terms = 1 + get_max_id(corpus)
    id2word = FakeDict(num_terms)
    return id2word


def is_corpus(obj):
    """
    Check whether `obj` is a corpus. Return (is_corpus, new) 2-tuple, where
    `new is obj` if `obj` was an iterable, or `new` yields the same sequence as
    `obj` if it was an iterator.

    `obj` is a corpus if it supports iteration over documents, where a document
    is in turn anything that acts as a sequence of 2-tuples (int, float).

    Note: An "empty" corpus (empty input sequence) is ambiguous, so in this case the
    result is forcefully defined as `is_corpus=False`.

    """
    try:
        if 'Corpus' in obj.__class__.__name__: # the most common case, quick hack
            return True, obj
    except:
        pass
    try:
        if hasattr(obj, 'next'):
            # the input is an iterator object, meaning once we call next()
            # that element could be gone forever. we must be careful to put
            # whatever we retrieve back again
            doc1 = next(obj)
            obj = itertools.chain([doc1], obj)
        else:
            doc1 = next(iter(obj)) # empty corpus is resolved to False here
        if len(doc1) == 0: # sparse documents must have a __len__ function (list, tu
            return True, obj # the first document is empty=>assume this is a corpus
        id1, val1 = next(iter(doc1)) # if obj is a numpy array, it resolves to False
        id1, val1 = int(id1), float(val1) # must be a 2-tuple (integer, float)
    except:
        return False, obj
```

```
    return True, obj



def get_my_ip():
    """
    Try to obtain our external ip (from the pyro nameserver's point of view)

    This tries to sidestep the issue of bogus `/etc/hosts` entries and other
    local misconfigurations, which often mess up hostname resolution.

    If all else fails, fall back to simple `socket.gethostbyname()` lookup.

    """
    import socket
    try:
        import Pyro4
        # we know the nameserver must exist, so use it as our anchor point
        ns = Pyro4.naming.locateNS()
        s = socket.socket(socket.AF_INET, socket.SOCK_DGRAM)
        s.connect((ns._pyroUri.host, ns._pyroUri.port))
        result, port = s.getsockname()
    except:
        try:
            # see what ifconfig says about our default interface
            import commands
            result = commands.getoutput("ifconfig").split("\n")[1].split()[1][5:]
            if len(result.split('.')) != 4:
                raise Exception()
        except:
            # give up, leave the resolution to gethostbyname
            result = socket.gethostbyname(socket.gethostname())
    return result


class RepeatCorpus(SaveLoad):
    """
    Used in the tutorial on distributed computing and likely not useful anywhere els

    """
    def __init__(self, corpus, reps):
        """
        Wrap a `corpus` as another corpus of length `reps`. This is achieved by
        repeating documents from `corpus` over and over again, until the requested
        length `len(result)==reps` is reached. Repetition is done
        on-the-fly=efficiently, via `itertools`.

        >>> corpus = [[(1, 0.5)], []] # 2 documents
```

```
        >>> list(RepeatCorpus(corpus, 5)) # repeat 2.5 times to get 5 documents
        [[(1, 0.5)], [], [(1, 0.5)], [], [(1, 0.5)]]

        """
        self.corpus = corpus
        self.reps = reps

    def __iter__(self):
        return itertools.islice(itertools.cycle(self.corpus), self.reps)

class ClippedCorpus(SaveLoad):
    def __init__(self, corpus, max_docs=None):
        """
        Return a corpus that is the "head" of input iterable `corpus`.

        Any documents after `max_docs` are ignored. This effectively limits the
        length of the returned corpus to <= `max_docs`. Set `max_docs=None` for
        "no limit", effectively wrapping the entire input corpus.

        """
        self.corpus = corpus
        self.max_docs = max_docs

    def __iter__(self):
        return itertools.islice(self.corpus, self.max_docs)

    def __len__(self):
        return min(self.max_docs, len(self.corpus))

def decode_htmlentities(text):
    """
    Decode HTML entities in text, coded as hex, decimal or named.

    Adapted from http://github.com/sku/python-twitter-ircbot/blob/321d94e0e40d0acc92

    >>> u = u'E tu vivrai nel terrore - L&#x27;aldil&#xE0; (1981)'
    >>> print(decode_htmlentities(u).encode('UTF-8'))
    E tu vivrai nel terrore - L'aldilà (1981)
    >>> print(decode_htmlentities("l&#39;eau"))
    l'eau
    >>> print(decode_htmlentities("foo &lt; bar"))
    foo < bar

    """
    def substitute_entity(match):
        ent = match.group(3)
        if match.group(1) == "#":
            # decoding by number
```

```
                if match.group(2) == '':
                    # number is in decimal
                    return unichr(int(ent))
                elif match.group(2) == 'x':
                    # number is in hex
                    return unichr(int('0x' + ent, 16))
            else:
                # they were using a name
                cp = n2cp.get(ent)
                if cp:
                    return unichr(cp)
                else:
                    return match.group()

    try:
        return RE_HTML_ENTITY.sub(substitute_entity, text)
    except:
        # in case of errors, return input
        # e.g., ValueError: unichr() arg not in range(0x10000) (narrow Python build)
        return text


def chunkize_serial(iterable, chunksize, as_numpy=False):
    """
    Return elements from the iterable in `chunksize`-ed lists. The last returned
    element may be smaller (if length of collection is not divisible by `chunksize`)

    >>> print(list(grouper(range(10), 3)))
    [[0, 1, 2], [3, 4, 5], [6, 7, 8], [9]]

    """
    import numpy
    it = iter(iterable)
    while True:
        if as_numpy:
            # convert each document to a 2d numpy array (~6x faster when transmittin
            # chunk data over the wire, in Pyro)
            wrapped_chunk = [[numpy.array(doc) for doc in itertools.islice(it, int(c
        else:
            wrapped_chunk = [list(itertools.islice(it, int(chunksize)))]
        if not wrapped_chunk[0]:
            break
        # memory opt: wrap the chunk and then pop(), to avoid leaving behind a dangl
        yield wrapped_chunk.pop()

grouper = chunkize_serial
```

```
class InputQueue(multiprocessing.Process):
    def __init__(self, q, corpus, chunksize, maxsize, as_numpy):
        super(InputQueue, self).__init__()
        self.q = q
        self.maxsize = maxsize
        self.corpus = corpus
        self.chunksize = chunksize
        self.as_numpy = as_numpy

    def run(self):
        if self.as_numpy:
            import numpy # don't clutter the global namespace with a dependency on n
        it = iter(self.corpus)
        while True:
            chunk = itertools.islice(it, self.chunksize)
            if self.as_numpy:
                # HACK XXX convert documents to numpy arrays, to save memory.
                # This also gives a scipy warning at runtime:
                # "UserWarning: indices array has non-integer dtype (float64)"
                wrapped_chunk = [[numpy.asarray(doc) for doc in chunk]]
            else:
                wrapped_chunk = [list(chunk)]

            if not wrapped_chunk[0]:
                self.q.put(None, block=True)
                break

            try:
                qsize = self.q.qsize()
            except NotImplementedError:
                qsize = '?'
            logger.debug("prepared another chunk of %i documents (qsize=%s)" %
                         (len(wrapped_chunk[0]), qsize))
            self.q.put(wrapped_chunk.pop(), block=True)
#endclass InputQueue


if os.name == 'nt':
    logger.info("detected Windows; aliasing chunkize to chunkize_serial")

    def chunkize(corpus, chunksize, maxsize=0, as_numpy=False):
        for chunk in chunkize_serial(corpus, chunksize, as_numpy=as_numpy):
            yield chunk
else:
    def chunkize(corpus, chunksize, maxsize=0, as_numpy=False):
        """
        Split a stream of values into smaller chunks.
```

```
    Each chunk is of length `chunksize`, except the last one which may be smalle
    A once-only input stream (`corpus` from a generator) is ok, chunking is done
    efficiently via itertools.

    If `maxsize > 1`, don't wait idly in between successive chunk `yields`, but
    rather keep filling a short queue (of size at most `maxsize`) with forthcomi
    chunks in advance. This is realized by starting a separate process, and is
    meant to reduce I/O delays, which can be significant when `corpus` comes
    from a slow medium (like harddisk).

    If `maxsize==0`, don't fool around with parallelism and simply yield the chu
    via `chunkize_serial()` (no I/O optimizations).

    >>> for chunk in chunkize(range(10), 4): print(chunk)
    [0, 1, 2, 3]
    [4, 5, 6, 7]
    [8, 9]

    """
    assert chunksize > 0

    if maxsize > 0:
        q = multiprocessing.Queue(maxsize=maxsize)
        worker = InputQueue(q, corpus, chunksize, maxsize=maxsize, as_numpy=as_nu
        worker.daemon = True
        worker.start()
        while True:
            chunk = [q.get(block=True)]
            if chunk[0] is None:
                break
            yield chunk.pop()
    else:
        for chunk in chunkize_serial(corpus, chunksize, as_numpy=as_numpy):
            yield chunk


def make_closing(base, **attrs):
    """
    Add support for `with Base(attrs) as fout:` to the base class if it's missing.
    The base class' `close()` method will be called on context exit, to always close

    This is needed for gzip.GzipFile, bz2.BZ2File etc in older Pythons (<=2.6), which
    raise "AttributeError: GzipFile instance has no attribute '__exit__'".

    """
    if not hasattr(base, '__enter__'):
        attrs['__enter__'] = lambda self: self
    if not hasattr(base, '__exit__'):
```

```
        attrs['__exit__'] = lambda self, type, value, traceback: self.close()
    return type('Closing' + base.__name__, (base, object), attrs)


def smart_open(fname, mode='rb'):
    _, ext = os.path.splitext(fname)
    if ext == '.bz2':
        from bz2 import BZ2File
        return make_closing(BZ2File)(fname, mode)
    if ext == '.gz':
        from gzip import GzipFile
        return make_closing(GzipFile)(fname, mode)
    return open(fname, mode)


def pickle(obj, fname, protocol=-1):
    """Pickle object `obj` to file `fname`."""
    with smart_open(fname, 'wb') as fout: # 'b' for binary, needed on Windows
        _pickle.dump(obj, fout, protocol=protocol)


def unpickle(fname):
    """Load pickled object from `fname`"""
    with smart_open(fname) as f:
        return _pickle.load(f)


def revdict(d):
    """
    Reverse a dictionary mapping.

    When two keys map to the same value, only one of them will be kept in the
    result (which one is kept is arbitrary).

    """
    return dict((v, k) for (k, v) in iteritems(d))


def toptexts(query, texts, index, n=10):
    """
    Debug fnc to help inspect the top `n` most similar documents (according to a
    similarity index `index`), to see if they are actually related to the query.

    `texts` is any object that can return something insightful for each document
    via `texts[docid]`, such as its fulltext or snippet.

    Return a list of 3-tuples (docid, doc's similarity to the query, texts[docid]).
```

```
    """
    sims = index[query] # perform a similarity query against the corpus
    sims = sorted(enumerate(sims), key=lambda item: -item[1])

    result = []
    for topid, topcosine in sims[:n]: # only consider top-n most similar docs
        result.append((topid, topcosine, texts[topid]))
    return result


def randfname(prefix='gensim'):
    randpart = hex(random.randint(0, 0xffffff))[2:]
    return os.path.join(tempfile.gettempdir(), prefix + randpart)


def upload_chunked(server, docs, chunksize=1000, preprocess=None):
    """
    Memory-friendly upload of documents to a SimServer (or Pyro SimServer proxy).

    Use this function to train or index large collections -- avoid sending the
    entire corpus over the wire as a single Pyro in-memory object. The documents
    will be sent in smaller chunks, of `chunksize` documents each.

    """
    start = 0
    for chunk in grouper(docs, chunksize):
        end = start + len(chunk)
        logger.info("uploading documents %i-%i" % (start, end - 1))
        if preprocess is not None:
            pchunk = []
            for doc in chunk:
                doc['tokens'] = preprocess(doc['text'])
                del doc['text']
                pchunk.append(doc)
            chunk = pchunk
        server.buffer(chunk)
        start = end


def getNS():
    """
    Return a Pyro name server proxy. If there is no name server running,
    start one on 0.0.0.0 (all interfaces), as a background process.

    """
    import Pyro4
    try:
        return Pyro4.locateNS()
```

```python
    except Pyro4.errors.NamingError:
        logger.info("Pyro name server not found; starting a new one")
    os.system("python -m Pyro4.naming -n 0.0.0.0 &")
    # TODO: spawn a proper daemon ala http://code.activestate.com/recipes/278731/ ?
    # like this, if there's an error somewhere, we'll never know... (and the loop
    # below will block). And it probably doesn't work on windows, either.
    while True:
        try:
            return Pyro4.locateNS()
        except:
            pass


def pyro_daemon(name, obj, random_suffix=False, ip=None, port=None):
    """
    Register object with name server (starting the name server if not running
    yet) and block until the daemon is terminated. The object is registered under
    `name`, or `name`+ some random suffix if `random_suffix` is set.

    """
    if random_suffix:
        name += '.' + hex(random.randint(0, 0xffffff))[2:]
    import Pyro4
    with getNS() as ns:
        with Pyro4.Daemon(ip or get_my_ip(), port or 0) as daemon:
            # register server for remote access
            uri = daemon.register(obj, name)
            ns.remove(name)
            ns.register(name, uri)
            logger.info("%s registered with nameserver (URI '%s')" % (name, uri))
            daemon.requestLoop()


if HAS_PATTERN:
    def lemmatize(content, allowed_tags=re.compile('(NN|VB|JJ|RB)'), light=False, st
        """
        This function is only available when the optional 'pattern' package is insta

        Use the English lemmatizer from `pattern` to extract tokens in
        their base form=lemma, e.g. "are, is, being" -> "be" etc.
        This is a smarter version of stemming, taking word context into account.

        Only considers nouns, verbs, adjectives and adverbs by default (=all other l

        >>> lemmatize('Hello World! How is it going?! Nonexistentword, 21')
        ['world/NN', 'be/VB', 'go/VB', 'nonexistentword/NN']

        >>> lemmatize('The study ranks high.')
```

```
        ['study/NN', 'rank/VB', 'high/JJ']

        >>> lemmatize('The ranks study hard.')
        ['rank/NN', 'study/VB', 'hard/RB']

        """
        if light:
            import warnings
            warnings.warn("The light flag is no longer supported by pattern.")

        # tokenization in `pattern` is weird; it gets thrown off by non-letters,
        # producing '==relate/VBN' or '**/NN'... try to preprocess the text a little
        # FIXME this throws away all fancy parsing cues, including sentence structur
        # abbreviations etc.
        content = u(' ').join(tokenize(content, lower=True, errors='ignore'))

        parsed = parse(content, lemmata=True, collapse=False)
        result = []
        for sentence in parsed:
            for token, tag, _, _, lemma in sentence:
                if 2 <= len(lemma) <= 15 and not lemma.startswith('_') and lemma not
                    if allowed_tags.match(tag):
                        lemma += "/" + tag[:2]
                        result.append(lemma.encode('utf8'))
        return result
#endif HAS_PATTERN
```

In [267]:
```
# %load word2vecReader.py
import logging
import word2vecReaderUtils as utils
from numpy import exp, dot, zeros, outer, random, dtype, float32 as REAL,\
    uint32, seterr, array, uint8, vstack, argsort, fromstring, sqrt, newaxis,\
    ndarray, empty, sum as np_sum, prod
from six import string_types
from gensim import matutils

class Vocab(object):
    """A single vocabulary item, used internally for constructing binary trees (incl
    def __init__(self, **kwargs):
        self.count = 0
        self.__dict__.update(kwargs)

    def __lt__(self, other):  # used for sorting in a priority queue
        return self.count < other.count

    def __str__(self):
        vals = ['%s:%r' % (key, self.__dict__[key]) for key in sorted(self.__dict__)
        return "<" + ', '.join(vals) + ">"
```

```python
class Word2Vec:
    """
    Class for training, using and evaluating neural networks described in https://co

    The model can be stored/loaded via its `save()` and `load()` methods, or stored/
    compatible with the original word2vec implementation via `save_word2vec_format()

    """
    def __init__(self, sentences=None, size=100, alpha=0.025, window=5, min_count=5,
        sample=0, seed=1, workers=1, min_alpha=0.0001, sg=1, hs=1, negative=0, cbow_
        """
        Initialize the model from an iterable of `sentences`. Each sentence is a
        list of words (unicode strings) that will be used for training.

        The `sentences` iterable can be simply a list, but for larger corpora,
        consider an iterable that streams the sentences directly from disk/network.
        See :class:`BrownCorpus`, :class:`Text8Corpus` or :class:`LineSentence` in
        this module for such examples.

        If you don't supply `sentences`, the model is left uninitialized -- use if
        you plan to initialize it in some other way.

        `sg` defines the training algorithm. By default (`sg=1`), skip-gram is used.

        `size` is the dimensionality of the feature vectors.

        `window` is the maximum distance between the current and predicted word with

        `alpha` is the initial learning rate (will linearly drop to zero as training

        `seed` = for the random number generator.

        `min_count` = ignore all words with total frequency lower than this.

        `sample` = threshold for configuring which higher-frequency words are random
            default is 0 (off), useful value is 1e-5.

        `workers` = use this many worker threads to train the model (=faster trainin

        `hs` = if 1 (default), hierarchical sampling will be used for model training

        `negative` = if > 0, negative sampling will be used, the int for negative
        specifies how many "noise words" should be drawn (usually between 5-20).

        `cbow_mean` = if 0 (default), use the sum of the context word vectors. If 1,
        Only applies when cbow is used.
```

```
        """
        self.vocab = {}  # mapping from a word (string) to a Vocab object
        self.index2word = []  # map from a word's matrix index (int) to word (string
        self.sg = int(sg)
        self.table = None # for negative sampling --> this needs a lot of RAM! consi
        self.layer1_size = int(size)
        #if size % 4 != 0:
        #    logger.warning("consider setting layer size to a multiple of 4 for grea
        self.alpha = float(alpha)
        self.window = int(window)
        self.seed = seed
        self.min_count = min_count
        self.sample = sample
        self.workers = workers
        self.min_alpha = min_alpha
        self.hs = hs
        self.negative = negative
        self.cbow_mean = int(cbow_mean)
        if sentences is not None:
            self.build_vocab(sentences)
            self.train(sentences)

    @classmethod
    def load_word2vec_format(cls, fname, fvocab=None, binary=False, norm_only=True):
        """
        Load the input-hidden weight matrix from the original C word2vec-tool format

        Note that the information stored in the file is incomplete (the binary tree
        so while you can query for word similarity etc., you cannot continue trainin
        with a model loaded this way.

        `binary` is a boolean indicating whether the data is in binary word2vec form
        `norm_only` is a boolean indicating whether to only store normalised word2ve
        Word counts are read from `fvocab` filename, if set (this is the file genera
        by `-save-vocab` flag of the original C tool).
        """
        counts = None
        if fvocab is not None:
            #logger.info("loading word counts from %s" % (fvocab))
            counts = {}
            with utils.smart_open(fvocab) as fin:
                for line in fin:
                    word, count = utils.to_unicode(line).strip().split()
                    counts[word] = int(count)

        #logger.info("loading projection weights from %s" % (fname))
        with utils.smart_open(fname) as fin:
            header = utils.to_unicode(fin.readline())
```

```
        vocab_size, layer1_size = map(int, header.split())  # throws for invalid
        result = Word2Vec(size=layer1_size)
        result.syn0 = zeros((vocab_size, layer1_size), dtype=REAL)
        if binary:
            binary_len = dtype(REAL).itemsize * layer1_size
            for line_no in xrange(vocab_size):
                # mixed text and binary: read text first, then binary
                word = []
                while True:
                    ch = fin.read(1)
                    if ch == b' ':
                        break
                    if ch != b'\n':  # ignore newlines in front of words (some b
                        word.append(ch)
                word = utils.to_unicode(b''.join(word),encoding='latin-1')

                if counts is None:
                    result.vocab[word] = Vocab(index=line_no, count=vocab_size -
                elif word in counts:
                    result.vocab[word] = Vocab(index=line_no, count=counts[word]
                else:
                    #logger.warning("vocabulary file is incomplete")
                    result.vocab[word] = Vocab(index=line_no, count=None)
                result.index2word.append(word)
                result.syn0[line_no] = fromstring(fin.read(binary_len), dtype=RE
        else:
            for line_no, line in enumerate(fin):
                parts = utils.to_unicode(line).split()
                if len(parts) != layer1_size + 1:
                    raise ValueError("invalid vector on line %s (is this really t
                word, weights = parts[0], map(REAL, parts[1:])
                if counts is None:
                    result.vocab[word] = Vocab(index=line_no, count=vocab_size -
                elif word in counts:
                    result.vocab[word] = Vocab(index=line_no, count=counts[word]
                else:
                    #logger.warning("vocabulary file is incomplete")
                    result.vocab[word] = Vocab(index=line_no, count=None)
                result.index2word.append(word)
                result.syn0[line_no] = weights
    #logger.info("loaded %s matrix from %s" % (result.syn0.shape, fname))
    result.init_sims(norm_only)
    return result

def init_sims(self, replace=False):
    """
    Precompute L2-normalized vectors.
```

```
        If `replace` is set, forget the original vectors and only keep the normalize
        ones = saves lots of memory!

        Note that you **cannot continue training** after doing a replace. The model
        effectively read-only = you can call `most_similar`, `similarity` etc., but

        """
        if getattr(self, 'syn0norm', None) is None or replace:
            #logger.info("precomputing L2-norms of word weight vectors")
            if replace:
                for i in xrange(self.syn0.shape[0]):
                    self.syn0[i, :] /= sqrt((self.syn0[i, :] ** 2).sum(-1))
                self.syn0norm = self.syn0
                if hasattr(self, 'syn1'):
                    del self.syn1
            else:
                self.syn0norm = (self.syn0 / sqrt((self.syn0 ** 2).sum(-1))[..., newa

    def __getitem__(self, word):

        return self.syn0[self.vocab[word].index]


    def __contains__(self, word):
        return word in self.vocab

    def most_similar(self, positive=[], negative=[], topn=10):


        if isinstance(positive, string_types) and not negative:
            # allow calls like most_similar('dog'), as a shorthand for most_similar(
            positive = [positive]

        # add weights for each word, if not already present; default to 1.0 for posi
        positive = [(word, 1.0) if isinstance(word, string_types + (ndarray,))
                                else word for word in positive]
        negative = [(word, -1.0) if isinstance(word, string_types + (ndarray,))
                                 else word for word in negative]

        # compute the weighted average of all words
        all_words, mean = set(), []
        for word, weight in positive + negative:
            if isinstance(word, ndarray):
                mean.append(weight * word)
            elif word in self.vocab:
                mean.append(weight * self.syn0norm[self.vocab[word].index])
                all_words.add(self.vocab[word].index)
            else:
```

```
                raise KeyError("word '%s' not in vocabulary" % word)
        if not mean:
            raise ValueError("cannot compute similarity with no input")
        mean = matutils.unitvec(array(mean).mean(axis=0)).astype(REAL)

        dists = dot(self.syn0norm, mean)
        if not topn:
            return dists
        best = argsort(dists)[::-1][:topn + len(all_words)]
        # ignore (don't return) words from the input
        result = [(self.index2word[sim], float(dists[sim]), self.syn0[sim]) for sim i
        return result[:topn]

    def most_similar_cosmul(self, positive=[], negative=[], topn=10):

        self.init_sims()

        if isinstance(positive, string_types) and not negative:
            # allow calls like most_similar_cosmul('dog'), as a shorthand for most_s
            positive = [positive]

        all_words = set()

        def word_vec(word):
            if isinstance(word, ndarray):
                return word
            elif word in self.vocab:
                all_words.add(self.vocab[word].index)
                return self.syn0norm[self.vocab[word].index]
            else:
                raise KeyError("word '%s' not in vocabulary" % word)

        positive = [word_vec(word) for word in positive]
        negative = [word_vec(word) for word in negative]
        if not positive:
            raise ValueError("cannot compute similarity with no input")

        # equation (4) of Levy & Goldberg "Linguistic Regularities...",
        # with distances shifted to [0,1] per footnote (7)
        pos_dists = [((1 + dot(self.syn0norm, term)) / 2) for term in positive]
        neg_dists = [((1 + dot(self.syn0norm, term)) / 2) for term in negative]
        dists = prod(pos_dists, axis=0) / (prod(neg_dists, axis=0) + 0.000001)

        if not topn:
            return dists
        best = argsort(dists)[::-1][:topn + len(all_words)]
        # ignore (don't return) words from the input
        result = [(self.index2word[sim], float(dists[sim],)) for sim in best if sim n
```

```
                return result[:topn]

        if __name__ == "__main__":

            model_path = "./word2vec_twitter_model.bin"
            print("Loading the model, this can take some time...")
            model = Word2Vec.load_word2vec_format(model_path, binary=True)
            print("The vocabulary size is: "+str(len(model.vocab)))
```

```
Loading the model, this can take some time...


C:\Users\h_air\Anaconda3\envs\tensorflow-gpu\lib\site-packages\ipykernel_launcher.py:142: Depre


The vocabulary size is: 3039345
```

- Modelo entrenado

```
In [201]: model # model ya te lo da la función anterior

Out[201]: <__main__.Word2Vec at 0x15be03d6a58>

In [136]:  model.syn0.shape # tamaño

Out[136]: (3039345, 400)

In [268]: modelo_twitter=model
          modelo_twitter

Out[268]: <__main__.Word2Vec at 0x1abfd414f28>

In [269]: # Bibliotecas
          import numpy as np
          import pandas as pd
          import re # lidia con expresiones regulares
          import nltk
          from bs4 import BeautifulSoup
          from nltk.corpus import stopwords
          from sklearn.feature_extraction.text import CountVectorizer
          from nltk import word_tokenize # sentencia en palabras
          from nltk.stem import SnowballStemmer # idioma steam
          from nltk.stem.porter import PorterStemmer
          from nltk.stem import WordNetLemmatizer
          from sklearn.ensemble import RandomForestClassifier
          from sklearn.feature_extraction.text import TfidfVectorizer
          from sklearn import feature_extraction, model_selection, naive_bayes, metrics, svm
```

17.1 word2vec twitter México

In [139]:
```
x_train.head()
print(x_train.shape)
```

```
(2400,)
```

In [140]:
```
x_test.head()
print(x_test.shape)
```

```
(600,)
```

- Pre-proceso corpus de entrenamiento y de prueba

In [270]:
```
#Limpiando datos de entrenamiento
num= x_train.size

clean_train = []


for i in range( 0, num):

    clean_train.append( review_to_words2(x_train.values[i] ) )

x_train_w2vtwit_mx = clean_train
```

In [271]:
```
#Limpiando datos de prueba
num= x_test.size

clean_test = []


for i in range( 0, num):

    clean_test.append( review_to_words2(x_test.values[i] ) )

x_test_w2vtwit_mx = clean_test
```

In [272]:
```
x_train_w2vtwit_mx = train["TOPIC"].astype(str).str.cat(x_train_w2vtwit_mx, sep=' ')
x_test_w2vtwit_mx = test["TOPIC_y"].astype(str).str.cat(x_test_w2vtwit_mx, sep=' ')
```

In [103]:
```
x_train_w2vtwit_mx[0]
```

Out[103]:
```
'asuntosConacyt rica económicamente pobre objetividad'
```

In [104]:
```
x_test_w2vtwit_mx[0]
```

Out[104]:
```
'divorcioEPN indigna postura mujer mexicana venderse años ser esposa telenovela llama
```

- Word2Vec Twitter Avg

```
In [273]: mean_embedding_vectorizer_twitter_mx = MeanEmbeddingVectorizer(modelo_twitter)
          mean_emb_train_w2vtwit_mx = mean_embedding_vectorizer_twitter_mx.fit_transform(x_trai

          mean_emb_test_w2vtwit_mx = mean_embedding_vectorizer_twitter_mx.fit_transform(x_test_
```

```
In [274]: print(mean_emb_train_w2vtwit_mx.shape)
          print(mean_emb_test_w2vtwit_mx.shape)
```

```
(2400, 400)
(600, 400)
```

17.1.1 Clasificador NN

```
In [275]: from keras.utils import to_categorical

          y_train_w2vtwit_mx = to_categorical(y_train)
          y_test_w2vtwit_mx  = to_categorical(y_test)
```

```
In [276]: num_mx, sz_mx = y_train_w2vtwit_mx.shape

          print(num_mx)
          print(sz_mx)
```

```
2400
2
```

- Selección de modelo

```
In [109]: import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 100
          epochs = 5

          nn_w2vtwit_mx = Sequential()
          nn_w2vtwit_mx.add(Dense(512, activation='relu'))
          nn_w2vtwit_mx.add(Dropout(0.25))
          nn_w2vtwit_mx.add(Dense(sz_mx, activation='softmax'))
          nn_w2vtwit_mx.compile(loss='binary_crossentropy',
                        optimizer='nadam',
                        metrics=['accuracy'])

          history_w2vtwit_mx = nn_w2vtwit_mx.fit(mean_emb_train_w2vtwit_mx,
```

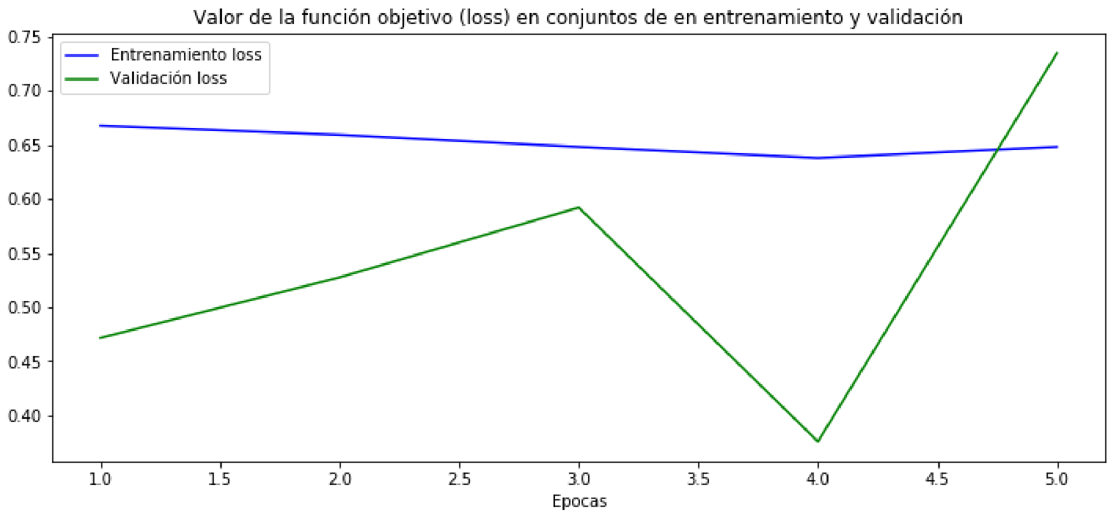
```
                        y_train_w2vtwit_mx,
                        validation_split=.2,
                        batch_size= batch_size,
                        shuffle   =True,
                        epochs=epochs,
                        verbose=2)

        print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
WARNING: Logging before flag parsing goes to stderr.
W0625 01:00:53.243121  9968 deprecation_wrapper.py:119] From C:\Users\h_air\Anaconda3\envs\tens

W0625 01:00:55.097902  9968 deprecation_wrapper.py:119] From C:\Users\h_air\Anaconda3\envs\tens

W0625 01:00:55.478055  9968 deprecation_wrapper.py:119] From C:\Users\h_air\Anaconda3\envs\tens

W0625 01:00:55.481060  9968 deprecation_wrapper.py:119] From C:\Users\h_air\Anaconda3\envs\tens

W0625 01:00:55.612801  9968 deprecation_wrapper.py:119] From C:\Users\h_air\Anaconda3\envs\tens

W0625 01:00:55.619782  9968 deprecation.py:506] From C:\Users\h_air\Anaconda3\envs\tensorflow-g
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep_prob`.
W0625 01:00:55.669651  9968 deprecation_wrapper.py:119] From C:\Users\h_air\Anaconda3\envs\tens

W0625 01:00:55.674636  9968 deprecation.py:323] From C:\Users\h_air\Anaconda3\envs\tensorflow-g
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where


Train on 1920 samples, validate on 480 samples
Epoch 1/5
 - 19s - loss: 0.6676 - acc: 0.6000 - val_loss: 0.4717 - val_acc: 0.8854
Epoch 2/5
 - 0s - loss: 0.6591 - acc: 0.6198 - val_loss: 0.5276 - val_acc: 0.8854
Epoch 3/5
 - 0s - loss: 0.6479 - acc: 0.6349 - val_loss: 0.5920 - val_acc: 0.8729
Epoch 4/5
 - 0s - loss: 0.6377 - acc: 0.6490 - val_loss: 0.3760 - val_acc: 0.8854
Epoch 5/5
 - 0s - loss: 0.6480 - acc: 0.6333 - val_loss: 0.7345 - val_acc: 0.3729
Tiempo de procesamiento (secs):  23.04626750946045
```

Gráfica loss values entrenamiento y validación respecto al número de epocas

```
In [113]: history_dict_w2vtwit_mx= history_w2vtwit_mx.history
          dictkeys_w2vtwit_mx=list(history_dict_w2vtwit_mx.keys())
          loss_values_w2vtwit_mx = history_w2vtwit_mx.history['loss']
```

```
val_loss_values_w2vtwit_mx= history_w2vtwit_mx.history['val_loss']
epochs_w2vtwit_mx = range(1, len(loss_values_w2vtwit_mx) + 1)

plt.figure(figsize=(12,5))
plt.plot(epochs_w2vtwit_mx, loss_values_w2vtwit_mx, 'b', label='Entrenamiento loss')
plt.plot(epochs_w2vtwit_mx, val_loss_values_w2vtwit_mx, 'g', label='Validación loss')
plt.title('Valor de la función objetivo (loss) en conjuntos de en entrenamiento y val
plt.xlabel('Epocas')
plt.ylabel('')
plt.legend()

plt.show()
```



- Selección del número de epocas

In [114]:
```
batch_size = 100
epochs = 3 # epocas seleccionadas

list_nn_w2vtwit_mx = np.arange( 1, 800, 50) # parámetro de regularización
score_train_w2vtwit_mx = np.zeros(len(list_nn_w2vtwit_mx)) # almacena acurr_w2vgoogl
score_test_w2vtwit_mx = np.zeros(len(list_nn_w2vtwit_mx)) # almacena acurracy prueba
count = 0
for i in list_nn_w2vtwit_mx:
    # Build the model
    nn_w2vtwit_mx = Sequential()
    nn_w2vtwit_mx.add(Dense(i, activation='relu'))
    nn_w2vtwit_mx.add(Dropout(0.25))
    nn_w2vtwit_mx.add(Dense(sz_mx, activation='softmax'))
    nn_w2vtwit_mx.compile(loss='binary_crossentropy',
              optimizer='nadam',
```

```
                metrics=['accuracy'])

    # No se utilizan datos de validación
        nn_w2vtwit_mx.fit(mean_emb_train_w2vtwit_mx,
                  y_train_w2vtwit_mx,
                  batch_size= batch_size,
                  shuffle   =True,
                  epochs=epochs,
                  verbose=0)

        temp1_w2vtwit_mx = nn_w2vtwit_mx.evaluate(mean_emb_train_w2vtwit_mx, y_train_w2v
        score_train_w2vtwit_mx[count] = temp1_w2vtwit_mx[1]
        temp2_w2vtwit_mx = nn_w2vtwit_mx.evaluate(mean_emb_test_w2vtwit_mx, y_test_w2vtwi
        score_test_w2vtwit_mx[count]= temp2_w2vtwit_mx[1]
        count = count + 1
```

Gráfica accuracy datos de entrenamienro y de prueba respecto al número de epocas

```
In [116]: matriz_w2vtwit_mx = np.matrix(np.c_[list_nn_w2vtwit_mx, score_train_w2vtwit_mx, score
          models_w2vtwit_mx = pd.DataFrame(data = matriz_w2vtwit_mx, columns =
                        ['Nodos', 'Train Accuracy', 'Test Accuracy'])
          plt.plot(models_w2vtwit_mx['Nodos'],models_w2vtwit_mx['Train Accuracy'])
          plt.plot(models_w2vtwit_mx['Nodos'],models_w2vtwit_mx['Test Accuracy'])
          plt.title('Train vs Test')
          plt.xlabel('Nodos')
          plt.legend()
          plt.show()
```

```
In [117]: models_w2vtwit_mx
```

```
Out[117]:     Nodos  Train Accuracy  Test Accuracy
          0     1.0        0.666667       0.668333
          1    51.0        0.672917       0.675000
          2   101.0        0.672083       0.675000
          3   151.0        0.674167       0.675000
          4   201.0        0.671667       0.675000
          5   251.0        0.673333       0.676667
          6   301.0        0.700417       0.661667
          7   351.0        0.705417       0.686667
          8   401.0        0.682917       0.671667
          9   451.0        0.674167       0.673333
          10  501.0        0.695833       0.658333
          11  551.0        0.707083       0.678333
          12  601.0        0.706667       0.683333
          13  651.0        0.684167       0.668333
          14  701.0        0.682083       0.673333
          15  751.0        0.682917       0.675000
```

```
In [241]: #nodo_w2vgoogle_mx = list_nn_w2vgoogle_mx[np.argmax(np.array(models_w2vgoogle_mx['Te
          nodo_w2vtwit_mx=351 # Número de nodos seleccionados
```

- Diseño final

```
In [247]: import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 100
          epochs = 6

          nn_w2vtwit_mx = Sequential()
          nn_w2vtwit_mx.add(Dense(nodo_w2vtwit_mx, activation='relu'))
          nn_w2vtwit_mx.add(Dropout(0.25))
          nn_w2vtwit_mx.add(Dense(sz_mx, activation='softmax'))
          nn_w2vtwit_mx.compile(loss='binary_crossentropy',
                        optimizer='nadam',
                        metrics=['accuracy'])

          history_w2vtwit_mx = nn_w2vtwit_mx.fit(mean_emb_train_w2vtwit_mx,
                        y_train_w2vtwit_mx,
                        validation_split=.2,
                        batch_size= batch_size,
                        shuffle   =True,
```

```
                    epochs=epochs,
                    verbose=2)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
Train on 1920 samples, validate on 480 samples
Epoch 1/6
 - 2s - loss: 0.6681 - acc: 0.5984 - val_loss: 0.4649 - val_acc: 0.8854
Epoch 2/6
 - 0s - loss: 0.6586 - acc: 0.6182 - val_loss: 0.5298 - val_acc: 0.8854
Epoch 3/6
 - 0s - loss: 0.6503 - acc: 0.6312 - val_loss: 0.6091 - val_acc: 0.8729
Epoch 4/6
 - 0s - loss: 0.6388 - acc: 0.6396 - val_loss: 0.3952 - val_acc: 0.8854
Epoch 5/6
 - 0s - loss: 0.6429 - acc: 0.6375 - val_loss: 0.7079 - val_acc: 0.4500
Epoch 6/6
 - 0s - loss: 0.6318 - acc: 0.6526 - val_loss: 0.6592 - val_acc: 0.6250
Tiempo de procesamiento (secs):  3.2391672134399414
```

- Guardar modelos

```
In [277]: from keras.models import load_model
          #nn_w2vtwit_mx.save('nn_mexico_w2vtwit')  # Guardar modelos
          nn_w2vtwit_mx = load_model('nn_mexico_w2vtwit') # Cargar modelos

In [278]: results_w2vtwit_mx = nn_w2vtwit_mx.evaluate(mean_emb_test_w2vtwit_mx, y_test_w2vtwit_
          print('Test loss:', results_w2vtwit_mx[0])
          print('Test accuracy:', results_w2vtwit_mx[1])
```

```
600/600 [==============================] - 1s 2ms/step
Test loss: 0.6610420449574789
Test accuracy: 0.6083333341280619
```

```
In [279]: y_pred_w2vtwit_mx = nn_w2vtwit_mx.predict(mean_emb_test_w2vtwit_mx).squeeze()

          import numpy as np
          from sklearn.metrics import confusion_matrix, precision_score, recall_score, f1_score

          y_test_label_w2vtwit_mx = np.argmax(y_test_w2vtwit_mx,1)
          y_pred_label_w2vtwit_mx = np.argmax(y_pred_w2vtwit_mx,1)


          # Confusion matrix
          C=confusion_matrix(y_test_label_w2vtwit_mx, y_pred_label_w2vtwit_mx)
          print(C)
```

```
[[285 116]
 [119  80]]
```

17.1.2 Resultados

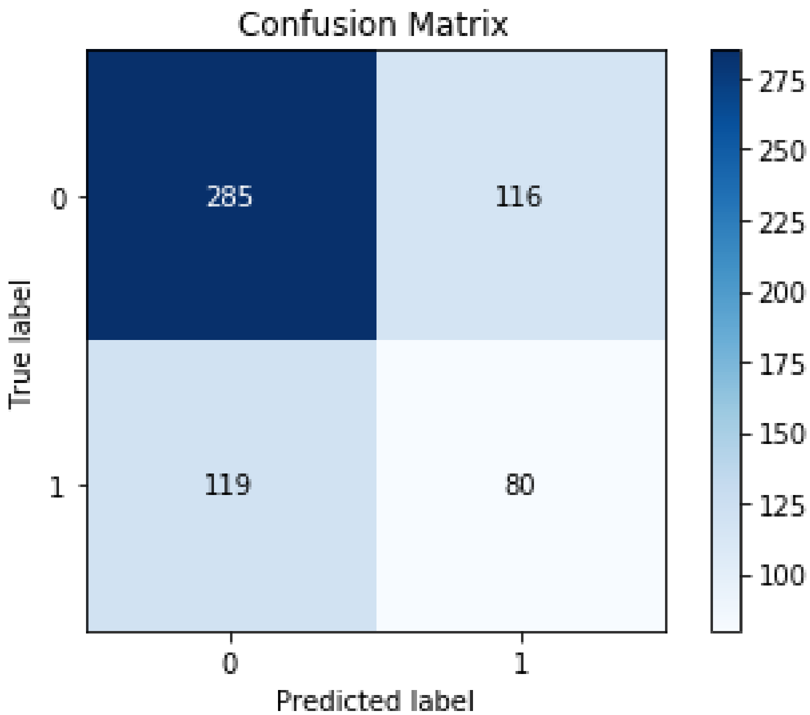
```
In [280]: print('Accuracy score:', results_w2vtwit_mx[1])  # nn evaluate keras
          print("F1 score", f1_score( y_test_label_w2vtwit_mx,  y_pred_label_w2vtwit_mx, averag
          print("F1 weighted", f1_score( y_test_label_w2vtwit_mx,  y_pred_label_w2vtwit_mx,   a
          print("Recall score", recall_score( y_test_label_w2vtwit_mx,  y_pred_label_w2vtwit_m
          print("Precision score", precision_score( y_test_label_w2vtwit_mx,  y_pred_label_w2v
```

```
Accuracy score: 0.6083333341280619
F1 score 0.5565689126503657
F1 weighted 0.6075758052257777
Recall score 0.5563666211356032
Precision score 0.5568044049302889
```

```
In [112]: from sklearn.metrics import classification_report
          print(classification_report(y_test_label_w2vtwit_mx, y_pred_label_w2vtwit_mx, target_
```

```
              precision    recall  f1-score   support

   no-ironia       0.71      0.71      0.71       401
      ironia       0.41      0.40      0.41       199

   micro avg       0.61      0.61      0.61       600
   macro avg       0.56      0.56      0.56       600
weighted avg       0.61      0.61      0.61       600
```

```
In [254]: %matplotlib inline
          import matplotlib.pyplot as plt
          import scikitplot

          scikitplot.metrics.plot_confusion_matrix(y_test_label_w2vtwit_mx, y_pred_label_w2vtwi

Out[254]: <matplotlib.axes._subplots.AxesSubplot at 0x15d4aa8da20>
```



18 Clasificador SVM

- Selección de modelos

```
In [265]: from sklearn.pipeline import Pipeline
          from sklearn.svm import LinearSVC
          from sklearn.model_selection import GridSearchCV
          from sklearn.preprocessing import StandardScaler
          import time
          tic=time.time()

          SVCpipe = Pipeline([('SVC',LinearSVC(class_weight="balanced", random_state=1,verbose=

          # Gridsearch to determine the value of C
          param_grid = {'SVC__C':np.arange(.1,2,.1)}
          linearSVC = GridSearchCV(SVCpipe,param_grid,cv=5,return_train_score=True, verbose=0)
          linearSVC.fit(mean_emb_train_w2vtwit_mx, y_train.values)
          print(linearSVC.best_params_)
          #linearSVC.coef_
          #linearSVC.intercept_

          svc_w2vtwit_mx = linearSVC.best_estimator_
          svc_w2vtwit_mx.fit(mean_emb_train_w2vtwit_mx, y_train.values)
```

```
        svc_w2vtwit_mx.coef_ = svc_w2vgoogle_mx.named_steps['SVC'].coef_
        svc_w2vtwit_mx.score(mean_emb_train_w2vtwit_mx, y_train.values)
```

```
{'SVC__C': 1.7000000000000002}
```

```
Out[265]: 0.7283333333333334
```

- Guardar modelo

```
In [281]: from joblib import dump, load
          #dump(svc_w2vtwit_mx, 'svc__w2vtwit_mx_mx.joblib')  # Guardar modelo
          svc_w2vtwit_mx = load('svc__w2vtwit_mx_mx.joblib') # Cargar modelo
          prediction_w2vtwit_mx=svc_w2vtwit_mx.predict(mean_emb_test_w2vtwit_mx)
          print("Acurracy Test",metrics.accuracy_score(prediction_w2vtwit_mx, y_test.values))
```

```
Acurracy Test 0.6533333333333333
```

```
In [282]: print("Confusion Metrix:\n",metrics.confusion_matrix(y_test.values, prediction_w2vtw
```

```
Confusion Metrix:
 [[277 124]
 [ 84 115]]
```

18.0.1 Resultados

```
In [283]: print('Accuracy score:', metrics.accuracy_score( y_test.values, prediction_w2vtwit_m
          print("F1 score", f1_score(y_test.values, prediction_w2vtwit_mx,  average='macro'))
          print("F1 weighted", f1_score(y_test.values, prediction_w2vtwit_mx, average='weighte
          print("Recall score", recall_score(y_test.values, prediction_w2vtwit_mx,  average='m
          print("Precision score", precision_score(y_test.values, prediction_w2vtwit_mx, avera
```

```
Accuracy score: 0.6533333333333333
F1 score 0.6260741379930248
F1 weighted 0.6600639988494589
Recall score 0.6343312572839259
Precision score 0.6242422837538683
```

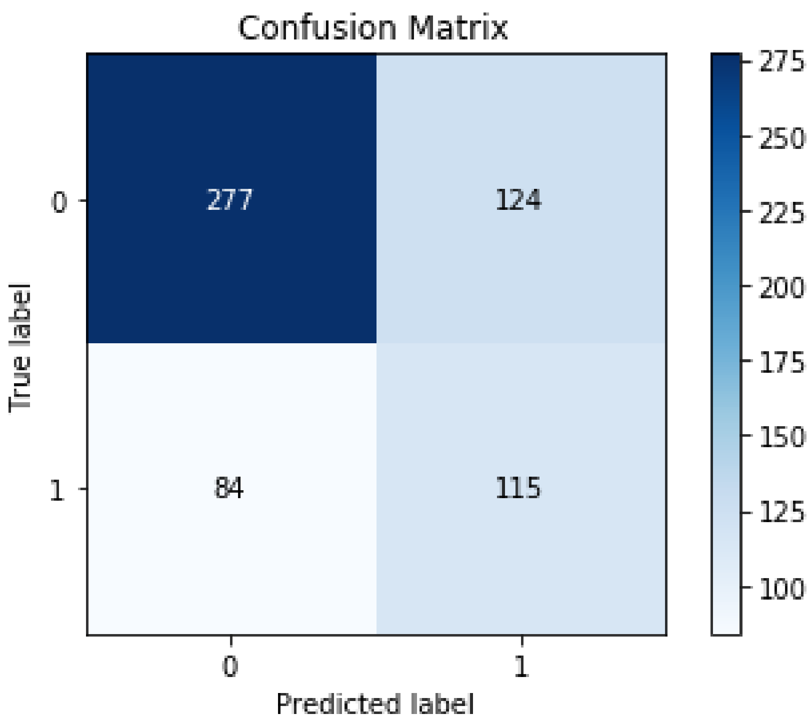
```
In [269]: from sklearn.metrics import classification_report
          print(classification_report(y_test.values, prediction_w2vtwit_mx,  target_names=['no
```

```
              precision    recall  f1-score   support

   no-ironia       0.77      0.69      0.73       401
      ironia       0.48      0.58      0.53       199

   micro avg       0.65      0.65      0.65       600
```

```
   macro avg       0.62      0.63      0.63       600
weighted avg       0.67      0.65      0.66       600
```

```
In [158]: %matplotlib inline
          import matplotlib.pyplot as plt
          import scikitplot

          scikitplot.metrics.plot_confusion_matrix(y_test.values, prediction_w2vtwit_mx)
```

```
Out[158]: <matplotlib.axes._subplots.AxesSubplot at 0x21b985070f0>
```



18.1 word2vec twitter España

```
In [159]: x_train_españa.head()
          print(x_train_españa.shape)
```

```
(2400,)
```

```
In [160]: x_test_españa.head()
          print(x_test_españa.shape)
```

(600,)

- Limpiar corpus de entrenamiento y de prueba

```
In [284]: #Limpiando datos de entrenamiento
          num= x_train_españa.size

          clean_train_es = []


          for i in range( 0, num):

              clean_train_es.append( review_to_words2(x_train_españa.values[i] ) )

          x_train_w2vtwit_es = clean_train_es

In [285]: #Limpiando datos de prueba
          num= x_test_españa.size
          # Lista para guardar twits limpios
          clean_test_es = []


          for i in range( 0, num):

              clean_test_es.append( review_to_words2(x_test_españa.values[i] ) )

          x_test_w2vtwit_es = clean_test_es

In [286]: x_train_w2vtwit_es = train_es["TOPIC"].astype(str).str.cat(x_train_w2vtwit_es, sep='
          x_test_w2vtwit_es = test_es["TOPIC_y"].astype(str).str.cat(x_test_w2vtwit_es, sep='

In [164]: x_train_w2vtwit_es[0]

Out[164]: 'TARDÀ armandoruido007 anti_merma50 joantarda vez joan tarda van llamarle tarda call

In [165]: x_test_w2vtwit_es[0]

Out[165]: 'FRANCO suspenden exhumación francisco franco caso da giro inesperado https t co lao
```

- Modelo W2V Twitter Avg

```
In [287]: mean_embedding_vectorizer_twitter_es = MeanEmbeddingVectorizer(modelo_twitter)
          mean_emb_train_w2vtwit_es = mean_embedding_vectorizer_twitter_es.fit_transform(x_tra

          mean_emb_test_w2vtwit_es = mean_embedding_vectorizer_twitter_es.fit_transform(x_test

          print(mean_emb_train_w2vtwit_es.shape)
          print(mean_emb_test_w2vtwit_es.shape)

(2400, 400)
(600, 400)
```

18.1.1 Clasificador NN

```
In [288]: from keras.utils import to_categorical

          y_train_w2vtwit_es = to_categorical(y_train_es)
          y_test_w2vtwit_es  = to_categorical(y_test_es)

          num_es, sz_es = y_train_w2vtwit_es.shape

          print(num_es)
          print(sz_es)
```

```
2400
2
```

- Selecicón de modelo

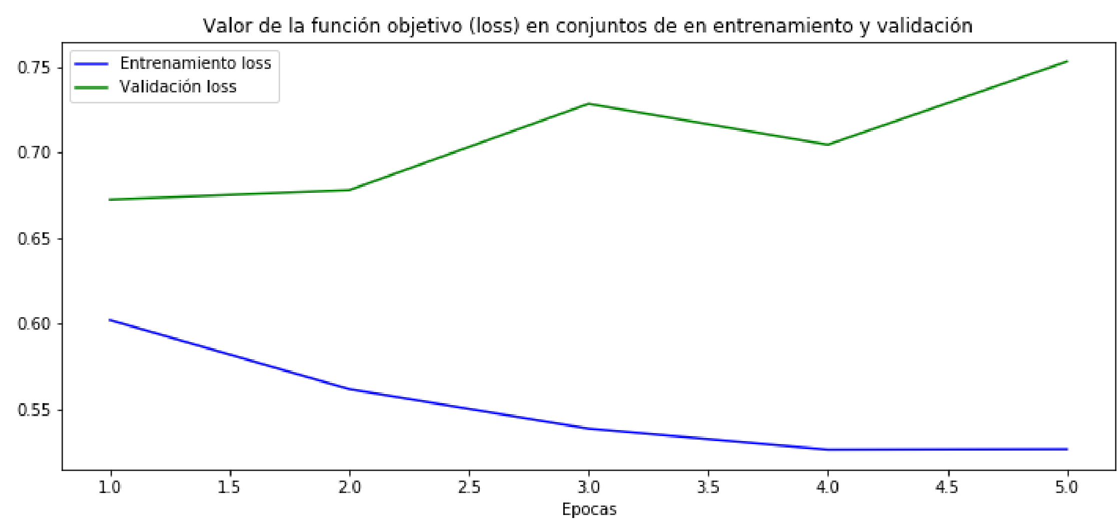
```
In [201]: import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 100
          epochs = 5

          nn_w2vtwit_es = Sequential()
          nn_w2vtwit_es.add(Dense(512, activation='relu'))
          nn_w2vtwit_es.add(Dropout(0.25))
          nn_w2vtwit_es.add(Dense(sz_es, activation='softmax'))
          nn_w2vtwit_es.compile(loss='binary_crossentropy',
                        optimizer='nadam',
                        metrics=['accuracy'])

          history_w2vtwit_es = nn_w2vtwit_es.fit(mean_emb_train_w2vtwit_es,
                        y_train_w2vtwit_es,
                        validation_split=.2,
                        batch_size= batch_size,
                        shuffle   =True,
                        epochs=epochs,
                        verbose=2)

          print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
Train on 1920 samples, validate on 480 samples
Epoch 1/5
 - 3s - loss: 0.6021 - acc: 0.6776 - val_loss: 0.6725 - val_acc: 0.6188
Epoch 2/5
 - 0s - loss: 0.5617 - acc: 0.7219 - val_loss: 0.6780 - val_acc: 0.5625
```

```
Epoch 3/5
 - 0s - loss: 0.5387 - acc: 0.7474 - val_loss: 0.7285 - val_acc: 0.5250
Epoch 4/5
 - 0s - loss: 0.5264 - acc: 0.7464 - val_loss: 0.7045 - val_acc: 0.6354
Epoch 5/5
 - 0s - loss: 0.5267 - acc: 0.7375 - val_loss: 0.7531 - val_acc: 0.6417
Tiempo de procesamiento (secs):  3.270796060562134
```

Gráfico loss values de entrenamiento y de prueba respecto al número de epocas

```
In [144]: history_dict_w2vtwit_es = history_w2vtwit_es.history
          dictkeys_w2vtwit_es=list(history_dict_w2vtwit_es.keys())
          loss_values_w2vtwit_es = history_w2vtwit_es.history['loss']
          val_loss_values_w2vtwit_es = history_w2vtwit_es.history['val_loss']
          epochs_w2vtwit_es = range(1, len(loss_values_w2vtwit_es) + 1)

          plt.figure(figsize=(12,5))
          plt.plot(epochs_w2vtwit_es, loss_values_w2vtwit_es, 'b', label='Entrenamiento loss')
          plt.plot(epochs_w2vtwit_es, val_loss_values_w2vtwit_es, 'g', label='Validación loss'
          plt.title('Valor de la función objetivo (loss) en conjuntos de en entrenamiento y val
          plt.xlabel('Epocas')
          plt.ylabel('')
          plt.legend()

          plt.show()
```



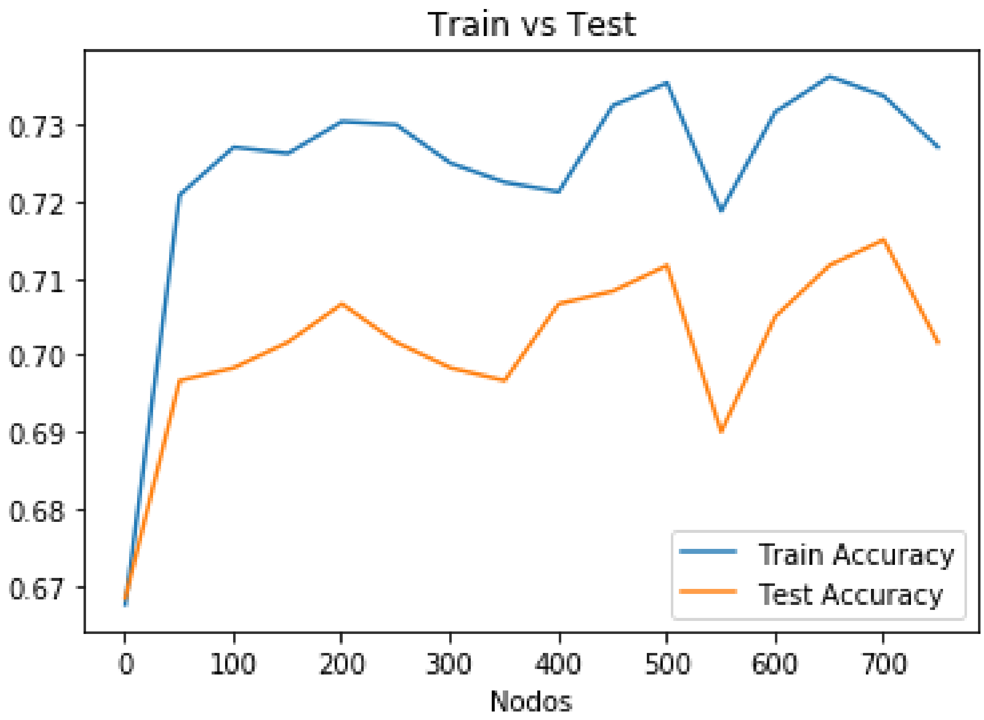
- Selección del número de nodos

```
In [145]: batch_size = 100
          epochs = 3 # epocas seleccionadas
```

```
list_nn_w2vtwit_es= np.arange( 1, 800, 50) # parámetro de regularización
score_train_w2vtwit_es = np.zeros(len(list_nn_w2vtwit_es)) # almacena acurr_w2vtwit_
score_test_w2vtwit_es = np.zeros(len(list_nn_w2vtwit_es)) # almacena acurracy prueba
count = 0
for i in list_nn_w2vtwit_es:
    # Build the model
    nn_w2vtwit_es = Sequential()
    nn_w2vtwit_es.add(Dense(i, activation='relu'))
    nn_w2vtwit_es.add(Dropout(0.25))
    nn_w2vtwit_es.add(Dense(sz_es, activation='softmax'))
    nn_w2vtwit_es.compile(loss='binary_crossentropy',
              optimizer='nadam',
              metrics=['accuracy'])

# No se utilizan datos de validación
    nn_w2vtwit_es.fit(mean_emb_train_w2vtwit_es,
              y_train_w2vtwit_es,
              batch_size= batch_size,
              shuffle   =True,
              epochs=epochs,
              verbose=0)

    temp1_w2vtwit_es = nn_w2vtwit_es.evaluate(mean_emb_train_w2vtwit_es, y_train_w2v
    score_train_w2vtwit_es[count] = temp1_w2vtwit_es[1]
    temp2_w2vtwit_es = nn_w2vtwit_es.evaluate(mean_emb_test_w2vtwit_es, y_test_w2vtwi
    score_test_w2vtwit_es[count]= temp2_w2vtwit_es[1]
    count = count + 1
```

Gráfica accuracy datos de entrenamietno y de prueba respecto al número de nodos

```
In [146]: matriz_w2vtwit_es = np.matrix(np.c_[list_nn_w2vtwit_es, score_train_w2vtwit_es, score
          models_w2vtwit_es = pd.DataFrame(data = matriz_w2vtwit_es, columns =
                       ['Nodos', 'Train Accuracy', 'Test Accuracy'])
          plt.plot(models_w2vtwit_es['Nodos'],models_w2vtwit_es['Train Accuracy'])
          plt.plot(models_w2vtwit_es['Nodos'],models_w2vtwit_es['Test Accuracy'])
          plt.title('Train vs Test')
          plt.xlabel('Nodos')
          plt.legend()
          plt.show()
```




```
In [147]: models_w2vtwit_es
```

Out[147]:

	Nodos	Train Accuracy	Test Accuracy
0	1.0	0.667500	0.668333
1	51.0	0.720833	0.696667
2	101.0	0.727083	0.698333
3	151.0	0.726250	0.701667
4	201.0	0.730417	0.706667
5	251.0	0.730000	0.701667
6	301.0	0.725000	0.698333
7	351.0	0.722500	0.696667
8	401.0	0.721250	0.706667
9	451.0	0.732500	0.708333
10	501.0	0.735417	0.711667
11	551.0	0.718750	0.690000
12	601.0	0.731667	0.705000
13	651.0	0.736250	0.711667
14	701.0	0.733750	0.715000
15	751.0	0.727083	0.701667

```
In [170]: #nodo_w2vtwit_mx = list_nn_w2vtwit_mx[np.argmax(np.array(models_w2vtwit_mx['Test Acc
          nodo_w2vtwit_es=151 # Selección del número de nodos
```

- Diseño final

```
In [171]: import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 100
          epochs = 3

          nn_w2vtwit_es = Sequential()
          nn_w2vtwit_es.add(Dense(nodo_w2vtwit_es, activation='relu'))
          nn_w2vtwit_es.add(Dropout(0.25))
          nn_w2vtwit_es.add(Dense(sz_es, activation='softmax'))
          nn_w2vtwit_es.compile(loss='binary_crossentropy',
                        optimizer='nadam',
                        metrics=['accuracy'])

          history_w2vtwit_es = nn_w2vtwit_es.fit(mean_emb_train_w2vtwit_es,
                        y_train_w2vtwit_es,
                        validation_split=.2,
                        batch_size= batch_size,
                        shuffle   =True,
                        epochs=epochs,
                        verbose=2)

          print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
Train on 1920 samples, validate on 480 samples
Epoch 1/3
 - 3s - loss: 0.6219 - acc: 0.6521 - val_loss: 0.6532 - val_acc: 0.6521
Epoch 2/3
 - 0s - loss: 0.5686 - acc: 0.7172 - val_loss: 0.6756 - val_acc: 0.5771
Epoch 3/3
 - 0s - loss: 0.5492 - acc: 0.7328 - val_loss: 0.6879 - val_acc: 0.5479
Tiempo de procesamiento (secs):  3.3132855892181396
```

- Guardar modelo

```
In [289]: from keras.models import load_model
          #nn_w2vtwit_es.save('nn_españa_w2vtwit')  # Guardar modelo
          nn_w2vtwit_es = load_model('nn_españa_w2vtwit') # Cargar modelo
```

```
In [290]: results_w2vtwit_es = nn_w2vtwit_es.evaluate(mean_emb_test_w2vtwit_es, y_test_w2vtwit_
          print('Test loss:', results_w2vtwit_es[0])
          print('Test accuracy:', results_w2vtwit_es[1])

          y_pred_w2vtwit_es = nn_w2vtwit_es.predict(mean_emb_test_w2vtwit_es).squeeze()
```

```
600/600 [==============================] - 1s 2ms/step
Test loss: 0.5863975771268208
```

```
Test accuracy: 0.6733333333333333
```

```
In [291]: import numpy as np
          from sklearn.metrics import confusion_matrix, precision_score, recall_score, f1_score

          y_test_label_w2vtwit_es = np.argmax(y_test_w2vtwit_es,1)
          y_pred_label_w2vtwit_es = np.argmax(y_pred_w2vtwit_es,1)

          # Confusion matrix
          C=confusion_matrix(y_test_label_w2vtwit_es , y_pred_label_w2vtwit_es)
          print(C)
```

```
[[311  89]
 [107  93]]
```

18.1.2 Resultados

```
In [292]: print('Accuracy score:', results_w2vtwit_es[1])  # nn evaluate keras
          print("F1 score", f1_score(y_test_label_w2vtwit_es,  y_pred_label_w2vtwit_es,  averag
          print("F1 weighted", f1_score(y_test_label_w2vtwit_es,  y_pred_label_w2vtwit_es,  ave
          print("Recall score", recall_score(y_test_label_w2vtwit_es,  y_pred_label_w2vtwit_es
          print("Precision score", precision_score(y_test_label_w2vtwit_es,  y_pred_label_w2vt
```

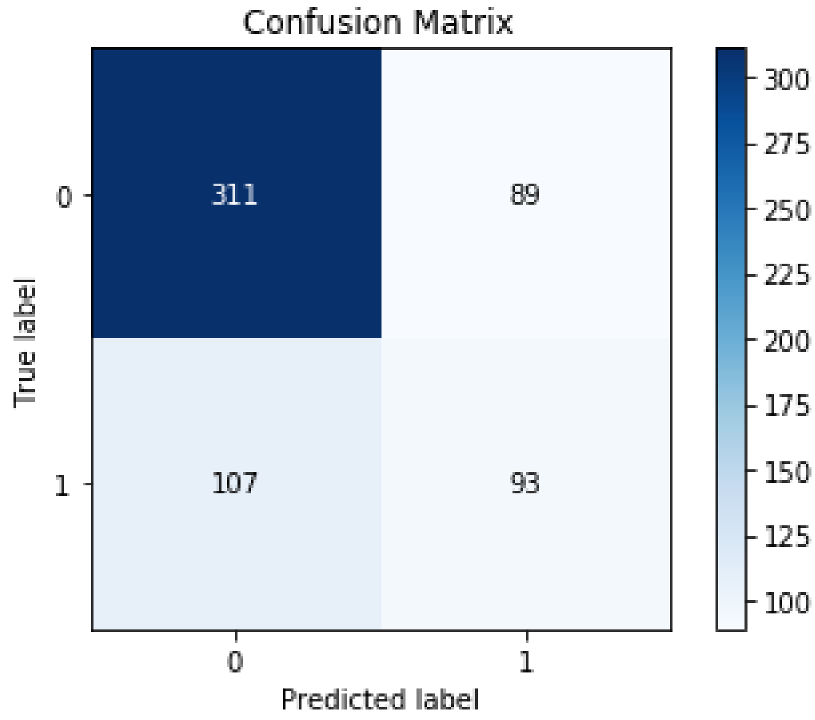
```
Accuracy score: 0.6733333333333333
F1 score 0.6236510964042039
F1 weighted 0.6692311302841393
Recall score 0.62125
Precision score 0.6275040748724959
```

```
In [174]: from sklearn.metrics import classification_report
          print(classification_report(y_test_label_w2vtwit_es, y_pred_label_w2vtwit_es,target_n
```

```
              precision    recall  f1-score   support

   no-ironia       0.74      0.78      0.76       400
      ironia       0.51      0.47      0.49       200

   micro avg       0.67      0.67      0.67       600
   macro avg       0.63      0.62      0.62       600
weighted avg       0.67      0.67      0.67       600
```

```
In [288]: %matplotlib inline
          import matplotlib.pyplot as plt
          import scikitplot

          scikitplot.metrics.plot_confusion_matrix(y_test_label_w2vtwit_es, y_pred_label_w2vtwi
```

Out[288]: <matplotlib.axes._subplots.AxesSubplot at 0x1b435efd630>



18.1.3 Clasificador SVM

In [289]:
```
from sklearn.pipeline import Pipeline
from sklearn.svm import LinearSVC
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
import time
tic=time.time()

SVCpipe = Pipeline([('SVC',LinearSVC(class_weight="balanced", random_state=1,verbose=

# Gridsearch to determine the value of C
param_grid = {'SVC__C':np.arange(.1,2,.1)}
linearSVC = GridSearchCV(SVCpipe,param_grid,cv=5,return_train_score=True, verbose=0)
linearSVC.fit(mean_emb_train_w2vtwit_es, y_train_es.values)
print(linearSVC.best_params_)
#linearSVC.coef_
#linearSVC.intercept_

svc_w2vtwit_es = linearSVC.best_estimator_
svc_w2vtwit_es.fit(mean_emb_train_w2vtwit_es, y_train_es.values)
svc_w2vtwit_es.coef_ = svc_w2vtwit_es.named_steps['SVC'].coef_
```

```
svc_w2vtwit_es.score(mean_emb_train_w2vtwit_es, y_train_es.values)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
{'SVC__C': 0.1}
Tiempo de procesamiento (secs):  15.205628156661987
```

```
In [124]: from joblib import dump, load
          #dump(svc_w2vtwit_es, 'svc_w2vtwit_es.joblib')
          svc_w2vtwit_es = load('svc_w2vtwit_es.joblib')
          prediction_w2vtwit_es=svc_w2vtwit_es.predict(mean_emb_test_w2vtwit_es)
          print("Acurracy Test",metrics.accuracy_score(prediction_w2vtwit_es, y_test_es.values)
```

```
Acurracy Test 0.6616666666666666
```

```
In [293]: print("Confusion Metrix:\n",metrics.confusion_matrix(y_test_es.values, prediction_w2v
```

```
Confusion Metrix:
 [[247 153]
 [ 50 150]]
```

18.1.4 Resultados

```
In [294]: print('Accuracy score:', metrics.accuracy_score(y_test_es.values, prediction_w2vtwit_
          print("F1 score", f1_score(y_test_es.values, prediction_w2vtwit_es,  average='macro')
          print("F1 weighted", f1_score(y_test_es.values, prediction_w2vtwit_es,  average='weig
          print("Recall score", recall_score(y_test_es.values, prediction_w2vtwit_es,  average=
          print("Precision score", precision_score(y_test_es.values, prediction_w2vtwit_es,  av
```

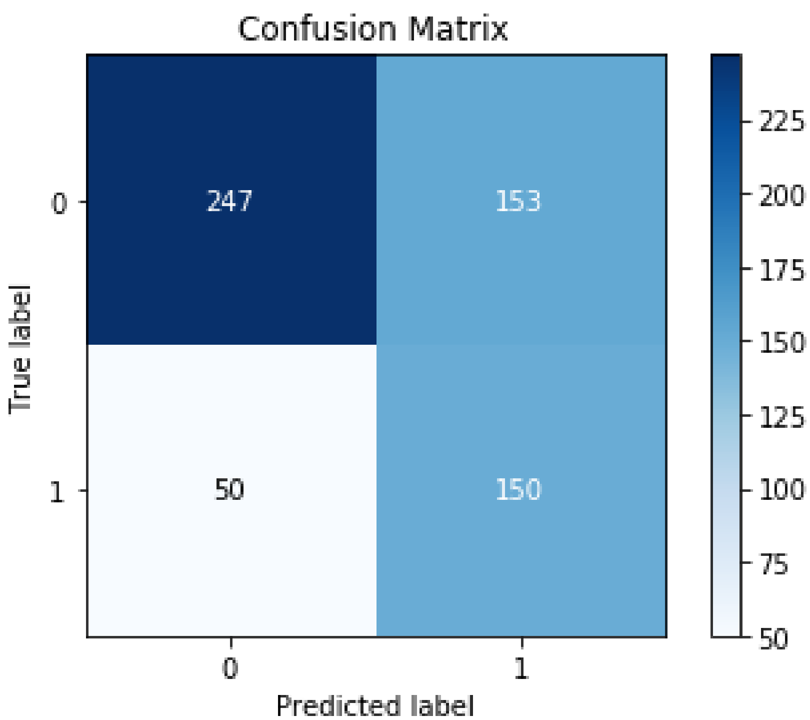
```
Accuracy score: 0.6616666666666666
F1 score 0.6525866322866245
F1 weighted 0.6713083526578454
Recall score 0.6837500000000001
Precision score 0.6633496683001634
```

```
In [178]: from sklearn.metrics import classification_report
          print(classification_report( y_test_es.values, prediction_w2vtwit_es, target_names=[
```

```
              precision    recall  f1-score   support

   no-ironia       0.83      0.62      0.71       400
      ironia       0.50      0.75      0.60       200

   micro avg       0.66      0.66      0.66       600
   macro avg       0.66      0.68      0.65       600
weighted avg       0.72      0.66      0.67       600
```

```
In [179]: %matplotlib inline
          import matplotlib.pyplot as plt
          import scikitplot

          scikitplot.metrics.plot_confusion_matrix(y_test_es.values, prediction_w2vtwit_es)
```

```
Out[179]: <matplotlib.axes._subplots.AxesSubplot at 0x21bab7436a0>
```



18.2 word2vec twitter Cuba

```
In [184]: x_train_cuba.head()
          print(x_train_cuba.shape)
```

```
(2400,)
```

```
In [185]: x_test_cuba.head()
          print(x_test_cuba.shape)
```

```
(600,)
```

- Limpieza del corpus de entrenamiento y de prueba

In [295]:
```
#Limpiando datos de entrenamiento
num= x_train_cuba.size

clean_train_cu = []

for i in range( 0, num):

    clean_train_cu.append( review_to_words2(x_train_cuba.values[i] ) )
x_train_w2vtwit_cu = clean_train_cu
```

In [296]:
```
#Limpiando datos de prueba
num= x_test_cuba.size

clean_test_cu = []

for i in range( 0, num):
    clean_test_cu.append( review_to_words2(x_test_cuba.values[i] ) )

x_test_w2vtwit_cu = clean_test_cu
```

In [297]:
```
x_train_w2vtwit_cu = train_cu["TOPIC"].astype(str).str.cat(x_train_w2vtwit_cu, sep='
x_test_w2vtwit_cu = test_cu["TOPIC_y"].astype(str).str.cat(x_test_w2vtwit_cu, sep='
```

In [189]:
```
x_train_w2vtwit_cu[0]
```

Out[189]:
```
'TELEVISIÓN DIGITAL, CAJAS DECODIFICADORAS, TELEVISIÓN CUBANA, AUDIOVISUALES magnific
```

In [190]:
```
x_test_w2vtwit_cu[0]
```

Out[190]:
```
'ECONOMÍA. TURISMOS, HOTELES oferta persona noche habitación doble hoy febrero precio
```

- W2V Twitter Avg

In [298]:
```
mean_embedding_vectorizer_twitter_cu = MeanEmbeddingVectorizer(modelo_twitter)
mean_emb_train_w2vtwit_cu = mean_embedding_vectorizer_twitter_cu.fit_transform(x_trai
mean_emb_test_w2vtwit_cu = mean_embedding_vectorizer_twitter_cu.fit_transform(x_test_
print(mean_emb_train_w2vtwit_cu.shape)
print(mean_emb_test_w2vtwit_cu.shape)
```

```
(2400, 400)
(600, 400)
```

18.2.1 Clasificador NN

In [299]:
```
from keras.utils import to_categorical

y_train_w2vtwit_cu = to_categorical(y_train_cu)
y_test_w2vtwit_cu  = to_categorical(y_test_cu)
```

```
num_cu, sz_cu = y_train_w2vtwit_cu.shape

print(num_cu)
print(sz_cu)
```

```
2400
2
```

- Selección del múmero de epocas

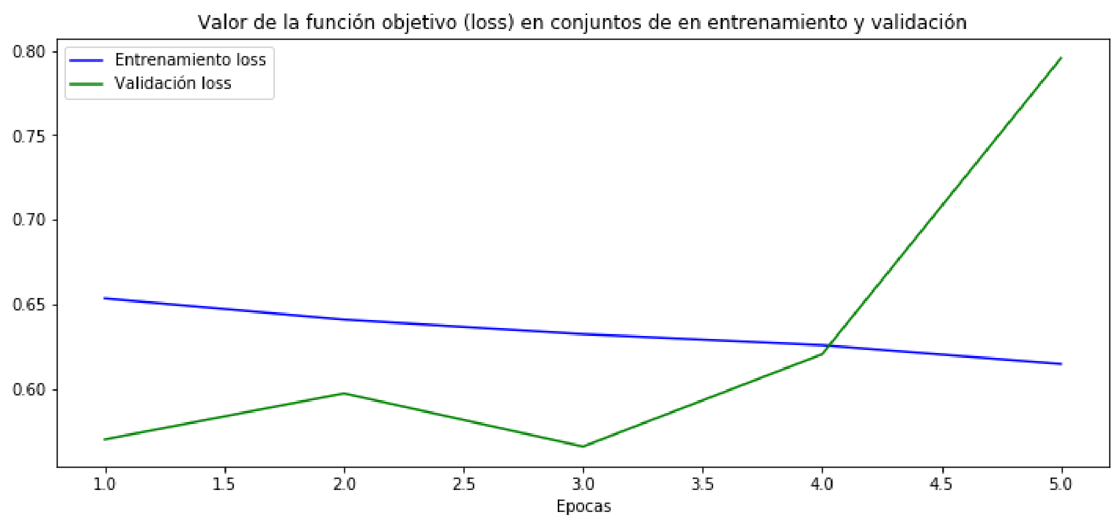
```
In [306]: import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 100
          epochs = 5

          nn_w2vtwit_cu = Sequential()
          nn_w2vtwit_cu.add(Dense(512, activation='relu'))
          nn_w2vtwit_cu.add(Dropout(0.25))
          nn_w2vtwit_cu.add(Dense(sz_cu, activation='softmax'))
          nn_w2vtwit_cu.compile(loss='binary_crossentropy',
                        optimizer='nadam',
                        metrics=['accuracy'])

          history_w2vtwit_cu = nn_w2vtwit_cu.fit(mean_emb_train_w2vtwit_cu,
                        y_train_w2vtwit_cu,
                        validation_split=.2,
                        batch_size= batch_size,
                        shuffle   =True,
                        epochs=epochs,
                        verbose=2)

          print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
Train on 1920 samples, validate on 480 samples
Epoch 1/5
 - 5s - loss: 0.6534 - acc: 0.6432 - val_loss: 0.5701 - val_acc: 0.7583
Epoch 2/5
 - 0s - loss: 0.6409 - acc: 0.6490 - val_loss: 0.5973 - val_acc: 0.7542
Epoch 3/5
 - 0s - loss: 0.6323 - acc: 0.6510 - val_loss: 0.5659 - val_acc: 0.7583
Epoch 4/5
 - 0s - loss: 0.6258 - acc: 0.6578 - val_loss: 0.6204 - val_acc: 0.6979
Epoch 5/5
 - 0s - loss: 0.6147 - acc: 0.6646 - val_loss: 0.7955 - val_acc: 0.3667
```

```
Tiempo de procesamiento (secs):  6.610992193222046
```

Gráfica loss values datos de entrenamiento y validación respecto al número de epocas

```
In [307]: history_dict_w2vtwit_cu = history_w2vtwit_cu.history
          dictkeys_w2vtwit_cu=list(history_dict_w2vtwit_cu.keys())
          loss_values_w2vtwit_cu = history_w2vtwit_cu.history['loss']
          val_loss_values_w2vtwit_cu = history_w2vtwit_cu.history['val_loss']
          epochs_w2vtwit_cu = range(1, len(loss_values_w2vtwit_cu) + 1)


          plt.figure(figsize=(12,5))
          plt.plot(epochs_w2vtwit_cu, loss_values_w2vtwit_cu, 'b', label='Entrenamiento loss')
          plt.plot(epochs_w2vtwit_cu, val_loss_values_w2vtwit_cu, 'g', label='Validación loss')
          plt.title('Valor de la función objetivo (loss) en conjuntos de en entrenamiento y val
          plt.xlabel('Epocas')
          plt.ylabel('')
          plt.legend()

          plt.show()
```



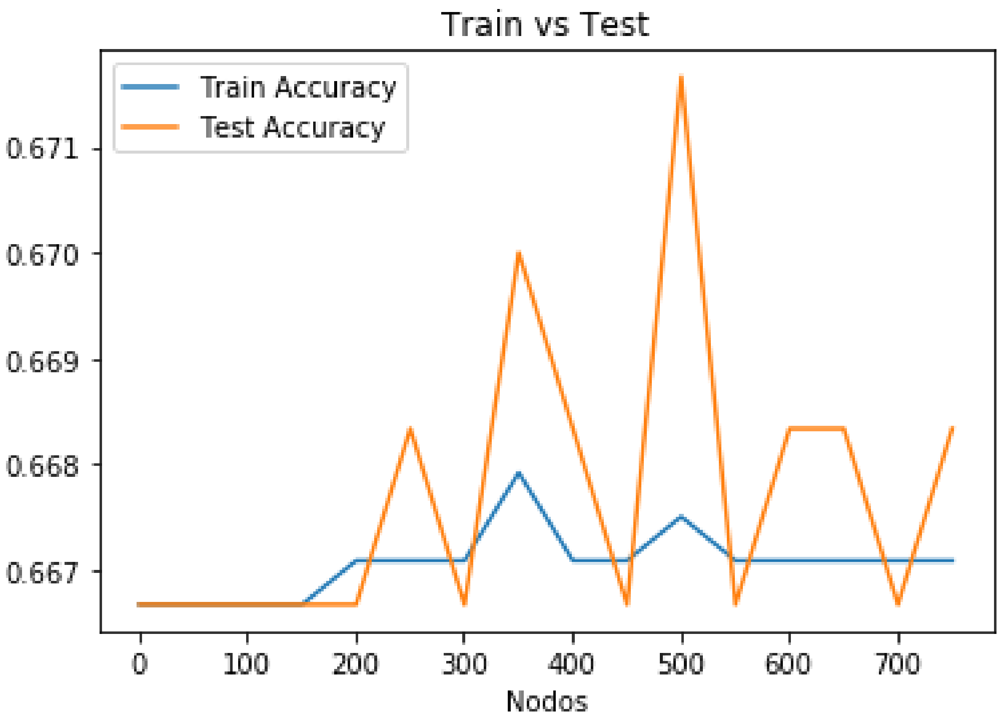
- Selección del número de nodos

```
In [308]: batch_size = 100
          epochs = 3 # epocas seleccionadas

          list_nn_w2vtwit_cu= np.arange( 1, 800, 50) # parámetro de regularización
          score_train_w2vtwit_cu = np.zeros(len(list_nn_w2vtwit_cu)) # almacena acurr_w2vtwit_
          score_test_w2vtwit_cu = np.zeros(len(list_nn_w2vtwit_cu)) # almacena acurracy prueba
```

```
count = 0
for i in list_nn_w2vtwit_cu:
    # Build the model
    nn_w2vtwit_cu = Sequential()
    nn_w2vtwit_cu.add(Dense(i, activation='relu'))
    nn_w2vtwit_cu.add(Dropout(0.25))
    nn_w2vtwit_cu.add(Dense(sz_cu, activation='softmax'))
    nn_w2vtwit_cu.compile(loss='binary_crossentropy',
              optimizer='nadam',
              metrics=['accuracy'])

# No se utilizan datos de validación
    nn_w2vtwit_cu.fit(mean_emb_train_w2vtwit_cu,
              y_train_w2vtwit_cu,
              batch_size= batch_size,
              shuffle   =True,
              epochs=epochs,
              verbose=0)

    temp1_w2vtwit_cu = nn_w2vtwit_cu.evaluate(mean_emb_train_w2vtwit_cu, y_train_w2v
    score_train_w2vtwit_cu[count] = temp1_w2vtwit_cu[1]
    temp2_w2vtwit_cu = nn_w2vtwit_cu.evaluate(mean_emb_test_w2vtwit_cu, y_test_w2vtwi
    score_test_w2vtwit_cu[count]= temp2_w2vtwit_cu[1]
    count = count + 1
```

Gráfica accuracy datos de entrenamiento y de prueba respecto al número de nodos

```
In [309]: matriz_w2vtwit_cu = np.matrix(np.c_[list_nn_w2vtwit_cu, score_train_w2vtwit_cu, score
          models_w2vtwit_cu = pd.DataFrame(data = matriz_w2vtwit_cu, columns =
                        ['Nodos', 'Train Accuracy', 'Test Accuracy'])
          plt.plot(models_w2vtwit_cu['Nodos'],models_w2vtwit_cu['Train Accuracy'])
          plt.plot(models_w2vtwit_cu['Nodos'],models_w2vtwit_cu['Test Accuracy'])
          plt.title('Train vs Test')
          plt.xlabel('Nodos')
          plt.legend()
          plt.show()
```




```
In [310]: models_w2vtwit_cu
```

Out[310]:

	Nodos	Train Accuracy	Test Accuracy
0	1.0	0.666667	0.666667
1	51.0	0.666667	0.666667
2	101.0	0.666667	0.666667
3	151.0	0.666667	0.666667
4	201.0	0.667083	0.666667
5	251.0	0.667083	0.668333
6	301.0	0.667083	0.666667
7	351.0	0.667917	0.670000
8	401.0	0.667083	0.668333
9	451.0	0.667083	0.666667
10	501.0	0.667500	0.671667
11	551.0	0.667083	0.666667
12	601.0	0.667083	0.668333
13	651.0	0.667083	0.668333
14	701.0	0.667083	0.666667
15	751.0	0.667083	0.668333

```
In [289]: #nodo_w2vtwit_mx = list_nn_w2vtwit_mx[np.argmax(np.array(models_w2vtwit_mx['Test Acc
          nodo_w2vtwit_cu=512 # selección del número de nodo
```

- Diseño Final

```
In [294]: import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 100
          epochs = 5

          nn_w2vtwit_cu = Sequential()
          nn_w2vtwit_cu.add(Dense(nodo_w2vtwit_cu, activation='relu'))
          nn_w2vtwit_cu.add(Dropout(0.25))
          nn_w2vtwit_cu.add(Dense(sz_cu, activation='softmax'))
          nn_w2vtwit_cu.compile(loss='binary_crossentropy',
                        optimizer='nadam',
                        metrics=['accuracy'])

          history_w2vtwit_cu = nn_w2vtwit_cu.fit(mean_emb_train_w2vtwit_cu,
                        y_train_w2vtwit_cu,
                        validation_split=.2,
                        batch_size= batch_size,
                        shuffle   =True,
                        epochs=epochs,
                        verbose=2)

          print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
Train on 1920 samples, validate on 480 samples
Epoch 1/5
 - 2s - loss: 0.6534 - acc: 0.6432 - val_loss: 0.5701 - val_acc: 0.7583
Epoch 2/5
 - 0s - loss: 0.6409 - acc: 0.6490 - val_loss: 0.5973 - val_acc: 0.7542
Epoch 3/5
 - 0s - loss: 0.6323 - acc: 0.6510 - val_loss: 0.5659 - val_acc: 0.7583
Epoch 4/5
 - 0s - loss: 0.6258 - acc: 0.6578 - val_loss: 0.6204 - val_acc: 0.6979
Epoch 5/5
 - 0s - loss: 0.6147 - acc: 0.6646 - val_loss: 0.7955 - val_acc: 0.3667
Tiempo de procesamiento (secs):  4.292276382446289
```

- Guardar modelo

```
In [300]: from keras.models import load_model
          #nn_w2vtwit_cu.save('nn_cuba_w2vtwit')  # Guardar modelo
          nn_w2vtwit_cu = load_model('nn_cuba_w2vtwit') # Cargar modelo
```

```
In [301]: from keras.models import load_model
          #nn_w2vtwit_cu.save('nn_cuba_w2vtwit')  # Guardar modelo
          nn_w2vtwit_cu = load_model('nn_cuba_w2vtwit') # Cargar modelo
```

```
600/600 [==============================] - 1s 2ms/step
Test loss: 0.6970452682177226
Test accuracy: 0.531666667064031
```

```
In [302]: y_pred_w2vtwit_cu = nn_w2vtwit_cu.predict(mean_emb_test_w2vtwit_cu).squeeze()

          import numpy as np
          from sklearn.metrics import confusion_matrix, precision_score, recall_score, f1_score

          y_test_label_w2vtwit_cu = np.argmax(y_test_w2vtwit_cu,1)
          y_pred_label_w2vtwit_cu = np.argmax(y_pred_w2vtwit_cu,1)

          # Confusion matrix
          C=confusion_matrix(y_test_label_w2vtwit_cu , y_pred_label_w2vtwit_cu)
          print(C)
```

```
[[185 215]
 [ 66 134]]
```

18.2.2 Resultados

```
In [135]: print('Accuracy score:', results_w2vtwit_cu[1])  # nn evaluate keras
          print("F1 score", f1_score(y_test_label_w2vtwit_cu,  y_pred_label_w2vtwit_cu,  averag
          print("F1 weighted", f1_score(y_test_label_w2vtwit_cu,  y_pred_label_w2vtwit_cu,  ave
          print("Recall score", recall_score(y_test_label_w2vtwit_cu,  y_pred_label_w2vtwit_cu
          print("Precision score", precision_score(y_test_label_w2vtwit_cu,  y_pred_label_w2vtw
```

```
Accuracy score: 0.531666667064031
F1 score 0.5282583331234838
F1 weighted 0.5416243470183184
Recall score 0.56625
Precision score 0.5605029737782394
```

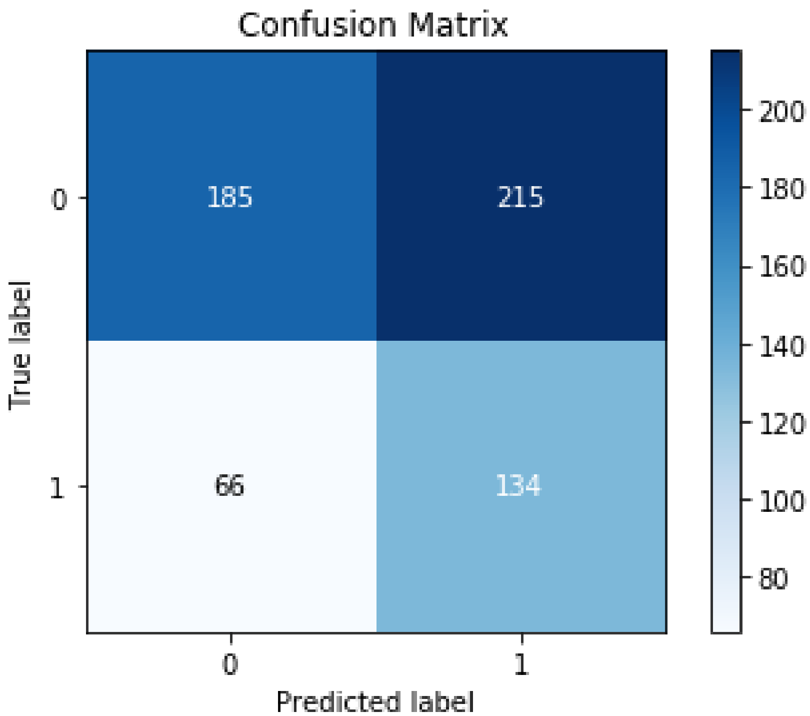
```
In [136]: y_test_label_w2vtwit_cu.shape

Out[136]: (600,)

In [198]: from sklearn.metrics import classification_report
          print(classification_report(y_test_label_w2vtwit_cu, y_pred_label_w2vtwit_cu,target_n
```

```
             precision    recall  f1-score   support

   no-ironia       0.74      0.46      0.57       400
      ironia       0.38      0.67      0.49       200

   micro avg       0.53      0.53      0.53       600
```

```
   macro avg       0.56      0.57      0.53       600
weighted avg       0.62      0.53      0.54       600
```

```
In [386]: %matplotlib inline
          import matplotlib.pyplot as plt
          import scikitplot

          scikitplot.metrics.plot_confusion_matrix(y_test_label_w2vtwit_cu, y_pred_label_w2vtwi
```

```
Out[386]: <matplotlib.axes._subplots.AxesSubplot at 0x1b4676e5b38>
```



18.2.3 Clasificador SVM

- Selección de modelo

```
In [387]: from sklearn.pipeline import Pipeline
          from sklearn.svm import LinearSVC
          from sklearn.model_selection import GridSearchCV
          from sklearn.preprocessing import StandardScaler
          import time
          tic=time.time()
```

```
SVCpipe = Pipeline([('SVC',LinearSVC(class_weight="balanced", random_state=1,verbose=

# Gridsearch to determine the value of C
param_grid = {'SVC__C':np.arange(1,10,.1)}
linearSVC = GridSearchCV(SVCpipe,param_grid,cv=5,return_train_score=True, verbose=0)
linearSVC.fit(mean_emb_train_w2vtwit_cu, y_train_cu.values)
print(linearSVC.best_params_)
#linearSVC.coef_
#linearSVC.intercept_

svc_w2vtwit_cu = linearSVC.best_estimator_
svc_w2vtwit_cu.fit(mean_emb_train_w2vtwit_cu, y_train_cu.values)
svc_w2vtwit_cu.coef_ = svc_w2vtwit_cu.named_steps['SVC'].coef_
svc_w2vtwit_cu.score(mean_emb_train_w2vtwit_cu, y_train_cu.values)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
{'SVC__C': 2.4000000000000012}
Tiempo de procesamiento (secs):  335.76003766059875
```

In [303]:
```
from joblib import dump, load
#dump(svc_w2vtwit_cu, 'svc_w2vtwit_cu.joblib')
svc_w2vtwit_cu = load('svc_w2vtwit_cu.joblib')
prediction_w2vtwit_cu=svc_w2vtwit_cu.predict(mean_emb_test_w2vtwit_cu)
print("Acurracy Test",metrics.accuracy_score( y_test_cu.values, prediction_w2vtwit_cu
```

```
Acurracy Test 0.6366666666666667
```

In [304]:
```
print("Confusion Metrix:\n",metrics.confusion_matrix(y_test_cu.values, prediction_w2v
```

```
Confusion Metrix:
 [[274 126]
 [ 92 108]]
```

18.2.4 Resultados

In [305]:
```
print('Accuracy score:', metrics.accuracy_score(y_test_cu.values, prediction_w2vtwit_
print("F1 score", f1_score(y_test_cu.values, prediction_w2vtwit_cu,  average='macro')
print("F1 weighted", f1_score(y_test_cu.values, prediction_w2vtwit_cu,  average='weig
print("Recall score", recall_score(y_test_cu.values, prediction_w2vtwit_cu,  average=
print("Precision score", precision_score(y_test_cu.values, prediction_w2vtwit_cu,  av
```

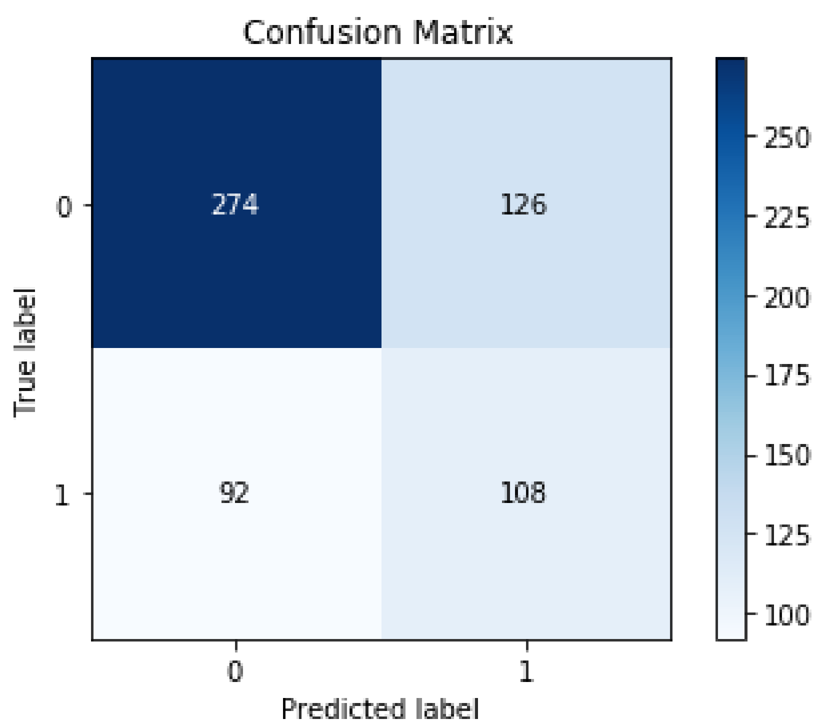
```
Accuracy score: 0.6366666666666667
F1 score 0.6065502761367327
F1 weighted 0.642835084004123
Recall score 0.6125
Precision score 0.6050861706599412
```

In [303]:
```
from sklearn.metrics import classification_report
print(classification_report( y_test_cu.values, prediction_w2vtwit_cu, target_names=[
```

```
              precision    recall  f1-score   support

   no-ironia       0.75      0.69      0.72       400
      ironia       0.46      0.54      0.50       200

   micro avg       0.64      0.64      0.64       600
   macro avg       0.61      0.61      0.61       600
weighted avg       0.65      0.64      0.64       600
```

In [392]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import scikitplot

scikitplot.metrics.plot_confusion_matrix(y_test_cu.values, prediction_w2vtwit_cu)
```

Out[392]: `<matplotlib.axes._subplots.AxesSubplot at 0x1b468c89da0>`



In [306]:
```
del modelo_twitter
```

19 PARTE IV Desempeño

19.1 Por representación

19.1.1 Clasificador SVM

- Acurracy

```
In [213]: # intialise data of lists.
          accuracy_svm = {'País':['México', 'España', 'Cuba'],
                  'BoW TF-IDF':[metrics.accuracy_score(y_test.values,  prediction_mx, ),
                               metrics.accuracy_score(y_test_es.values,  prediction_es, ),
                               metrics.accuracy_score(y_test_cu.values,  prediction_cu, )],
                  'W2Vec Google':[metrics.accuracy_score(y_test.values, prediction_w2vgoogle_m
                               metrics.accuracy_score(y_test_es.values, prediction_w2vgoogle_
                               metrics.accuracy_score(y_test_cu.values, prediction_w2vgoogle_
                  'W2Vec Twitter':[metrics.accuracy_score(y_test.values, prediction_w2vtwit_mx
                               metrics.accuracy_score(y_test_es.values, prediction_w2vtwit_es
                               metrics.accuracy_score(y_test_cu.values, prediction_w2vtwit_cu

          # Create DataFrame
          accuracy_svm  = pd.DataFrame(accuracy_svm )
          accuracy_svm
```

Out[213]:

	País	BoW TF-IDF	W2Vec Google	W2Vec Twitter
0	México	0.663333	0.653333	0.653333
1	España	0.715000	0.691667	0.661667
2	Cuba	0.625000	0.626667	0.636667

- F1 Score macro

```
In [214]: # intialise data of lists.
          F1score_svm = {'País':['México', 'España', 'Cuba'],
                  'BoW TF-IDF':[f1_score( y_test.values,  prediction_mx,   average='macro'),
                               f1_score( y_test_es.values,  prediction_es,   average='macro')
                               f1_score( y_test_cu.values,  prediction_cu,   average='macro')
                  'W2Vec Google':[f1_score( y_test.values, prediction_w2vgoogle_mx,   average=
                               f1_score( y_test_es.values,  prediction_w2vgoogle_es,  average
                               f1_score( y_test_cu.values, prediction_w2vgoogle_cu,   average
                  'W2Vec Twitter':[f1_score( y_test.values, prediction_w2vtwit_mx,   average='
                               f1_score( y_test_es.values,  prediction_w2vtwit_es,  average='
                               f1_score( y_test_cu.values, prediction_w2vtwit_cu,   average='

          # Create DataFrame
          F1score_svm = pd.DataFrame(F1score_svm)
          F1score_svm
```

Out[214]:

	País	BoW TF-IDF	W2Vec Google	W2Vec Twitter
0	México	0.642756	0.625342	0.626074
1	España	0.685059	0.660042	0.652587
2	Cuba	0.601053	0.606447	0.606550

In [204]: F1score_svm['BoW TF-IDF'].values.mean()

Out[204]: 0.6429560031401762

In [205]: F1score_svm['W2Vec Google'].values.mean()

Out[205]: 0.6306103644490654

In [207]: F1score_svm['W2Vec Twitter'].values.mean()

Out[207]: 0.628403682138794

- F1 Score weighted

In [208]:
```
# intialise data of lists.
F1w_svm = {'País':['México', 'España', 'Cuba'],
        'BoW TF-IDF':[f1_score( y_test.values,  prediction_mx,   average='weighted')
                      f1_score( y_test_es.values,  prediction_es,   average='weighte
                      f1_score( y_test_cu.values,  prediction_cu,   average='weighte
        'W2Vec Google':[f1_score( y_test.values, prediction_w2vgoogle_mx,   average=
                      f1_score( y_test_es.values,  prediction_w2vgoogle_es,  average=
                      f1_score( y_test_cu.values, prediction_w2vgoogle_cu,   average=
        'W2Vec Twitter':[f1_score( y_test.values, prediction_w2vtwit_mx,   average='
                      f1_score( y_test_es.values,  prediction_w2vtwit_es,  average='
                      f1_score( y_test_cu.values, prediction_w2vtwit_cu,   average='

# Create DataFrame
F1w_svm = pd.DataFrame(F1w_svm)
F1w_svm
```

Out[208]:

	País	BoW TF-IDF	W2Vec Google	W2Vec Twitter
0	México	0.671621	0.659819	0.660064
1	España	0.717428	0.694604	0.671308
2	Cuba	0.633634	0.636182	0.642835

- Recall score

In [310]:
```
# intialise data of lists.
recall_svm = {'País':['México', 'España', 'Cuba'],
        'BoW TF-IDF':[recall_score( y_test.values,  prediction_mx,   average='macro'
                      recall_score( y_test_es.values,  prediction_es,   average='mac
                      recall_score( y_test_cu.values,  prediction_cu,   average='mac
        'W2Vec Google':[recall_score( y_test.values, prediction_w2vgoogle_mx,   avera
                      recall_score( y_test_es.values,  prediction_w2vgoogle_es,  ave
                      recall_score( y_test_cu.values, prediction_w2vgoogle_cu,   ave
        'W2Vec Twitter':[recall_score( y_test.values, prediction_w2vtwit_mx,   averag
                      recall_score( y_test_es.values,  prediction_w2vtwit_es,  averag
                      recall_score( y_test_cu.values, prediction_w2vtwit_cu,   averag

# Create DataFrame
recall_svm = pd.DataFrame(recall_svm)
recall_svm
```

Out[310]:

	País	BoW TF-IDF	W2Vec Google	W2Vec Twitter
0	México	0.657001	0.633066	0.634331
1	España	0.688750	0.663750	0.683750
2	Cuba	0.611250	0.620000	0.612500

- Precision score

In [209]:
```
# intialise data of lists.
precision_svm = {'País':['México', 'España', 'Cuba'],
        'BoW TF-IDF':[precision_score( y_test.values,  prediction_mx,   average='mac
                      precision_score( y_test_es.values,  prediction_es,   average='m
                      precision_score( y_test_cu.values,  prediction_cu,   average='m
        'W2Vec Google':[precision_score( y_test.values, prediction_w2vgoogle_mx,   av
                      precision_score( y_test_es.values,  prediction_w2vgoogle_es,  a
                      precision_score( y_test_cu.values, prediction_w2vgoogle_cu,   a
        'W2Vec Twitter':[precision_score( y_test.values, prediction_w2vtwit_mx,   ave
                      precision_score( y_test_es.values,  prediction_w2vtwit_es,  ave
                      precision_score( y_test_cu.values, prediction_w2vtwit_cu,   ave
# Create DataFrame
precision_svm = pd.DataFrame(precision_svm)
precision_svm
```

Out[209]:

	País	BoW TF-IDF	W2Vec Google	W2Vec Twitter
0	México	0.642125	0.623426	0.624242
1	España	0.682422	0.657621	0.663350
2	Cuba	0.601377	0.608225	0.605086

19.1.2 Clasificador NN

- Accuracy

In [312]:
```
# intialise data of lists.
accuracy_nn= {'País':['México', 'España', 'Cuba'],
        'BoW TF-IDF':[results_mx[1],
                      results_es[1],
                      results_cu[1]],
        'W2Vec Google':[results_w2vgoogle_mx[1],
                      results_w2vgoogle_es[1],
                      results_w2vgoogle_cu[1]],
        'W2Vec Twitter':[results_w2vtwit_mx[1],
                      results_w2vtwit_es[1],
                      results_w2vtwit_cu[1]]}

# Create DataFrame
accuracy_nn = pd.DataFrame(accuracy_nn)
accuracy_nn
```

Out[312]:

	País	BoW TF-IDF	W2Vec Google	W2Vec Twitter
0	México	0.693333	0.676667	0.608333

```
1  España    0.725000      0.698333       0.673333
2    Cuba    0.611667      0.575000       0.531667
```

- F1 score

```
In [313]: F1score_nn= {'País':['México', 'España', 'Cuba'],
                  'BoW TF-IDF':[f1_score(y_test_label_mx,  y_pred_label_mx,  average='macro'),
                                f1_score(y_test_label_es,  y_pred_label_es,  average='macro'),
                                 f1_score(y_test_label_cu,  y_pred_label_cu,  average='macro')]
                  'W2Vec Google':[f1_score(y_test_label_w2vgoogle_mx,  y_pred_label_w2vgoogle_
                                f1_score(y_test_label_w2vgoogle_es,  y_pred_label_w2vgoogle_es,
                                 f1_score(y_test_label_w2vgoogle_cu,  y_pred_label_w2vgoogle_cu
                  'W2Vec Twitter':[f1_score(y_test_label_w2vtwit_mx,  y_pred_label_w2vtwit_mx,
                                f1_score(y_test_label_w2vtwit_es,  y_pred_label_w2vtwit_es,  ave
                                 f1_score(y_test_label_w2vtwit_cu,  y_pred_label_w2vtwit_cu,  a

          # Create DataFrame
          F1score_nn = pd.DataFrame(F1score_nn)
          F1score_nn

Out[313]:      País  BoW TF-IDF  W2Vec Google  W2Vec Twitter
          0  México    0.604788      0.597572       0.556569
          1  España    0.673137      0.613577       0.623651
          2    Cuba    0.579056      0.555717       0.528258
```

- F1 weighted

```
In [314]: F1weighted_nn = {'País':['México', 'España', 'Cuba'],
                  'BoW TF-IDF':[f1_score(y_test_label_mx,  y_pred_label_mx,  average='weighted
                                f1_score(y_test_label_es,  y_pred_label_es,   average='weighted
                                 f1_score(y_test_label_cu,  y_pred_label_cu,   average='weighte
                  'W2Vec Google':[f1_score(y_test_label_w2vgoogle_mx,  y_pred_label_w2vgoogle_
                                f1_score(y_test_label_w2vgoogle_es,  y_pred_label_w2vgoogle_es,
                                 f1_score(y_test_label_w2vgoogle_cu,  y_pred_label_w2vgoogle_cu
                  'W2Vec Twitter':[f1_score(y_test_label_w2vtwit_mx,  y_pred_label_w2vtwit_mx,
                                f1_score(y_test_label_w2vtwit_es,  y_pred_label_w2vtwit_es,   a
                                 f1_score(y_test_label_w2vtwit_cu,  y_pred_label_w2vtwit_cu,

          # Create DataFrame
          F1weighted_nn = pd.DataFrame(F1weighted_nn)
          F1weighted_nn

Out[314]:      País  BoW TF-IDF  W2Vec Google  W2Vec Twitter
          0  México    0.667768      0.657636       0.607576
          1  España    0.716537      0.673902       0.669231
          2    Cuba    0.618111      0.586570       0.541624
```

- Recall score

```
In [315]: Recall_nn = {'País':['México', 'España', 'Cuba'],
                  'BoW TF-IDF':[recall_score( y_test_label_mx,  y_pred_label_mx,  average='mac
                               recall_score( y_test_label_es,  y_pred_label_es,  average='macro
                                recall_score( y_test_label_cu,  y_pred_label_cu,  average='mac
                  'W2Vec Google':[recall_score( y_test_label_w2vgoogle_mx,  y_pred_label_w2vgo
                               recall_score(y_test_label_w2vgoogle_es,  y_pred_label_w2vgoogle_
                                recall_score( y_test_label_w2vgoogle_cu,  y_pred_label_w2vgoog
                  'W2Vec Twitter':[recall_score( y_test_label_w2vtwit_mx,  y_pred_label_w2vtwi
                               recall_score(y_test_label_w2vtwit_es,  y_pred_label_w2vtwit_es,
                                recall_score( y_test_label_w2vtwit_cu,  y_pred_label_w2vtwit_c

          # Create DataFrame
          Recall_nn = pd.DataFrame(Recall_nn)
          Recall_nn
```

Out[315]:

	País	BoW TF-IDF	W2Vec Google	W2Vec Twitter
0	México	0.602238	0.594832	0.556367
1	España	0.666250	0.610000	0.621250
2	Cuba	0.583750	0.568750	0.566250

- Precisión score

```
In [316]: precison_nn = {'País':['México', 'España', 'Cuba'],
                  'BoW TF-IDF':[precision_score( y_test_label_mx,  y_pred_label_mx,  average='m
                               precision_score( y_test_label_es,  y_pred_label_es,  average='ma
                                precision_score( y_test_label_cu,  y_pred_label_cu,  average='m
                  'W2Vec Google':[precision_score(y_test_label_w2vgoogle_mx,  y_pred_label_w2v
                               precision_score(y_test_label_w2vgoogle_es,  y_pred_label_w2vgoo
                                precision_score(y_test_label_w2vgoogle_cu,  y_pred_label_w2vgo
                  'W2Vec Twitter':[precision_score(y_test_label_w2vtwit_mx,  y_pred_label_w2vt
                               precision_score(y_test_label_w2vtwit_es,  y_pred_label_w2vtwit_
                                precision_score(y_test_label_w2vtwit_cu,  y_pred_label_w2vtwit_

          # Create DataFrame
          precison_nn= pd.DataFrame(precison_nn)
          precison_nn
```

Out[316]:

	País	BoW TF-IDF	W2Vec Google	W2Vec Twitter
0	México	0.644370	0.620550	0.556804
1	España	0.688175	0.653741	0.627504
2	Cuba	0.578352	0.561538	0.560503

20 Por metrica

- BoW TF-IDF

Clasificación NN

```
In [318]: BoW_nn = {'País':['México', 'España', 'Cuba'],
                  'Accuracy':[results_mx[1],
                            results_es[1],
                            results_cu[1]],
                  'F1 score':[f1_score( y_test_label_mx,  y_pred_label_mx,  average='macro'),
                            f1_score( y_test_label_es,  y_pred_label_es,  average='macro'),
                            f1_score( y_test_label_cu,  y_pred_label_cu,  average='macro')],
                  'F1 weighted':[f1_score( y_test_label_mx,  y_pred_label_mx,  average='weighte
                            f1_score( y_test_label_es,  y_pred_label_es,  average='weighted'),
                            f1_score( y_test_label_cu,  y_pred_label_cu,  average='weighted')]
                 'Recall':[recall_score( y_test_label_mx,  y_pred_label_mx,  average='macro'),
                            recall_score( y_test_label_es,  y_pred_label_es,  average='macro')
                            recall_score( y_test_label_cu,  y_pred_label_cu,  average='macro')]
                 'Precision':[precision_score( y_test_label_mx,  y_pred_label_mx,  average='mac
                            precision_score( y_test_label_es,  y_pred_label_es,  average='macro
                            precision_score( y_test_label_cu,  y_pred_label_cu,  average='macro




          # Create DataFrame
          BoW_nn= pd.DataFrame(BoW_nn)
          BoW_nn
```

Out[318]:

	País	Accuracy	F1 score	F1 weighted	Recall	Precision
0	México	0.693333	0.604788	0.667768	0.602238	0.644370
1	España	0.725000	0.673137	0.716537	0.666250	0.688175
2	Cuba	0.611667	0.579056	0.618111	0.583750	0.578352

Clasificación SVM

```
In [319]: BoW_svm = {'País':['México', 'España', 'Cuba'],
                  'Accuracy':[metrics.accuracy_score(y_test.values,  prediction_mx, ),
                            metrics.accuracy_score(y_test_es.values,  prediction_es, ),
                            metrics.accuracy_score(y_test_cu.values,  prediction_cu, )],
                  'F1 score':[f1_score(y_test.values,  prediction_mx,  average='macro'),
                            f1_score(y_test_es.values,  prediction_es,  average='macro'),
                            f1_score(y_test_cu.values,  prediction_cu,  average='macro')],
                  'F1 weighted':[f1_score(y_test.values,  prediction_mx,   average='weighted')
                            f1_score(y_test_es.values,  prediction_es,   average='weighted'),
                            f1_score(y_test_cu.values,  prediction_cu,   average='weighted')],
                 'Recall':[recall_score(y_test.values,  prediction_mx,   average='macro'),
                            recall_score(y_test_es.values,  prediction_es,   average='macro'),
                            recall_score(y_test_cu.values,  prediction_cu,   average='macro')]
                 'Precision':[precision_score(y_test.values,  prediction_mx,  average='macro'),
                            precision_score(y_test_es.values,  prediction_es,  average='macro')
                            precision_score(y_test_es.values,  prediction_cu,  average='macro')
```

```
# Create DataFrame
BoW_svm= pd.DataFrame(BoW_svm)
BoW_svm
```

Out[319]:

	País	Accuracy	F1 score	F1 weighted	Recall	Precision
0	México	0.663333	0.642756	0.671621	0.657001	0.642125
1	España	0.715000	0.685059	0.717428	0.688750	0.682422
2	Cuba	0.625000	0.601053	0.633634	0.611250	0.474940

- W2Vec Google

Clasificación NN

In [320]:
```
w2vgoogle_nn = {'País':['México', 'España', 'Cuba'],
                'Accuracy':[results_w2vgoogle_mx[1],
                           results_w2vgoogle_es[1],
                           results_w2vgoogle_cu[1]],
                'F1 score':[f1_score(  y_test_label_w2vgoogle_mx,  y_pred_label_w2vgoogle_mx
                           f1_score( y_test_label_w2vgoogle_es,  y_pred_label_w2vgoogle_es,
                           f1_score(  y_test_label_w2vgoogle_cu,  y_pred_label_w2vgoogle_cu,
                'F1 weighted':[f1_score(y_test_label_w2vgoogle_mx,  y_pred_label_w2vgoogle_m
                           f1_score( y_test_label_w2vgoogle_es,  y_pred_label_w2vgoogle_es,
                           f1_score( y_test_label_w2vgoogle_cu,  y_pred_label_w2vgoogle_cu,
              'Recall':[recall_score(  y_test_label_w2vgoogle_mx,  y_pred_label_w2vgoogle_mx
                           recall_score(  y_test_label_w2vgoogle_es,  y_pred_label_w2vgoogle_
                           recall_score(  y_test_label_w2vgoogle_cu,  y_pred_label_w2vgoogle_
              'Precision':[precision_score(  y_test_label_w2vgoogle_mx,  y_pred_label_w2vgoo
                           precision_score(  y_test_label_w2vgoogle_es,  y_pred_label_w2vgoog
                           precision_score(  y_test_label_w2vgoogle_cu,  y_pred_label_w2vgoog

# Create DataFrame
w2vgoogle_nn= pd.DataFrame(w2vgoogle_nn)
w2vgoogle_nn
```

Out[320]:

	País	Accuracy	F1 score	F1 weighted	Recall	Precision
0	México	0.676667	0.597572	0.657636	0.594832	0.620550
1	España	0.698333	0.613577	0.673902	0.610000	0.653741
2	Cuba	0.575000	0.555717	0.586570	0.568750	0.561538

- Clasificador SVM

```
In [321]: w2vgoogle_svm = {'País':['México', 'España', 'Cuba'],
                'Accuracy':[metrics.accuracy_score( y_test.values, prediction_w2vgoogle_mx),
                          metrics.accuracy_score( y_test_es.values, prediction_w2vgoogle_es)
                          metrics.accuracy_score( y_test_cu.values, prediction_w2vgoogle_cu)]
                'F1 score':[ f1_score(y_test.values, prediction_w2vgoogle_mx,  average='macro
                           f1_score(y_test_es.values, prediction_w2vgoogle_es,  average='mac
                           f1_score(y_test_cu.values, prediction_w2vgoogle_cu,  average='mac
                'F1 weighted':[ f1_score(y_test.values, prediction_w2vgoogle_mx, average='wei
                           f1_score(y_test_es.values, prediction_w2vgoogle_es, average='weig
                           f1_score(y_test_cu.values, prediction_w2vgoogle_cu, average='weig
              'Recall':[recall_score(y_test.values, prediction_w2vgoogle_mx,  average='macro
                          recall_score(y_test_es.values, prediction_w2vgoogle_es,  average='m
                          recall_score(y_test_cu.values, prediction_w2vgoogle_cu,  average='m
              'Precision':[precision_score(y_test.values, prediction_w2vgoogle_mx, average='m
                          precision_score(y_test_es.values, prediction_w2vgoogle_es, average=
                          precision_score(y_test_cu.values, prediction_w2vgoogle_cu, average=



          # Create DataFrame
          w2vgoogle_svm= pd.DataFrame(w2vgoogle_svm)
          w2vgoogle_svm
```

Out[321]:

	País	Accuracy	F1 score	F1 weighted	Recall	Precision
0	México	0.653333	0.625342	0.659819	0.633066	0.623426
1	España	0.691667	0.660042	0.694604	0.663750	0.657621
2	Cuba	0.626667	0.606447	0.636182	0.620000	0.608225

- W2Vec Twitter

Clasificación NN

```
In [471]: w2vtwit_nn = {'País':['México', 'España', 'Cuba'],
                'Accuracy':[results_w2vtwit_mx[1],
                          results_w2vtwit_es[1],
                          results_w2vtwit_cu[1]],
                'F1 score':[f1_score(  y_test_label_w2vtwit_mx,  y_pred_label_w2vtwit_mx,   a
                          f1_score( y_test_label_w2vtwit_es,  y_pred_label_w2vtwit_es,   ave
                          f1_score(  y_test_label_w2vtwit_cu,  y_pred_label_w2vtwit_cu,   ave
                'F1 weighted':[f1_score(y_test_label_w2vtwit_mx,  y_pred_label_w2vtwit_mx,  a
                          f1_score( y_test_label_w2vtwit_es,  y_pred_label_w2vtwit_es,  avera
                          f1_score( y_test_label_w2vtwit_cu,  y_pred_label_w2vtwit_cu,  avera
              'Recall':[recall_score(  y_test_label_w2vtwit_mx,  y_pred_label_w2vtwit_mx,  av
                          recall_score(  y_test_label_w2vtwit_es,  y_pred_label_w2vtwit_es,
                          recall_score(  y_test_label_w2vtwit_cu,  y_pred_label_w2vtwit_cu,
              'Precision':[precision_score(  y_test_label_w2vtwit_mx,  y_pred_label_w2vtwit_m
                          precision_score(  y_test_label_w2vtwit_es,  y_pred_label_w2vtwit_es
                          precision_score(  y_test_label_w2vtwit_cu,  y_pred_label_w2vtwit_cu
```

```
# Create DataFrame
w2vtwit_nn= pd.DataFrame(w2vtwit_nn)
w2vtwit_nn
```

Out[471]:

	País	Accuracy	F1 score	F1 weighted	Recall	Precision
0	México	0.608333	0.556569	0.607576	0.556367	0.556804
1	España	0.673333	0.623651	0.669231	0.621250	0.627504
2	Cuba	0.531667	0.528258	0.541624	0.566250	0.560503

Clasificación SVM

```
In [323]: w2vtwit_svm = {'País':['México', 'España', 'Cuba'],
                'Accuracy':[metrics.accuracy_score( y_test.values, prediction_w2vtwit_mx),
                           metrics.accuracy_score( y_test_es.values, prediction_w2vtwit_es),
                           metrics.accuracy_score( y_test_cu.values, prediction_w2vtwit_cu)],
                'F1 score':[ f1_score(y_test.values, prediction_w2vtwit_mx,  average='macro')
                            f1_score(y_test_es.values, prediction_w2vtwit_es,  average='macro
                            f1_score(y_test_cu.values, prediction_w2vtwit_cu,  average='macro
                'F1 weighted':[ f1_score(y_test.values, prediction_w2vtwit_mx, average='weig
                            f1_score(y_test_es.values, prediction_w2vtwit_es, average='weight
                            f1_score(y_test_cu.values, prediction_w2vtwit_cu, average='weight
              'Recall':[recall_score(y_test.values, prediction_w2vtwit_mx,  average='macro')
                           recall_score(y_test_es.values, prediction_w2vtwit_es,  average='ma
                           recall_score(y_test_cu.values, prediction_w2vtwit_cu,  average='ma
              'Precision':[precision_score(y_test.values, prediction_w2vtwit_mx, average='ma
                           precision_score(y_test_es.values, prediction_w2vtwit_es, average='
                           precision_score(y_test_cu.values, prediction_w2vtwit_cu, average='



          # Create DataFrame
          w2vtwit_svm= pd.DataFrame(w2vtwit_svm)
          w2vtwit_svm
```

Out[323]:

	País	Accuracy	F1 score	F1 weighted	Recall	Precision
0	México	0.653333	0.626074	0.660064	0.634331	0.624242
1	España	0.661667	0.652587	0.671308	0.683750	0.663350
2	Cuba	0.636667	0.606550	0.642835	0.612500	0.605086

```
In [ ]:

In [352]: # Liberando memoria

          #del modelo_google
          #del modelo_twitter
```

In [243]:
```
#import os

# introducit path
#os.chdir('C:\\Users\\h_air\\Documents\\Diplomado Deep Learning\\Estancia\\Datos\\Da

#import dill
#dill.dump_session('Estancia.db')
#dill.load_session('Estancia.db')
```

Páginas de referencia
https://www.kaggle.com/pankajb64/classification-using-bow-tf-idf-and-nb
https://www.kaggle.com/nirajvermafcb/support-vector-machine-detail-analysis#Performing-K-fold-cross-validation-with-different-kernels
https://www.kaggle.com/jinilcs/grid-search-to-find-best-tuning-parameters
https://www.kaggle.com/mayu0116/hyper-parameters-tuning-of-dtree-rf-svm-knn

21 F1 score

In [307]:
```
# intialise data of lists.
F1score_svm = {'País':['México', 'España', 'Cuba'],
        'BoW TF-IDF':[f1_score( y_test.values,  prediction_mx,   average='macro'),
                      f1_score( y_test_es.values,  prediction_es,   average='macro')
                      f1_score( y_test_cu.values,  prediction_cu,   average='macro')]
        'W2Vec Google':[f1_score( y_test.values, prediction_w2vgoogle_mx,   average=
                      f1_score( y_test_es.values,  prediction_w2vgoogle_es,  average=
                      f1_score( y_test_cu.values, prediction_w2vgoogle_cu,   average=
        'W2Vec Twitter':[f1_score( y_test.values, prediction_w2vtwit_mx,   average='r
                      f1_score( y_test_es.values,  prediction_w2vtwit_es,  average='r
                      f1_score( y_test_cu.values, prediction_w2vtwit_cu,   average='r

# Create DataFrame
F1score_svm = pd.DataFrame(F1score_svm)
F1score_svm
```

Out[307]:

	País	BoW TF-IDF	W2Vec Google	W2Vec Twitter
0	México	0.642756	0.625342	0.626074
1	España	0.685059	0.660042	0.652587
2	Cuba	0.601053	0.606447	0.606550

In [308]:
```
F1score_nn= {'País':['México', 'España', 'Cuba'],
        'BoW TF-IDF':[f1_score(y_test_label_mx,  y_pred_label_mx,  average='macro'),
                     f1_score(y_test_label_es,  y_pred_label_es,  average='macro'),
                      f1_score(y_test_label_cu,  y_pred_label_cu,  average='macro')]
        'W2Vec Google':[f1_score(y_test_label_w2vgoogle_mx,  y_pred_label_w2vgoogle_r
                     f1_score(y_test_label_w2vgoogle_es,  y_pred_label_w2vgoogle_es,
                      f1_score(y_test_label_w2vgoogle_cu,  y_pred_label_w2vgoogle_cu
        'W2Vec Twitter':[f1_score(y_test_label_w2vtwit_mx,  y_pred_label_w2vtwit_mx,
                     f1_score(y_test_label_w2vtwit_es,  y_pred_label_w2vtwit_es,  ave
```

```
f1_score(y_test_label_w2vtwit_cu,  y_pred_label_w2vtwit_cu,  av

# Create DataFrame
F1score_nn = pd.DataFrame(F1score_nn)
F1score_nn
```

Out[308]:

	País	BoW TF-IDF	W2Vec Google	W2Vec Twitter
0	México	0.604788	0.597572	0.556569
1	España	0.673137	0.613577	0.623651
2	Cuba	0.579056	0.555717	0.528258

22 Representaciones Concatenadas

23 Concatenar BoW TF-IDF + W2VGoogle

Clasificador SVM

23.0.1 México

In [335]:
```
print(np.concatenate((x_train_tf_mx,mean_emb_train_w2vgoogle_mx),axis=1).shape)
BoW_W2VGoogle_mx_train = np.concatenate((x_train_tf_mx, mean_emb_train_w2vgoogle_mx)

print(np.concatenate((x_test_tf_mx,mean_emb_test_w2vgoogle_mx),axis=1).shape)
BoW_W2VGoogle_mx_test= np.concatenate((x_test_tf_mx, mean_emb_test_w2vgoogle_mx),axis
```

```
(2400, 486)
(600, 486)
```

In [336]:
```
from sklearn.pipeline import Pipeline
from sklearn.svm import LinearSVC
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
import time
tic=time.time()

SVCpipe = Pipeline([('SVC',LinearSVC(class_weight="balanced", random_state=1,verbose=

# Gridsearch to determine the value of C
param_grid = {'SVC__C':np.arange(.1,2,.1)}
linearSVC = GridSearchCV(SVCpipe,param_grid,cv=5,return_train_score=True, verbose=0)
linearSVC.fit(BoW_W2VGoogle_mx_train, y_train.values)
print(linearSVC.best_params_)
#linearSVC.coef_
#linearSVC.intercept_

svc_BoW_W2VGoogle_mx = linearSVC.best_estimator_
svc_BoW_W2VGoogle_mx.fit(BoW_W2VGoogle_mx_train, y_train.values)
```

```
    svc_BoW_W2VGoogle_mx.coef_ = svc_BoW_W2VGoogle_mx.named_steps['SVC'].coef_
    svc_BoW_W2VGoogle_mx.score(BoW_W2VGoogle_mx_train, y_train.values)

    print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
{'SVC__C': 0.2}
Tiempo de procesamiento (secs):  40.46106505393982
```

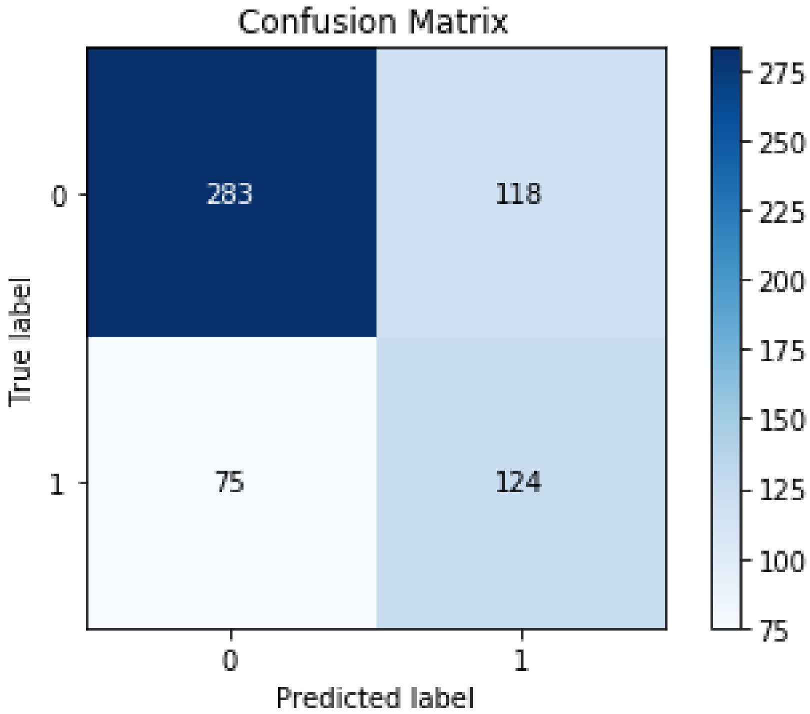
```
In [338]: from joblib import dump, load
          dump(svc_BoW_W2VGoogle_mx, 'svc_W2VGoogle_mx.joblib')
          #svc_w2vtwit_cu = load('svc_w2vtwit_cu.joblib')
          prediction_BoW_W2VGoogle_mx=svc_BoW_W2VGoogle_mx.predict(BoW_W2VGoogle_mx_test)
          print("Acurracy Test",metrics.accuracy_score( y_test.values, prediction_BoW_W2VGoogl
```

```
Acurracy Test 0.6783333333333333
```

```
In [339]: print('Accuracy score:', metrics.accuracy_score(y_test.values, prediction_BoW_W2VGoo
          print("F1 score", f1_score(y_test.values, prediction_BoW_W2VGoogle_mx,  average='mac
          print("F1 weighted", f1_score(y_test.values, prediction_BoW_W2VGoogle_mx,  average='
          print("Recall score", recall_score(y_test.values, prediction_BoW_W2VGoogle_mx,  avera
          print("Precision score", precision_score(y_test.values, prediction_BoW_W2VGoogle_mx,


          from sklearn.metrics import classification_report
          print(classification_report( y_test.values, prediction_BoW_W2VGoogle_mx, target_name

          %matplotlib inline
          import matplotlib.pyplot as plt
          import scikitplot

          scikitplot.metrics.plot_confusion_matrix(y_test.values, prediction_BoW_W2VGoogle_mx)
```

```
Accuracy score: 0.6783333333333333
F1 score 0.6540381633549335
F1 weighted 0.6849037252142842
Recall score 0.6644256193686637
Precision score 0.6514497437554827
              precision    recall  f1-score   support

   no-ironia       0.79      0.71      0.75       401
      ironia       0.51      0.62      0.56       199

   micro avg       0.68      0.68      0.68       600
   macro avg       0.65      0.66      0.65       600
weighted avg       0.70      0.68      0.68       600
```

```
Out[339]: <matplotlib.axes._subplots.AxesSubplot at 0x1ab762eb198>
```



23.0.2 España

```
In [400]: print(np.concatenate((x_train_tf_es,mean_emb_train_w2vgoogle_es),axis=1).shape)
          BoW_W2VGoogle_es_train = np.concatenate((x_train_tf_es, mean_emb_train_w2vgoogle_es)

          print(np.concatenate((x_test_tf_es,mean_emb_test_w2vgoogle_es),axis=1).shape)
          BoW_W2VGoogle_es_test= np.concatenate((x_test_tf_es, mean_emb_test_w2vgoogle_es),axis
```

```
(2400, 7244)
(600, 7244)
```

```
In [401]: from sklearn.pipeline import Pipeline
          from sklearn.svm import LinearSVC
          from sklearn.model_selection import GridSearchCV
          from sklearn.preprocessing import StandardScaler
          import time
          tic=time.time()

          SVCpipe = Pipeline([('SVC',LinearSVC(class_weight="balanced", random_state=1,verbose=

          # Gridsearch to determine the value of C
```

```
param_grid = {'SVC__C':np.arange(.1,2,.1)}
linearSVC = GridSearchCV(SVCpipe,param_grid,cv=5,return_train_score=True, verbose=0)
linearSVC.fit(BoW_W2VGoogle_es_train, y_train_es.values)
print(linearSVC.best_params_)
#linearSVC.coef_
#linearSVC.intercept_

svc_BoW_W2VGoogle_es = linearSVC.best_estimator_
svc_BoW_W2VGoogle_es.fit(BoW_W2VGoogle_es_train, y_train_es.values)
svc_BoW_W2VGoogle_es.coef_ = svc_BoW_W2VGoogle_es.named_steps['SVC'].coef_
svc_BoW_W2VGoogle_es.score(BoW_W2VGoogle_es_train, y_train_es.values)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
{'SVC__C': 0.5}
Tiempo de procesamiento (secs):  30.431158542633057
```

```
In [402]: from joblib import dump, load
          dump(svc_BoW_W2VGoogle_es, 'svc_W2VGoogle_es.joblib')
          #svc_w2vtwit_cu = load('svc_w2vtwit_cu.joblib')
          prediction_BoW_W2VGoogle_es=svc_BoW_W2VGoogle_es.predict(BoW_W2VGoogle_es_test)
          print("Acurracy Test",metrics.accuracy_score( y_test_es.values, prediction_BoW_W2VGo
```

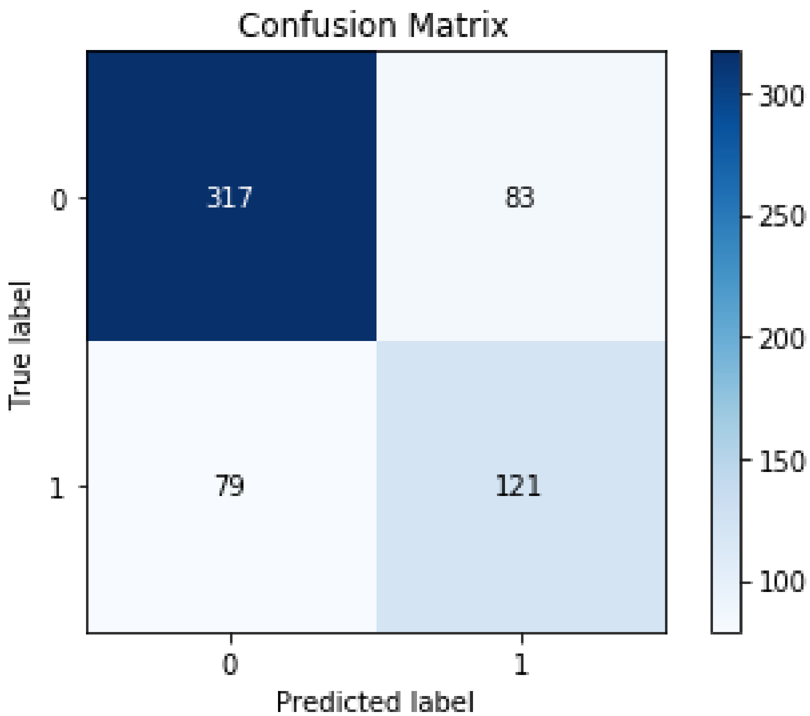
```
Acurracy Test 0.73
```

```
In [403]: print('Accuracy score:', metrics.accuracy_score(y_test_es.values, prediction_BoW_W2V
          print("F1 score", f1_score(y_test_es.values, prediction_BoW_W2VGoogle_es,  average='
          print("F1 weighted", f1_score(y_test_es.values, prediction_BoW_W2VGoogle_es,  averag
          print("Recall score", recall_score(y_test_es.values, prediction_BoW_W2VGoogle_es,  a
          print("Precision score", precision_score(y_test_es.values, prediction_BoW_W2VGoogle_


          from sklearn.metrics import classification_report
          print(classification_report( y_test_es.values, prediction_BoW_W2VGoogle_es, target_n

          %matplotlib inline
          import matplotlib.pyplot as plt
          import scikitplot

          scikitplot.metrics.plot_confusion_matrix(y_test_es.values, prediction_BoW_W2VGoogle_
```

```
Accuracy score: 0.73
F1 score 0.6977461565252001
F1 weighted 0.7306582417035672
Recall score 0.69875
Precision score 0.6968211527035056
              precision    recall  f1-score   support
```

```
   no-ironia       0.80      0.79      0.80       400
      ironia       0.59      0.60      0.60       200

   micro avg       0.73      0.73      0.73       600
   macro avg       0.70      0.70      0.70       600
weighted avg       0.73      0.73      0.73       600
```

Out[403]: <matplotlib.axes._subplots.AxesSubplot at 0x1ab94a99048>



23.0.3 Cuba

In [404]:
```
print(np.concatenate((x_train_tf_cu,mean_emb_train_w2vgoogle_cu),axis=1).shape)
BoW_W2VGoogle_cu_train = np.concatenate((x_train_tf_cu, mean_emb_train_w2vgoogle_cu)

print(np.concatenate((x_test_tf_cu,mean_emb_test_w2vgoogle_cu),axis=1).shape)
BoW_W2VGoogle_cu_test= np.concatenate((x_test_tf_cu, mean_emb_test_w2vgoogle_cu),axis
```

```
(2400, 591)
(600, 591)
```

In [408]:
```
from sklearn.pipeline import Pipeline
from sklearn.svm import LinearSVC
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
import time
tic=time.time()

SVCpipe = Pipeline([('SVC',LinearSVC(class_weight="balanced", random_state=1,verbose=

# Gridsearch to determine the value of C
param_grid = {'SVC__C':np.arange(.001,.1,.01)}
linearSVC = GridSearchCV(SVCpipe,param_grid,cv=5,return_train_score=True, verbose=0)
linearSVC.fit(BoW_W2VGoogle_cu_train, y_train_cu.values)
print(linearSVC.best_params_)
#linearSVC.coef_
#linearSVC.intercept_

svc_BoW_W2VGoogle_cu = linearSVC.best_estimator_
svc_BoW_W2VGoogle_cu.fit(BoW_W2VGoogle_cu_train, y_train_cu.values)
svc_BoW_W2VGoogle_cu.coef_ = svc_BoW_W2VGoogle_cu.named_steps['SVC'].coef_
svc_BoW_W2VGoogle_cu.score(BoW_W2VGoogle_cu_train, y_train_cu.values)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
{'SVC__C': 0.040999999999999995}
Tiempo de procesamiento (secs):  2.283169746398926
```

In [409]:
```
from joblib import dump, load
dump(svc_BoW_W2VGoogle_cu, 'svc_W2VGoogle_cu.joblib')
#svc_w2vtwit_cu = load('svc_w2vtwit_cu.joblib')
prediction_BoW_W2VGoogle_cu=svc_BoW_W2VGoogle_cu.predict(BoW_W2VGoogle_cu_test)
print("Acurracy Test",metrics.accuracy_score( y_test_cu.values, prediction_BoW_W2VGoo
```

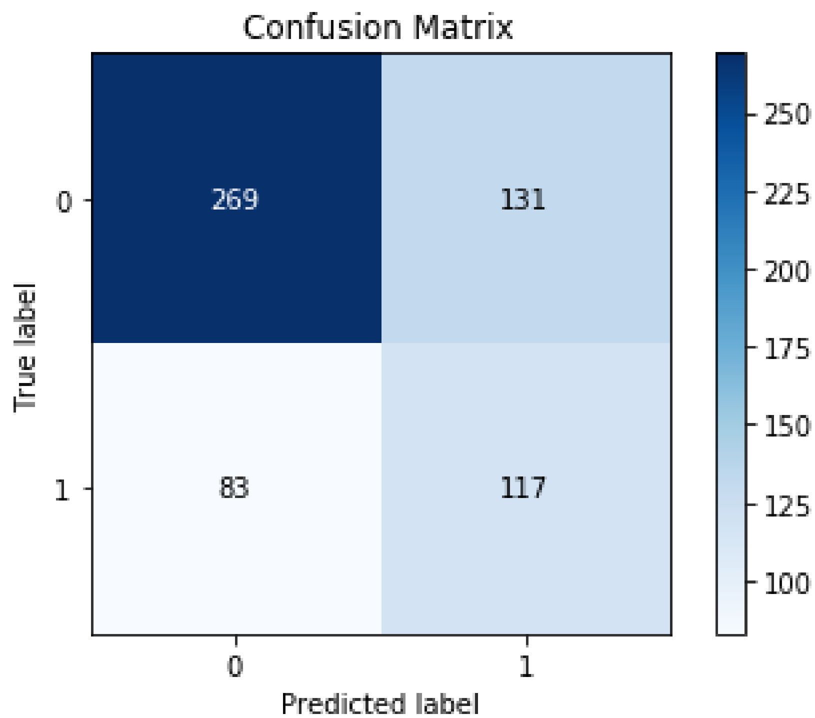
```
Acurracy Test 0.6433333333333333
```

In [410]:
```
print('Accuracy score:', metrics.accuracy_score(y_test_cu.values, prediction_BoW_W2V
print("F1 score", f1_score(y_test_cu.values, prediction_BoW_W2VGoogle_cu,  average='
print("F1 weighted", f1_score(y_test_cu.values, prediction_BoW_W2VGoogle_cu,  average
print("Recall score", recall_score(y_test_cu.values, prediction_BoW_W2VGoogle_cu,  av
print("Precision score", precision_score(y_test_cu.values, prediction_BoW_W2VGoogle_


from sklearn.metrics import classification_report
print(classification_report( y_test_cu.values, prediction_BoW_W2VGoogle_cu, target_na

%matplotlib inline
import matplotlib.pyplot as plt
```

```python
import scikitplot

scikitplot.metrics.plot_confusion_matrix(y_test_cu.values, prediction_BoW_W2VGoogle_c
```

```
Accuracy score: 0.6433333333333333
F1 score 0.6188734802431611
F1 weighted 0.651057497467072
Recall score 0.6287499999999999
Precision score 0.6179893695014662
              precision    recall  f1-score   support

   no-ironia       0.76      0.67      0.72       400
      ironia       0.47      0.58      0.52       200

   micro avg       0.64      0.64      0.64       600
   macro avg       0.62      0.63      0.62       600
weighted avg       0.67      0.64      0.65       600
```

```
Out[410]: <matplotlib.axes._subplots.AxesSubplot at 0x1abaca175c0>
```



Clasificador NN

23.0.4 México

```
In [ ]: del nn_BoW_W2VGoogle_mx
```

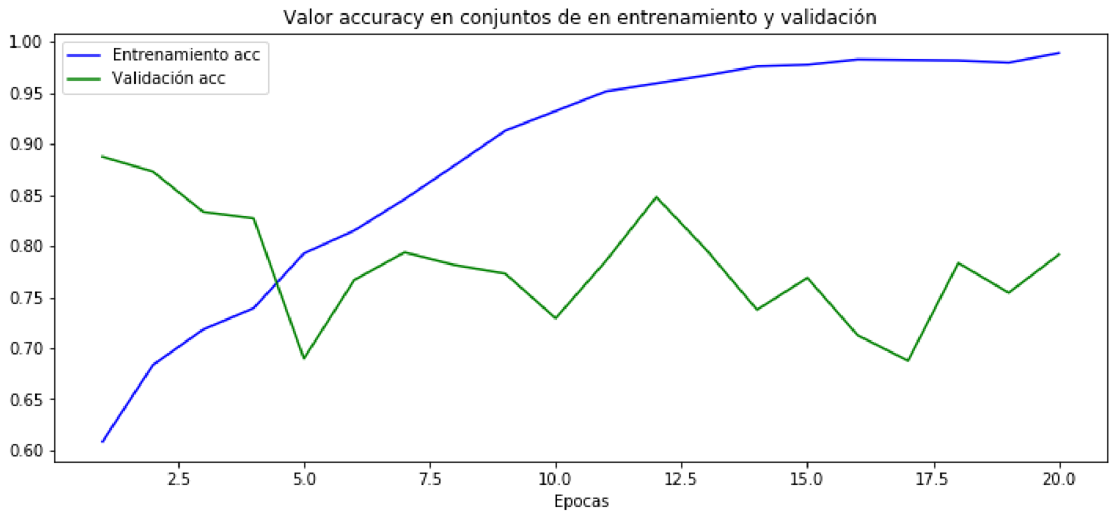
```
In [479]: from keras.utils import to_categorical

          y_train_BoW_W2VGoogle_mx = to_categorical(y_train)
          y_test_BoW_W2VGoogle_mx  = to_categorical(y_test)

          num_mx, sz_mx = y_train_BoW_W2VGoogle_mx.shape

          print(num_mx)
          print(sz_mx)


          import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 50
          epochs = 20

          nn_BoW_W2VGoogle_mx = Sequential()
          nn_BoW_W2VGoogle_mx.add(Dense(512, activation='relu'))
          nn_BoW_W2VGoogle_mx.add(Dropout(0.25))
          nn_BoW_W2VGoogle_mx.add(Dense(sz_mx, activation='softmax'))
          nn_BoW_W2VGoogle_mx.compile(loss='binary_crossentropy',
                        optimizer='nadam',
                        metrics=['accuracy'])

          history_BoW_W2VGoogle_mx = nn_BoW_W2VGoogle_mx.fit(BoW_W2VGoogle_mx_train,
                        y_train_BoW_W2VGoogle_mx,
                        validation_split=.2,
                        batch_size= batch_size,
                        shuffle   =True,
                        epochs=epochs,
                        verbose=2)

          print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
2400
2
Train on 1920 samples, validate on 480 samples
Epoch 1/20
 - 3s - loss: 0.6639 - acc: 0.6083 - val_loss: 0.4478 - val_acc: 0.8875
Epoch 2/20
 - 0s - loss: 0.5946 - acc: 0.6833 - val_loss: 0.4331 - val_acc: 0.8729
Epoch 3/20
```

```
 - 0s - loss: 0.5563 - acc: 0.7182 - val_loss: 0.4648 - val_acc: 0.8333
Epoch 4/20
 - 0s - loss: 0.5165 - acc: 0.7391 - val_loss: 0.4434 - val_acc: 0.8271
Epoch 5/20
 - 0s - loss: 0.4582 - acc: 0.7927 - val_loss: 0.5770 - val_acc: 0.6896
Epoch 6/20
 - 0s - loss: 0.4157 - acc: 0.8151 - val_loss: 0.5166 - val_acc: 0.7667
Epoch 7/20
 - 0s - loss: 0.3735 - acc: 0.8458 - val_loss: 0.4891 - val_acc: 0.7938
Epoch 8/20
 - 0s - loss: 0.3096 - acc: 0.8792 - val_loss: 0.5257 - val_acc: 0.7813
Epoch 9/20
 - 0s - loss: 0.2599 - acc: 0.9130 - val_loss: 0.5489 - val_acc: 0.7729
Epoch 10/20
 - 0s - loss: 0.2157 - acc: 0.9323 - val_loss: 0.6520 - val_acc: 0.7292
Epoch 11/20
 - 0s - loss: 0.1909 - acc: 0.9516 - val_loss: 0.5817 - val_acc: 0.7854
Epoch 12/20
 - 0s - loss: 0.1642 - acc: 0.9594 - val_loss: 0.5974 - val_acc: 0.8479
Epoch 13/20
 - 0s - loss: 0.1365 - acc: 0.9672 - val_loss: 0.6471 - val_acc: 0.7958
Epoch 14/20
 - 0s - loss: 0.1148 - acc: 0.9760 - val_loss: 0.7666 - val_acc: 0.7375
Epoch 15/20
 - 0s - loss: 0.0983 - acc: 0.9776 - val_loss: 0.7396 - val_acc: 0.7687
Epoch 16/20
 - 0s - loss: 0.0872 - acc: 0.9828 - val_loss: 0.8923 - val_acc: 0.7125
Epoch 17/20
 - 0s - loss: 0.0805 - acc: 0.9823 - val_loss: 0.9808 - val_acc: 0.6875
Epoch 18/20
 - 0s - loss: 0.0869 - acc: 0.9818 - val_loss: 0.8255 - val_acc: 0.7833
Epoch 19/20
 - 0s - loss: 0.0795 - acc: 0.9797 - val_loss: 0.8401 - val_acc: 0.7542
Epoch 20/20
 - 0s - loss: 0.0565 - acc: 0.9891 - val_loss: 0.8570 - val_acc: 0.7917
Tiempo de procesamiento (secs):  8.068376779556274
```

In [480]:
```
history_dict_BoW_W2VGoogle_mx = history_BoW_W2VGoogle_mx.history
dictkeys_BoW_W2VGoogle_mx=list(history_dict_BoW_W2VGoogle_mx.keys())
loss_values_BoW_W2VGoogle_mx = history_BoW_W2VGoogle_mx.history['acc']
val_loss_values_BoW_W2VGoogle_mx = history_BoW_W2VGoogle_mx.history['val_acc']
epochs_BoW_W2VGoogle_mx = range(1, len(loss_values_BoW_W2VGoogle_mx) + 1)


plt.figure(figsize=(12,5))
plt.plot(epochs_BoW_W2VGoogle_mx, loss_values_BoW_W2VGoogle_mx, 'b', label='Entrenami
plt.plot(epochs_BoW_W2VGoogle_mx, val_loss_values_BoW_W2VGoogle_mx, 'g', label='Valid
```

```
plt.title('Valor accuracy en conjuntos de en entrenamiento y validación')
plt.xlabel('Epocas')
plt.ylabel('')
plt.legend()

plt.show()
```




```
In [481]: del nn_BoW_W2VGoogle_mx

          import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 50
          epochs = 5

          nn_BoW_W2VGoogle_mx = Sequential()
          nn_BoW_W2VGoogle_mx.add(Dense(512, activation='relu'))
          nn_BoW_W2VGoogle_mx.add(Dropout(0.25))
          nn_BoW_W2VGoogle_mx.add(Dense(sz_es, activation='softmax'))
          nn_BoW_W2VGoogle_mx.compile(loss='binary_crossentropy',
                        optimizer='nadam',
                        metrics=['accuracy'])

          history_BoW_W2VGoogle_mx= nn_BoW_W2VGoogle_mx.fit(BoW_W2VGoogle_mx_train,
                        y_train_BoW_W2VGoogle_mx,
                        validation_split=.2,
                        batch_size= batch_size,
                        shuffle   =True,
```

```
                    epochs=epochs,
                    verbose=0)

    print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
Tiempo de procesamiento (secs):  3.8729870319366455
```

```
In [482]: from keras.models import load_model
          nn_BoW_W2VGoogle_mx.save('nn_BoW_W2VGoogle_mx')  # Guardar modelo
          #nn_w2vtwit_cu = load_model('nn_cuba_w2vtwit') # Cargar modelo


          y_pred_BoW_W2VGoogle_mx= nn_BoW_W2VGoogle_mx.predict(BoW_W2VGoogle_mx_test).squeeze(
          y_test_label_BoW_W2VGoogle_mx = np.argmax(y_test_BoW_W2VGoogle_mx,1)
          y_pred_label_BoW_W2VGoogle_mx = np.argmax(y_pred_BoW_W2VGoogle_mx,1)


          print("F1 score", f1_score(y_test_label_BoW_W2VGoogle_mx,  y_pred_label_BoW_W2VGoogl
          print("F1 weighted", f1_score(y_test_label_BoW_W2VGoogle_mx,  y_pred_label_BoW_W2VGo
          print("Recall score", recall_score(y_test_label_BoW_W2VGoogle_mx,  y_pred_label_BoW_
          print("Precision score", precision_score(y_test_label_BoW_W2VGoogle_mx,  y_pred_labe
```

```
F1 score 0.6253422354579952
F1 weighted 0.6598190755239606
Recall score 0.633065577262873
Precision score 0.6234264393067614
```

23.0.5 España

```
In [ ]: del nn_BoW_W2VGoogle_es
```

```
In [484]: from keras.utils import to_categorical

          y_train_BoW_W2VGoogle_es = to_categorical(y_train_es)
          y_test_BoW_W2VGoogle_es  = to_categorical(y_test_es)

          num_es, sz_es = y_train_BoW_W2VGoogle_es.shape

          print(num_es)
          print(sz_es)


          import time
          tic=time.time()

          np.random.seed(1)
```

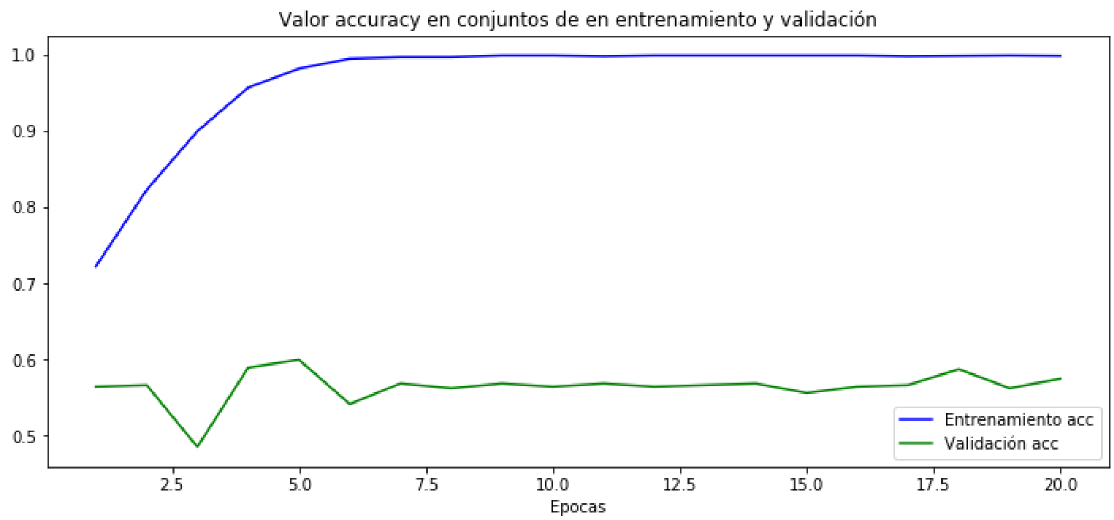
```python
batch_size = 50
epochs = 20

nn_BoW_W2VGoogle_es = Sequential()
nn_BoW_W2VGoogle_es.add(Dense(512, activation='relu'))
nn_BoW_W2VGoogle_es.add(Dropout(0.25))
nn_BoW_W2VGoogle_es.add(Dense(sz_es, activation='softmax'))
nn_BoW_W2VGoogle_es.compile(loss='binary_crossentropy',
              optimizer='nadam',
              metrics=['accuracy'])

history_BoW_W2VGoogle_es = nn_BoW_W2VGoogle_es.fit(BoW_W2VGoogle_es_train,
              y_train_BoW_W2VGoogle_es,
              validation_split=.2,
              batch_size= batch_size,
              shuffle   =True,
              epochs=epochs,
              verbose=2)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
2400
2
Train on 1920 samples, validate on 480 samples
Epoch 1/20
 - 4s - loss: 0.5507 - acc: 0.7224 - val_loss: 0.6960 - val_acc: 0.5646
Epoch 2/20
 - 1s - loss: 0.3935 - acc: 0.8229 - val_loss: 0.7426 - val_acc: 0.5667
Epoch 3/20
 - 1s - loss: 0.2504 - acc: 0.9000 - val_loss: 1.0953 - val_acc: 0.4854
Epoch 4/20
 - 1s - loss: 0.1390 - acc: 0.9573 - val_loss: 0.8452 - val_acc: 0.5896
Epoch 5/20
 - 1s - loss: 0.0701 - acc: 0.9823 - val_loss: 0.9203 - val_acc: 0.6000
Epoch 6/20
 - 1s - loss: 0.0354 - acc: 0.9953 - val_loss: 1.2213 - val_acc: 0.5417
Epoch 7/20
 - 1s - loss: 0.0214 - acc: 0.9974 - val_loss: 1.1342 - val_acc: 0.5688
Epoch 8/20
 - 1s - loss: 0.0141 - acc: 0.9974 - val_loss: 1.0863 - val_acc: 0.5625
Epoch 9/20
 - 1s - loss: 0.0096 - acc: 0.9995 - val_loss: 1.1577 - val_acc: 0.5687
Epoch 10/20
 - 1s - loss: 0.0079 - acc: 0.9995 - val_loss: 1.2370 - val_acc: 0.5646
Epoch 11/20
 - 1s - loss: 0.0078 - acc: 0.9984 - val_loss: 1.1980 - val_acc: 0.5688
Epoch 12/20
 - 1s - loss: 0.0050 - acc: 0.9995 - val_loss: 1.2485 - val_acc: 0.5646
```

```
Epoch 13/20
 - 1s - loss: 0.0042 - acc: 0.9995 - val_loss: 1.3487 - val_acc: 0.5667
Epoch 14/20
 - 1s - loss: 0.0045 - acc: 0.9995 - val_loss: 1.2665 - val_acc: 0.5687
Epoch 15/20
 - 1s - loss: 0.0047 - acc: 0.9995 - val_loss: 1.2627 - val_acc: 0.5563
Epoch 16/20
 - 1s - loss: 0.0036 - acc: 0.9995 - val_loss: 1.3168 - val_acc: 0.5646
Epoch 17/20
 - 1s - loss: 0.0060 - acc: 0.9984 - val_loss: 1.3923 - val_acc: 0.5667
Epoch 18/20
 - 1s - loss: 0.0054 - acc: 0.9990 - val_loss: 1.3073 - val_acc: 0.5875
Epoch 19/20
 - 1s - loss: 0.0035 - acc: 0.9995 - val_loss: 1.4356 - val_acc: 0.5625
Epoch 20/20
 - 1s - loss: 0.0067 - acc: 0.9990 - val_loss: 1.4235 - val_acc: 0.5750
Tiempo de procesamiento (secs):  20.298044443130493
```

In [485]:

```
history_dict_BoW_W2VGoogle_es = history_BoW_W2VGoogle_es.history
dictkeys_BoW_W2VGoogle_es=list(history_dict_BoW_W2VGoogle_es.keys())
loss_values_BoW_W2VGoogle_es = history_BoW_W2VGoogle_es.history['acc']
val_loss_values_BoW_W2VGoogle_es = history_BoW_W2VGoogle_es.history['val_acc']
epochs_BoW_W2VGoogle_es = range(1, len(loss_values_BoW_W2VGoogle_es) + 1)


plt.figure(figsize=(12,5))
plt.plot(epochs_BoW_W2VGoogle_es, loss_values_BoW_W2VGoogle_es, 'b', label='Entrenami
plt.plot(epochs_BoW_W2VGoogle_es, val_loss_values_BoW_W2VGoogle_es, 'g', label='Valid
plt.title('Valor accuracy en conjuntos de en entrenamiento y validación')
plt.xlabel('Epocas')
plt.ylabel('')
plt.legend()

plt.show()
```



In [486]:
```
del nn_BoW_W2VGoogle_es

import time
tic=time.time()

np.random.seed(1)

batch_size = 50
epochs = 5

nn_BoW_W2VGoogle_es = Sequential()
nn_BoW_W2VGoogle_es.add(Dense(512, activation='relu'))
nn_BoW_W2VGoogle_es.add(Dropout(0.25))
nn_BoW_W2VGoogle_es.add(Dense(sz_es, activation='softmax'))
nn_BoW_W2VGoogle_es.compile(loss='binary_crossentropy',
              optimizer='nadam',
              metrics=['accuracy'])

history_BoW_W2VGoogle_es= nn_BoW_W2VGoogle_es.fit(BoW_W2VGoogle_es_train,
              y_train_BoW_W2VGoogle_es,
              validation_split=.2,
              batch_size= batch_size,
              shuffle   =True,
              epochs=epochs,
              verbose=0)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
Tiempo de procesamiento (secs):  9.44196629524231
```

```
In [487]: from keras.models import load_model
          nn_BoW_W2VGoogle_es.save('nn_BoW_W2VGoogle_es')  # Guardar modelo
          #nn_w2vtwit_cu = load_model('nn_cuba_w2vtwit') # Cargar modelo


          y_pred_BoW_W2VGoogle_es= nn_BoW_W2VGoogle_es.predict(BoW_W2VGoogle_es_test).squeeze(
          y_test_label_BoW_W2VGoogle_es = np.argmax(y_test_BoW_W2VGoogle_es,1)
          y_pred_label_BoW_W2VGoogle_es = np.argmax(y_pred_BoW_W2VGoogle_es,1)


          print("F1 score", f1_score(y_test_label_BoW_W2VGoogle_es,  y_pred_label_BoW_W2VGoogl
          print("F1 weighted", f1_score(y_test_label_BoW_W2VGoogle_es,  y_pred_label_BoW_W2VGo
          print("Recall score", recall_score(y_test_label_BoW_W2VGoogle_es,  y_pred_label_BoW_
          print("Precision score", precision_score(y_test_label_BoW_W2VGoogle_es,  y_pred_label

F1 score 0.6332452012630254
F1 weighted 0.6921297217269062
Recall score 0.6275
Precision score 0.6879179793290222
```

23.0.6 Cuba

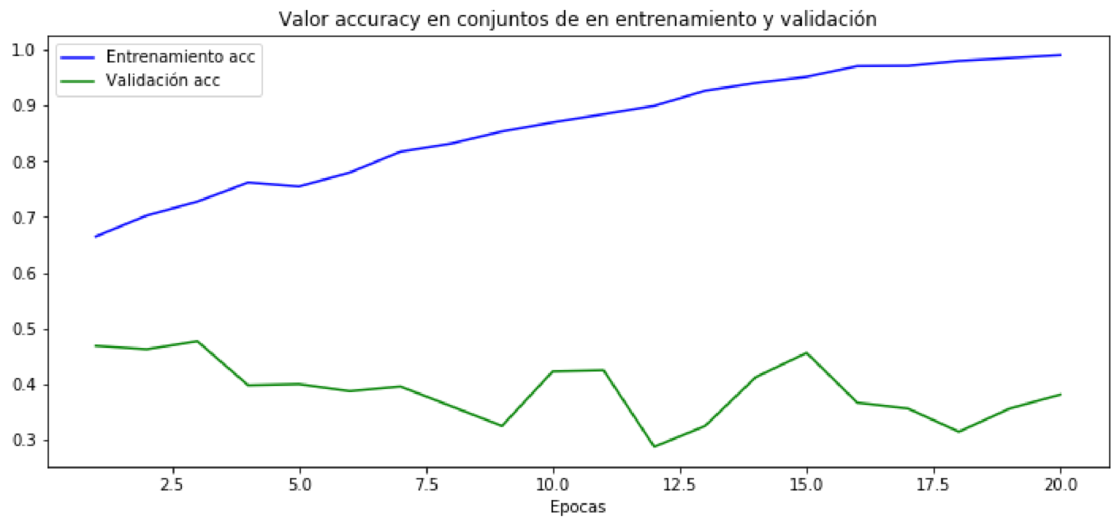
```
In [ ]: del nn_BoW_W2VGoogle_cu

In [490]: from keras.utils import to_categorical

          y_train_BoW_W2VGoogle_cu = to_categorical(y_train_cu)
          y_test_BoW_W2VGoogle_cu  = to_categorical(y_test_cu)

          num_cu, sz_cu = y_train_BoW_W2VGoogle_cu.shape

          print(num_cu)
          print(sz_cu)


          import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 50
          epochs = 20

          nn_BoW_W2VGoogle_cu = Sequential()
          nn_BoW_W2VGoogle_cu.add(Dense(512, activation='relu'))
          nn_BoW_W2VGoogle_cu.add(Dropout(0.25))
          nn_BoW_W2VGoogle_cu.add(Dense(sz_cu, activation='softmax'))
```

```python
nn_BoW_W2VGoogle_cu.compile(loss='binary_crossentropy',
              optimizer='nadam',
              metrics=['accuracy'])

history_BoW_W2VGoogle_cu = nn_BoW_W2VGoogle_cu.fit(BoW_W2VGoogle_cu_train,
              y_train_BoW_W2VGoogle_cu,
              validation_split=.2,
              batch_size= batch_size,
              shuffle   =True,
              epochs=epochs,
              verbose=2)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
2400
2
Train on 1920 samples, validate on 480 samples
Epoch 1/20
 - 3s - loss: 0.6317 - acc: 0.6651 - val_loss: 0.8530 - val_acc: 0.4688
Epoch 2/20
 - 0s - loss: 0.5725 - acc: 0.7026 - val_loss: 1.2477 - val_acc: 0.4625
Epoch 3/20
 - 0s - loss: 0.5433 - acc: 0.7276 - val_loss: 1.1943 - val_acc: 0.4771
Epoch 4/20
 - 0s - loss: 0.5034 - acc: 0.7620 - val_loss: 1.9831 - val_acc: 0.3979
Epoch 5/20
 - 0s - loss: 0.4899 - acc: 0.7547 - val_loss: 2.0068 - val_acc: 0.4000
Epoch 6/20
 - 0s - loss: 0.4602 - acc: 0.7797 - val_loss: 2.0704 - val_acc: 0.3875
Epoch 7/20
 - 0s - loss: 0.4161 - acc: 0.8172 - val_loss: 2.5075 - val_acc: 0.3958
Epoch 8/20
 - 0s - loss: 0.3983 - acc: 0.8318 - val_loss: 2.7877 - val_acc: 0.3604
Epoch 9/20
 - 0s - loss: 0.3510 - acc: 0.8536 - val_loss: 3.4628 - val_acc: 0.3250
Epoch 10/20
 - 0s - loss: 0.3214 - acc: 0.8698 - val_loss: 2.8765 - val_acc: 0.4229
Epoch 11/20
 - 0s - loss: 0.2929 - acc: 0.8844 - val_loss: 3.0240 - val_acc: 0.4250
Epoch 12/20
 - 0s - loss: 0.2622 - acc: 0.8995 - val_loss: 4.4587 - val_acc: 0.2875
Epoch 13/20
 - 0s - loss: 0.2216 - acc: 0.9266 - val_loss: 4.6539 - val_acc: 0.3250
Epoch 14/20
 - 0s - loss: 0.1924 - acc: 0.9406 - val_loss: 3.5614 - val_acc: 0.4125
Epoch 15/20
 - 0s - loss: 0.1645 - acc: 0.9516 - val_loss: 3.2150 - val_acc: 0.4563
Epoch 16/20
```

```
 - 0s - loss: 0.1432 - acc: 0.9708 - val_loss: 4.6747 - val_acc: 0.3667
Epoch 17/20
 - 0s - loss: 0.1133 - acc: 0.9714 - val_loss: 4.7916 - val_acc: 0.3562
Epoch 18/20
 - 0s - loss: 0.0972 - acc: 0.9802 - val_loss: 5.2168 - val_acc: 0.3146
Epoch 19/20
 - 0s - loss: 0.0950 - acc: 0.9854 - val_loss: 5.0093 - val_acc: 0.3563
Epoch 20/20
 - 0s - loss: 0.0674 - acc: 0.9906 - val_loss: 4.9556 - val_acc: 0.3812
Tiempo de procesamiento (secs):  8.626869201660156
```

```
In [491]: history_dict_BoW_W2VGoogle_cu = history_BoW_W2VGoogle_cu.history
          dictkeys_BoW_W2VGoogle_cu=list(history_dict_BoW_W2VGoogle_cu.keys())
          loss_values_BoW_W2VGoogle_cu = history_BoW_W2VGoogle_cu.history['acc']
          val_loss_values_BoW_W2VGoogle_cu = history_BoW_W2VGoogle_cu.history['val_acc']
          epochs_BoW_W2VGoogle_cu = range(1, len(loss_values_BoW_W2VGoogle_cu) + 1)


          plt.figure(figsize=(12,5))
          plt.plot(epochs_BoW_W2VGoogle_cu, loss_values_BoW_W2VGoogle_cu, 'b', label='Entrenami
          plt.plot(epochs_BoW_W2VGoogle_cu, val_loss_values_BoW_W2VGoogle_cu, 'g', label='Valic
          plt.title('Valor accuracy en conjuntos de en entrenamiento y validación')
          plt.xlabel('Epocas')
          plt.ylabel('')
          plt.legend()

          plt.show()
```




```
In [498]: del nn_BoW_W2VGoogle_cu
```

```python
import time
tic=time.time()

np.random.seed(1)

batch_size = 50
epochs = 10

nn_BoW_W2VGoogle_cu = Sequential()
nn_BoW_W2VGoogle_cu.add(Dense(512, activation='relu'))
nn_BoW_W2VGoogle_cu.add(Dropout(0.25))
nn_BoW_W2VGoogle_cu.add(Dense(sz_cu, activation='softmax'))
nn_BoW_W2VGoogle_cu.compile(loss='binary_crossentropy',
              optimizer='nadam',
              metrics=['accuracy'])

history_BoW_W2VGoogle_cu= nn_BoW_W2VGoogle_cu.fit(BoW_W2VGoogle_cu_train,
              y_train_BoW_W2VGoogle_cu,
              validation_split=.2,
              batch_size= batch_size,
              shuffle   =True,
              epochs=epochs,
              verbose=0)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
Tiempo de procesamiento (secs):  5.439519166946411
```

In [499]:
```python
from keras.models import load_model
nn_BoW_W2VGoogle_cu.save('nn_BoW_W2VGoogle_cu')  # Guardar modelo
#nn_w2vtwit_cu = load_model('nn_cuba_w2vtwit') # Cargar modelo


y_pred_BoW_W2VGoogle_cu= nn_BoW_W2VGoogle_cu.predict(BoW_W2VGoogle_cu_test).squeeze()
y_test_label_BoW_W2VGoogle_cu = np.argmax(y_test_BoW_W2VGoogle_cu,1)
y_pred_label_BoW_W2VGoogle_cu = np.argmax(y_pred_BoW_W2VGoogle_cu,1)


print("F1 score", f1_score(y_test_label_BoW_W2VGoogle_cu,  y_pred_label_BoW_W2VGoogle
print("F1 weighted", f1_score(y_test_label_BoW_W2VGoogle_cu,  y_pred_label_BoW_W2VGoo
print("Recall score", recall_score(y_test_label_BoW_W2VGoogle_cu,  y_pred_label_BoW_W
print("Precision score", precision_score(y_test_label_BoW_W2VGoogle_cu,  y_pred_label
```

```
F1 score 0.5453595317725752
F1 weighted 0.6039576365663322
Recall score 0.545
Precision score 0.5496031746031746
```

24 Concatenar BoW TF-IDF + W2VTwitter

24.1 Clasificador SVM

24.1.1 México

In [329]:
```
print(np.concatenate((x_train_tf_mx,mean_emb_train_w2vtwit_mx),axis=1).shape)
BoW_W2VTwitter_mx_train = np.concatenate((x_train_tf_mx, mean_emb_train_w2vtwit_mx),a

print(np.concatenate((x_test_tf_mx,mean_emb_test_w2vtwit_mx),axis=1).shape)
BoW_W2VTwitter_mx_test = np.concatenate((x_test_tf_mx, mean_emb_test_w2vtwit_mx),axis
```

```
(2400, 586)
(600, 586)
```

In [427]:
```
from sklearn.pipeline import Pipeline
from sklearn.svm import LinearSVC
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
import time
tic=time.time()

SVCpipe = Pipeline([('SVC',LinearSVC(class_weight="balanced", random_state=1,verbose=

# Gridsearch to determine the value of C
param_grid = {'SVC__C':np.arange(.001,.1,.001)}
linearSVC = GridSearchCV(SVCpipe,param_grid,cv=5,return_train_score=True, verbose=0)
linearSVC.fit(BoW_W2VTwitter_mx_train, y_train.values)
print(linearSVC.best_params_)
#linearSVC.coef_
#linearSVC.intercept_

svc_BoW_W2VTwit_mx = linearSVC.best_estimator_
svc_BoW_W2VTwit_mx.fit(BoW_W2VTwitter_mx_train, y_train.values)
svc_BoW_W2VTwit_mx.coef_ = svc_BoW_W2VTwit_mx.named_steps['SVC'].coef_
svc_BoW_W2VTwit_mx.score(BoW_W2VTwitter_mx_train, y_train.values)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
{'SVC__C': 0.098}
Tiempo de procesamiento (secs):  16.694931507110596
```

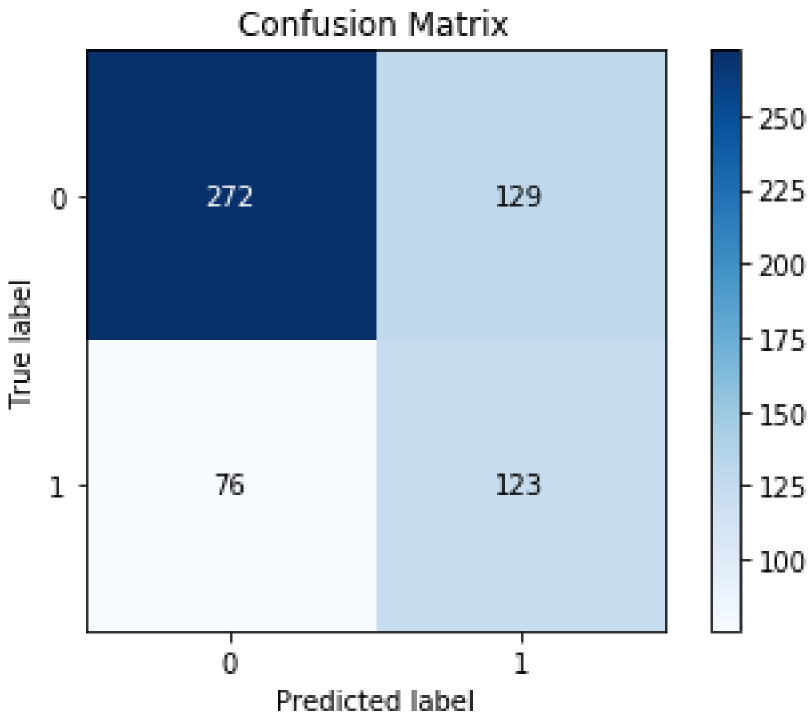
In [428]:
```
from joblib import dump, load
dump(svc_BoW_W2VTwit_mx, 'svc_BoW_W2VTwit_mx.joblib')
#svc_w2vtwit_cu = load('svc_w2vtwit_cu.joblib')
prediction_BoW_W2VTwitter_mx=svc_BoW_W2VTwit_mx.predict(BoW_W2VTwitter_mx_test)
print("Acurracy Test",metrics.accuracy_score( y_test.values, prediction_BoW_W2VTwitte
```

```
Acurracy Test 0.6583333333333333
```

```
In [429]: print('Accuracy score:', metrics.accuracy_score(y_test.values, prediction_BoW_W2VTwi
          print("F1 score", f1_score(y_test.values, prediction_BoW_W2VTwitter_mx,  average='mac
          print("F1 weighted", f1_score(y_test.values, prediction_BoW_W2VTwitter_mx,  average=
          print("Recall score", recall_score(y_test.values, prediction_BoW_W2VTwitter_mx,  aver
          print("Precision score", precision_score(y_test.values, prediction_BoW_W2VTwitter_mx


          from sklearn.metrics import classification_report
          print(classification_report( y_test.values, prediction_BoW_W2VTwitter_mx, target_name

          %matplotlib inline
          import matplotlib.pyplot as plt
          import scikitplot

          scikitplot.metrics.plot_confusion_matrix(y_test.values, prediction_BoW_W2VTwitter_mx)
```

```
Accuracy score: 0.6583333333333333
F1 score 0.6358781405510379
F1 weighted 0.6663207509001903
Recall score 0.6481973458314014
Precision score 0.6348522167487685
              precision    recall  f1-score   support

   no-ironia       0.78      0.68      0.73       401
      ironia       0.49      0.62      0.55       199

   micro avg       0.66      0.66      0.66       600
   macro avg       0.63      0.65      0.64       600
weighted avg       0.68      0.66      0.67       600
```

```
Out[429]: <matplotlib.axes._subplots.AxesSubplot at 0x1abaccd7ef0>
```



24.1.2 España

In [411]:
```
print(np.concatenate((x_train_tf_es,mean_emb_train_w2vtwit_es),axis=1).shape)
BoW_W2VTwitter_es_train = np.concatenate((x_train_tf_es, mean_emb_train_w2vtwit_es),a

print(np.concatenate((x_test_tf_es,mean_emb_test_w2vtwit_es),axis=1).shape)
BoW_W2VTwitter_es_test = np.concatenate((x_test_tf_es, mean_emb_test_w2vtwit_es),axis
```

```
(2400, 7344)
(600, 7344)
```

In [421]:
```
from sklearn.pipeline import Pipeline
from sklearn.svm import LinearSVC
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
import time
tic=time.time()

SVCpipe = Pipeline([('SVC',LinearSVC(class_weight="balanced", random_state=1,verbose=

# Gridsearch to determine the value of C
param_grid = {'SVC__C':np.arange(.01,2,.1)}
linearSVC = GridSearchCV(SVCpipe,param_grid,cv=5,return_train_score=True, verbose=0)
```

```
linearSVC.fit(BoW_W2VTwitter_es_train, y_train_es.values)
print(linearSVC.best_params_)
#linearSVC.coef_
#linearSVC.intercept_

svc_BoW_W2VTwit_es = linearSVC.best_estimator_
svc_BoW_W2VTwit_es.fit(BoW_W2VTwitter_es_train, y_train_es.values)
svc_BoW_W2VTwit_es.coef_ = svc_BoW_W2VTwit_es.named_steps['SVC'].coef_
svc_BoW_W2VTwit_es.score(BoW_W2VTwitter_es_train, y_train_es.values)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
{'SVC__C': 0.01}
Tiempo de procesamiento (secs):  20.656206130981445
```

```
In [422]: from joblib import dump, load
          dump(svc_BoW_W2VTwit_es, 'svc_BoW_W2VTwit_es.joblib')
          #svc_w2vtwit_cu = load('svc_w2vtwit_cu.joblib')
          prediction_BoW_W2VTwitter_es=svc_BoW_W2VTwit_es.predict(BoW_W2VTwitter_es_test)
          print("Acurracy Test",metrics.accuracy_score( y_test_es.values, prediction_BoW_W2VTw
```

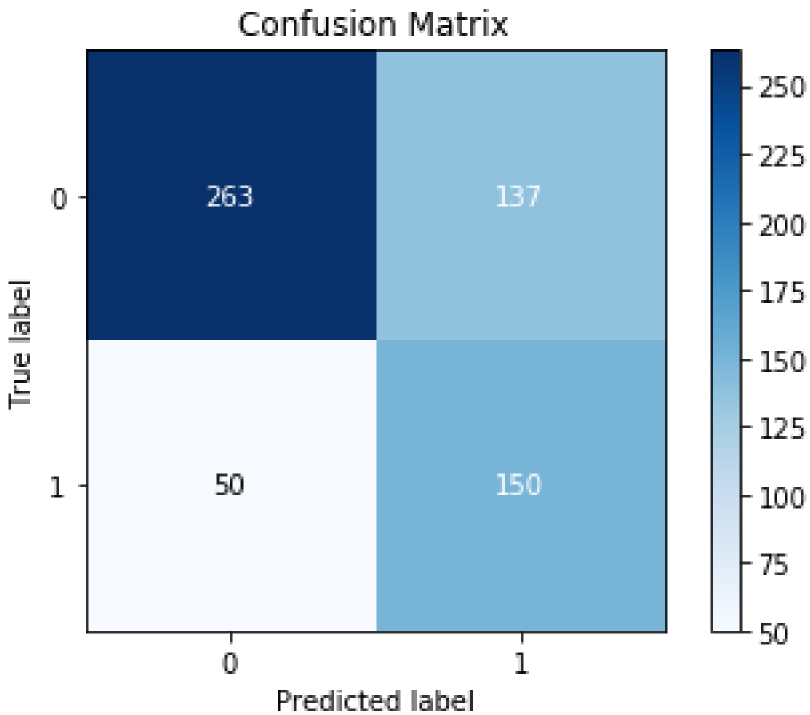
```
Acurracy Test 0.6883333333333334
```

```
In [423]: print('Accuracy score:', metrics.accuracy_score(y_test_es.values, prediction_BoW_W2V
          print("F1 score", f1_score(y_test_es.values, prediction_BoW_W2VTwitter_es,  average=
          print("F1 weighted", f1_score(y_test_es.values, prediction_BoW_W2VTwitter_es,  averag
          print("Recall score", recall_score(y_test_es.values, prediction_BoW_W2VTwitter_es,  a
          print("Precision score", precision_score(y_test_es.values, prediction_BoW_W2VTwitter_


          from sklearn.metrics import classification_report
          print(classification_report( y_test_es.values, prediction_BoW_W2VTwitter_es, target_n

          %matplotlib inline
          import matplotlib.pyplot as plt
          import scikitplot

          scikitplot.metrics.plot_confusion_matrix(y_test_es.values, prediction_BoW_W2VTwitter_
```

```
Accuracy score: 0.6883333333333334
F1 score 0.676872168671576
F1 weighted 0.697157415860527
Recall score 0.70375
Precision score 0.6814518373390033
              precision    recall  f1-score   support

   no-ironia       0.84      0.66      0.74       400
```

```
      ironia       0.52      0.75      0.62       200

   micro avg       0.69      0.69      0.69       600
   macro avg       0.68      0.70      0.68       600
weighted avg       0.73      0.69      0.70       600
```

```
Out[423]: <matplotlib.axes._subplots.AxesSubplot at 0x1abacbcbf28>
```



24.1.3 Cuba

```
In [430]: print(np.concatenate((x_train_tf_cu,mean_emb_train_w2vtwit_cu),axis=1).shape)
          BoW_W2VTwitter_cu_train = np.concatenate((x_train_tf_cu, mean_emb_train_w2vtwit_cu),a

          print(np.concatenate((x_test_tf_cu,mean_emb_test_w2vtwit_cu),axis=1).shape)
          BoW_W2VTwitter_cu_test = np.concatenate((x_test_tf_cu, mean_emb_test_w2vtwit_cu),axis
```

```
(2400, 691)
(600, 691)
```

```
In [434]: from sklearn.pipeline import Pipeline
          from sklearn.svm import LinearSVC
```

```
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
import time
tic=time.time()

SVCpipe = Pipeline([('SVC',LinearSVC(class_weight="balanced", random_state=1,verbose=

# Gridsearch to determine the value of C
param_grid = {'SVC__C':np.arange(.001,.1,.01)}
linearSVC = GridSearchCV(SVCpipe,param_grid,cv=5,return_train_score=True, verbose=0)
linearSVC.fit(BoW_W2VTwitter_cu_train, y_train_cu.values)
print(linearSVC.best_params_)
#linearSVC.coef_
#linearSVC.intercept_

svc_BoW_W2VTwit_cu = linearSVC.best_estimator_
svc_BoW_W2VTwit_cu.fit(BoW_W2VTwitter_cu_train, y_train_cu.values)
svc_BoW_W2VTwit_cu.coef_ = svc_BoW_W2VTwit_cu.named_steps['SVC'].coef_
svc_BoW_W2VTwit_cu.score(BoW_W2VTwitter_cu_train, y_train_cu.values)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
{'SVC__C': 0.001}
Tiempo de procesamiento (secs):  1.751384973526001
```

In [435]:
```
from joblib import dump, load
dump(svc_BoW_W2VTwit_cu, 'svc_BoW_W2VTwit_cu.joblib')
#svc_w2vtwit_cu = load('svc_w2vtwit_cu.joblib')
prediction_BoW_W2VTwitter_cu=svc_BoW_W2VTwit_cu.predict(BoW_W2VTwitter_cu_test)
print("Acurracy Test",metrics.accuracy_score( y_test_cu.values, prediction_BoW_W2VTw
```

```
Acurracy Test 0.6533333333333333
```

In [ ]:
```
print('Accuracy score:', metrics.accuracy_score(y_test_cu.values, prediction_BoW_W2VTw
print("F1 score", f1_score(y_test_cu.values, prediction_BoW_W2VTwitter_cu,  average='ma
print("F1 weighted", f1_score(y_test_cu.values, prediction_BoW_W2VTwitter_cu,  average=
print("Recall score", recall_score(y_test_cu.values, prediction_BoW_W2VTwitter_cu,  ave
print("Precision score", precision_score(y_test_cu.values, prediction_BoW_W2VTwitter_cu


from sklearn.metrics import classification_report
print(classification_report( y_test_cu.values, prediction_BoW_W2VTwitter_cu, target_nam

%matplotlib inline
import matplotlib.pyplot as plt
import scikitplot

scikitplot.metrics.plot_confusion_matrix(y_test_cu.values, prediction_BoW_W2VTwitter_cu
```

24.2 Clasificador NN

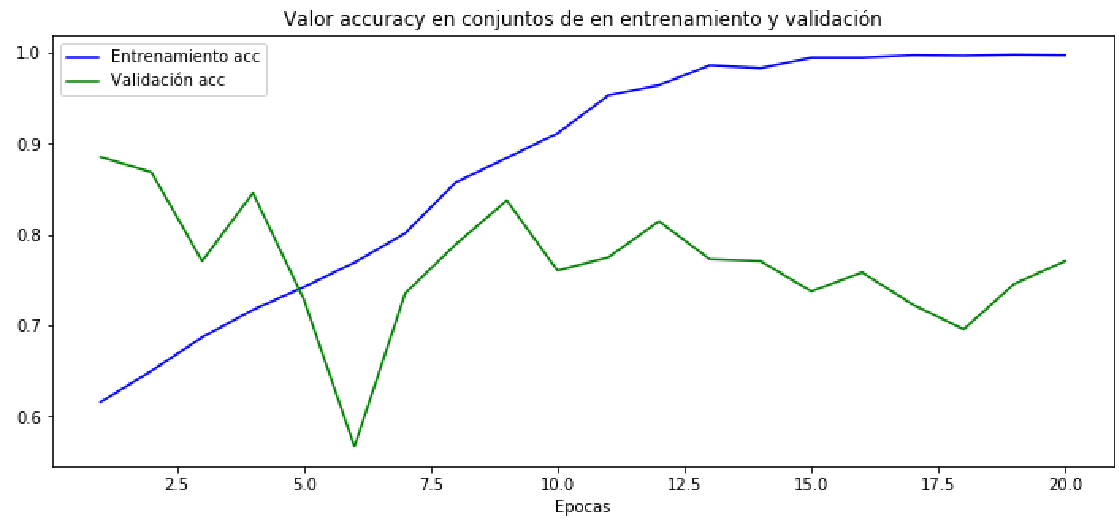
24.2.1 México

```
In [ ]: del nn_BoW_W2VTwitter_mx

In [500]: from keras.utils import to_categorical

          y_train_BoW_W2VTwitter_mx = to_categorical(y_train)
          y_test_BoW_W2VTwitter_mx  = to_categorical(y_test)

          num_mx, sz_mx = y_train_BoW_W2VTwitter_mx.shape

          print(num_mx)
          print(sz_mx)


          import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 50
          epochs = 20

          nn_BoW_W2VTwitter_mx = Sequential()
          nn_BoW_W2VTwitter_mx.add(Dense(512, activation='relu'))
          nn_BoW_W2VTwitter_mx.add(Dropout(0.25))
          nn_BoW_W2VTwitter_mx.add(Dense(sz_mx, activation='softmax'))
          nn_BoW_W2VTwitter_mx.compile(loss='binary_crossentropy',
                        optimizer='nadam',
                        metrics=['accuracy'])

          history_BoW_W2VTwitter_mx = nn_BoW_W2VTwitter_mx.fit(BoW_W2VTwitter_mx_train,
                        y_train_BoW_W2VTwitter_mx,
                        validation_split=.2,
                        batch_size= batch_size,
                        shuffle    =True,
                        epochs=epochs,
                        verbose=2)

          print('Tiempo de procesamiento (secs): ', time.time()-tic)

          history_dict_BoW_W2VTwitter_mx = history_BoW_W2VTwitter_mx.history
          dictkeys_BoW_W2VTwitter_mx=list(history_dict_BoW_W2VTwitter_mx.keys())
          loss_values_BoW_W2VTwitter_mx = history_BoW_W2VTwitter_mx.history['acc']
          val_loss_values_BoW_W2VTwitter_mx = history_BoW_W2VTwitter_mx.history['val_acc']
          epochs_BoW_W2VTwitter_mx = range(1, len(loss_values_BoW_W2VTwitter_mx) + 1)
```

```
plt.figure(figsize=(12,5))
plt.plot(epochs_BoW_W2VTwitter_mx, loss_values_BoW_W2VTwitter_mx, 'b', label='Entrena
plt.plot(epochs_BoW_W2VTwitter_mx, val_loss_values_BoW_W2VTwitter_mx, 'g', label='Val
plt.title('Valor accuracy en conjuntos de en entrenamiento y validación')
plt.xlabel('Epocas')
plt.ylabel('')
plt.legend()

plt.show()
```

```
2400
2
Train on 1920 samples, validate on 480 samples
Epoch 1/20
 - 2s - loss: 0.6588 - acc: 0.6156 - val_loss: 0.4527 - val_acc: 0.8854
Epoch 2/20
 - 0s - loss: 0.6104 - acc: 0.6500 - val_loss: 0.4557 - val_acc: 0.8687
Epoch 3/20
 - 0s - loss: 0.5795 - acc: 0.6870 - val_loss: 0.5236 - val_acc: 0.7708
Epoch 4/20
 - 0s - loss: 0.5489 - acc: 0.7172 - val_loss: 0.4350 - val_acc: 0.8458
Epoch 5/20
 - 0s - loss: 0.5129 - acc: 0.7422 - val_loss: 0.5643 - val_acc: 0.7292
Epoch 6/20
 - 0s - loss: 0.4752 - acc: 0.7693 - val_loss: 0.6684 - val_acc: 0.5667
Epoch 7/20
 - 0s - loss: 0.4381 - acc: 0.8016 - val_loss: 0.5588 - val_acc: 0.7354
Epoch 8/20
 - 0s - loss: 0.3689 - acc: 0.8578 - val_loss: 0.5127 - val_acc: 0.7896
Epoch 9/20
 - 0s - loss: 0.3187 - acc: 0.8844 - val_loss: 0.4727 - val_acc: 0.8375
Epoch 10/20
 - 0s - loss: 0.2619 - acc: 0.9115 - val_loss: 0.5675 - val_acc: 0.7604
Epoch 11/20
 - 0s - loss: 0.2028 - acc: 0.9531 - val_loss: 0.5557 - val_acc: 0.7750
Epoch 12/20
 - 0s - loss: 0.1737 - acc: 0.9646 - val_loss: 0.5366 - val_acc: 0.8146
Epoch 13/20
 - 0s - loss: 0.1243 - acc: 0.9865 - val_loss: 0.6245 - val_acc: 0.7729
Epoch 14/20
 - 0s - loss: 0.1117 - acc: 0.9833 - val_loss: 0.6092 - val_acc: 0.7708
Epoch 15/20
 - 0s - loss: 0.0793 - acc: 0.9948 - val_loss: 0.7356 - val_acc: 0.7375
Epoch 16/20
 - 0s - loss: 0.0642 - acc: 0.9948 - val_loss: 0.7041 - val_acc: 0.7583
Epoch 17/20
```

```
 - 0s - loss: 0.0516 - acc: 0.9974 - val_loss: 0.7919 - val_acc: 0.7229
Epoch 18/20
 - 0s - loss: 0.0422 - acc: 0.9969 - val_loss: 0.9263 - val_acc: 0.6958
Epoch 19/20
 - 0s - loss: 0.0366 - acc: 0.9979 - val_loss: 0.7965 - val_acc: 0.7458
Epoch 20/20
 - 0s - loss: 0.0309 - acc: 0.9974 - val_loss: 0.7562 - val_acc: 0.7708
Tiempo de procesamiento (secs):  5.922190427780151
```




```
In [503]: del nn_BoW_W2VTwitter_mx

          import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 50
          epochs = 5

          nn_BoW_W2VTwitter_mx = Sequential()
          nn_BoW_W2VTwitter_mx.add(Dense(512, activation='relu'))
          nn_BoW_W2VTwitter_mx.add(Dropout(0.25))
          nn_BoW_W2VTwitter_mx.add(Dense(sz_mx, activation='softmax'))
          nn_BoW_W2VTwitter_mx.compile(loss='binary_crossentropy',
                        optimizer='nadam',
                        metrics=['accuracy'])

          history_BoW_W2VTwitter_mx= nn_BoW_W2VTwitter_mx.fit(BoW_W2VTwitter_mx_train,
                        y_train_BoW_W2VTwitter_mx,
```

```
                 validation_split=.2,
                 batch_size= batch_size,
                 shuffle   =True,
                 epochs=epochs,
                 verbose=0)

print('Tiempo de procesamiento (secs): ', time.time()-tic)


from keras.models import load_model
nn_BoW_W2VTwitter_mx.save('nn_BoW_W2VTwitter_mx')  # Guardar modelo
#nn_w2vtwit_cu = load_model('nn_cuba_w2vtwit') # Cargar modelo


y_pred_BoW_W2VTwitter_mx= nn_BoW_W2VTwitter_mx.predict(BoW_W2VTwitter_mx_test).squeez
y_test_label_BoW_W2VTwitter_mx = np.argmax(y_test_BoW_W2VTwitter_mx,1)
y_pred_label_BoW_W2VTwitter_mx = np.argmax(y_pred_BoW_W2VTwitter_mx,1)


print("F1 score", f1_score(y_test_label_BoW_W2VTwitter_mx,  y_pred_label_BoW_W2VTwit
print("F1 weighted", f1_score(y_test_label_BoW_W2VTwitter_mx,  y_pred_label_BoW_W2VT
print("Recall score", recall_score(y_test_label_BoW_W2VTwitter_mx,  y_pred_label_BoW_
print("Precision score", precision_score(y_test_label_BoW_W2VTwitter_mx,  y_pred_labe
```

```
Tiempo de procesamiento (secs):  3.215589761734009
F1 score 0.6225329493327938
F1 weighted 0.6667993491802051
Recall score 0.621505282021078
Precision score 0.6237745098039216
```

24.2.2 España

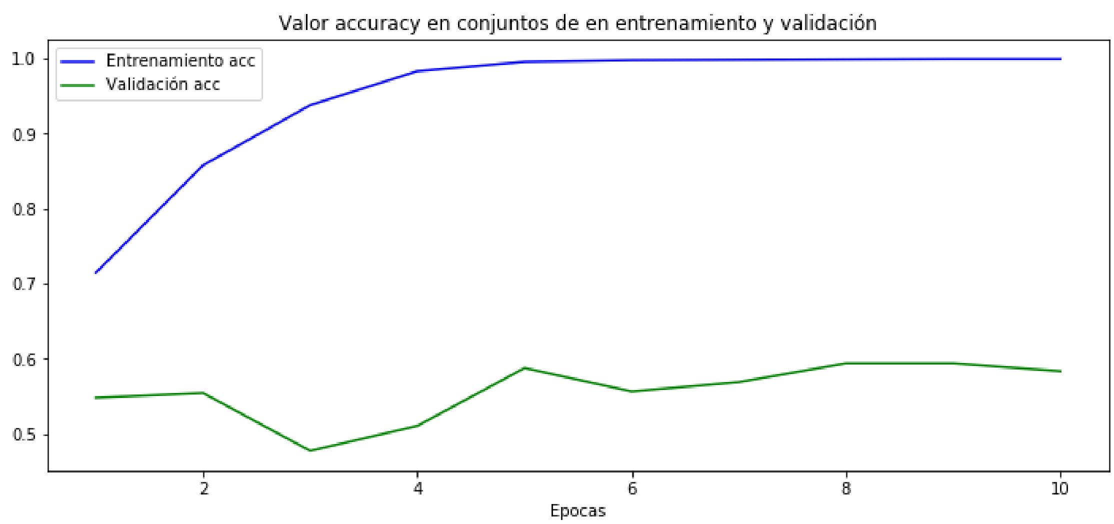
```
In [ ]: del nn_BoW_W2VTwitter_es
```

```
In [504]: from keras.utils import to_categorical

          y_train_BoW_W2VTwitter_es = to_categorical(y_train_es)
          y_test_BoW_W2VTwitter_es  = to_categorical(y_test_es)

          num_es, sz_es = y_train_BoW_W2VTwitter_es.shape

          print(num_es)
          print(sz_es)


          import time
          tic=time.time()
```

```
np.random.seed(1)

batch_size = 50
epochs = 10

nn_BoW_W2VTwitter_es = Sequential()
nn_BoW_W2VTwitter_es.add(Dense(512, activation='relu'))
nn_BoW_W2VTwitter_es.add(Dropout(0.25))
nn_BoW_W2VTwitter_es.add(Dense(sz_es, activation='softmax'))
nn_BoW_W2VTwitter_es.compile(loss='binary_crossentropy',
              optimizer='nadam',
              metrics=['accuracy'])

history_BoW_W2VTwitter_es = nn_BoW_W2VTwitter_es.fit(BoW_W2VTwitter_es_train,
              y_train_BoW_W2VTwitter_es,
              validation_split=.2,
              batch_size= batch_size,
              shuffle   =True,
              epochs=epochs,
              verbose=2)

print('Tiempo de procesamiento (secs): ', time.time()-tic)

history_dict_BoW_W2VTwitter_es = history_BoW_W2VTwitter_es.history
dictkeys_BoW_W2VTwitter_es=list(history_dict_BoW_W2VTwitter_es.keys())
loss_values_BoW_W2VTwitter_es = history_BoW_W2VTwitter_es.history['acc']
val_loss_values_BoW_W2VTwitter_es = history_BoW_W2VTwitter_es.history['val_acc']
epochs_BoW_W2VTwitter_es = range(1, len(loss_values_BoW_W2VTwitter_es) + 1)



plt.figure(figsize=(12,5))
plt.plot(epochs_BoW_W2VTwitter_es, loss_values_BoW_W2VTwitter_es, 'b', label='Entrena
plt.plot(epochs_BoW_W2VTwitter_es, val_loss_values_BoW_W2VTwitter_es, 'g', label='Val
plt.title('Valor accuracy en conjuntos de en entrenamiento y validación')
plt.xlabel('Epocas')
plt.ylabel('')
plt.legend()

plt.show()
```

```
2400
2
Train on 1920 samples, validate on 480 samples
Epoch 1/10
 - 3s - loss: 0.5433 - acc: 0.7146 - val_loss: 0.7139 - val_acc: 0.5479
Epoch 2/10
```

```
 - 1s - loss: 0.3371 - acc: 0.8578 - val_loss: 0.7635 - val_acc: 0.5542
Epoch 3/10
 - 1s - loss: 0.1715 - acc: 0.9380 - val_loss: 1.1933 - val_acc: 0.4771
Epoch 4/10
 - 1s - loss: 0.0734 - acc: 0.9833 - val_loss: 1.1235 - val_acc: 0.5104
Epoch 5/10
 - 1s - loss: 0.0325 - acc: 0.9958 - val_loss: 0.9634 - val_acc: 0.5875
Epoch 6/10
 - 1s - loss: 0.0177 - acc: 0.9979 - val_loss: 1.2088 - val_acc: 0.5563
Epoch 7/10
 - 1s - loss: 0.0113 - acc: 0.9984 - val_loss: 1.1642 - val_acc: 0.5687
Epoch 8/10
 - 1s - loss: 0.0076 - acc: 0.9990 - val_loss: 1.1494 - val_acc: 0.5937
Epoch 9/10
 - 1s - loss: 0.0054 - acc: 0.9995 - val_loss: 1.1794 - val_acc: 0.5938
Epoch 10/10
 - 1s - loss: 0.0049 - acc: 0.9995 - val_loss: 1.2465 - val_acc: 0.5833
Tiempo de procesamiento (secs):  8.65994381904602
```




```
In [505]: del nn_BoW_W2VTwitter_es

          import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 50
          epochs = 3
```

```
nn_BoW_W2VTwitter_es = Sequential()
nn_BoW_W2VTwitter_es.add(Dense(512, activation='relu'))
nn_BoW_W2VTwitter_es.add(Dropout(0.25))
nn_BoW_W2VTwitter_es.add(Dense(sz_es, activation='softmax'))
nn_BoW_W2VTwitter_es.compile(loss='binary_crossentropy',
              optimizer='nadam',
              metrics=['accuracy'])

history_BoW_W2VTwitter_es= nn_BoW_W2VTwitter_es.fit(BoW_W2VTwitter_es_train,
              y_train_BoW_W2VTwitter_es,
              validation_split=.2,
              batch_size= batch_size,
              shuffle   =True,
              epochs=epochs,
              verbose=0)

print('Tiempo de procesamiento (secs): ', time.time()-tic)


from keras.models import load_model
nn_BoW_W2VTwitter_es.save('nn_BoW_W2VTwitter_es')  # Guardar modelo
#nn_w2vtwit_cu = load_model('nn_cuba_w2vtwit') # Cargar modelo


y_pred_BoW_W2VTwitter_es= nn_BoW_W2VTwitter_es.predict(BoW_W2VTwitter_es_test).squee
y_test_label_BoW_W2VTwitter_es = np.argmax(y_test_BoW_W2VTwitter_es,1)
y_pred_label_BoW_W2VTwitter_es = np.argmax(y_pred_BoW_W2VTwitter_es,1)


print("F1 score", f1_score(y_test_label_BoW_W2VTwitter_es,  y_pred_label_BoW_W2VTwit
print("F1 weighted", f1_score(y_test_label_BoW_W2VTwitter_es,  y_pred_label_BoW_W2VT
print("Recall score", recall_score(y_test_label_BoW_W2VTwitter_es,  y_pred_label_BoW
print("Precision score", precision_score(y_test_label_BoW_W2VTwitter_es,  y_pred_lab
```

```
Tiempo de procesamiento (secs):  4.407065153121948
F1 score 0.6536495695839312
F1 weighted 0.6644249163079866
Recall score 0.70375
Precision score 0.6850926598837209
```

24.2.3 Cuba

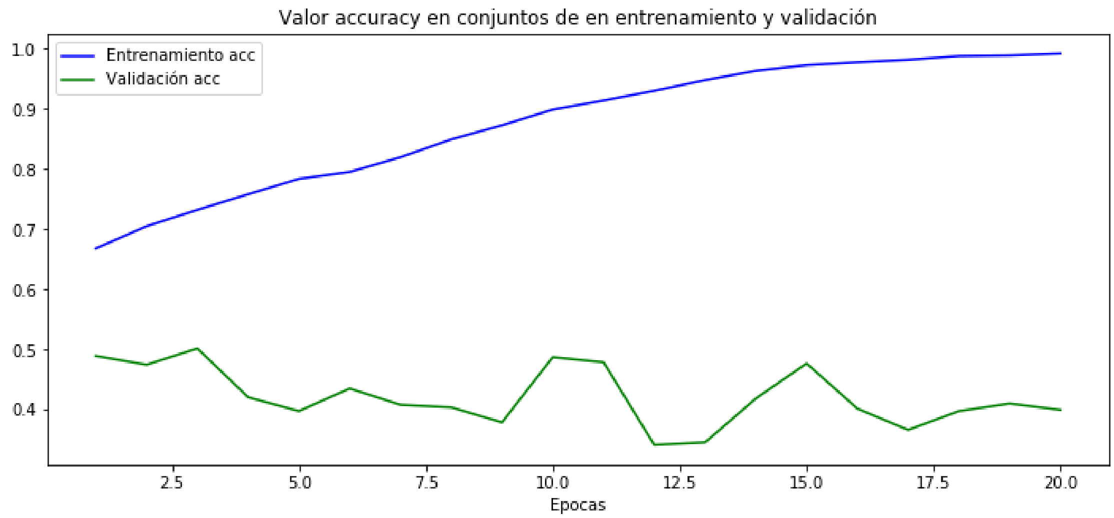
```
In [512]: del nn_BoW_W2VTwitter_cu
```

```
In [513]: from keras.utils import to_categorical

          y_train_BoW_W2VTwitter_cu = to_categorical(y_train_cu)
```

```
y_test_BoW_W2VTwitter_cu  = to_categorical(y_test_cu)

num_cu, sz_cu = y_train_BoW_W2VTwitter_cu.shape

print(num_cu)
print(sz_cu)


import time
tic=time.time()

np.random.seed(1)

batch_size = 50
epochs = 20

nn_BoW_W2VTwitter_cu = Sequential()
nn_BoW_W2VTwitter_cu.add(Dense(512, activation='relu'))
nn_BoW_W2VTwitter_cu.add(Dropout(0.25))
nn_BoW_W2VTwitter_cu.add(Dense(sz_cu, activation='softmax'))
nn_BoW_W2VTwitter_cu.compile(loss='binary_crossentropy',
              optimizer='nadam',
              metrics=['accuracy'])

history_BoW_W2VTwitter_cu = nn_BoW_W2VTwitter_cu.fit(BoW_W2VTwitter_cu_train,
              y_train_BoW_W2VTwitter_cu,
              validation_split=.2,
              batch_size= batch_size,
              shuffle   =True,
              epochs=epochs,
              verbose=2)

print('Tiempo de procesamiento (secs): ', time.time()-tic)

history_dict_BoW_W2VTwitter_cu = history_BoW_W2VTwitter_cu.history
dictkeys_BoW_W2VTwitter_cu=list(history_dict_BoW_W2VTwitter_cu.keys())
loss_values_BoW_W2VTwitter_cu = history_BoW_W2VTwitter_cu.history['acc']
val_loss_values_BoW_W2VTwitter_cu = history_BoW_W2VTwitter_cu.history['val_acc']
epochs_BoW_W2VTwitter_cu = range(1, len(loss_values_BoW_W2VTwitter_cu) + 1)



plt.figure(figsize=(12,5))
plt.plot(epochs_BoW_W2VTwitter_cu, loss_values_BoW_W2VTwitter_cu, 'b', label='Entrena
plt.plot(epochs_BoW_W2VTwitter_cu, val_loss_values_BoW_W2VTwitter_cu, 'g', label='Va
plt.title('Valor accuracy en conjuntos de en entrenamiento y validación')
plt.xlabel('Epocas')
plt.ylabel('')
```

```
        plt.legend()

        plt.show()
```

```
2400
2
Train on 1920 samples, validate on 480 samples
Epoch 1/20
 - 3s - loss: 0.6261 - acc: 0.6682 - val_loss: 0.8988 - val_acc: 0.4896
Epoch 2/20
 - 0s - loss: 0.5626 - acc: 0.7052 - val_loss: 1.2769 - val_acc: 0.4750
Epoch 3/20
 - 0s - loss: 0.5247 - acc: 0.7323 - val_loss: 1.3855 - val_acc: 0.5021
Epoch 4/20
 - 0s - loss: 0.4921 - acc: 0.7583 - val_loss: 2.0695 - val_acc: 0.4208
Epoch 5/20
 - 0s - loss: 0.4637 - acc: 0.7839 - val_loss: 2.3767 - val_acc: 0.3979
Epoch 6/20
 - 0s - loss: 0.4451 - acc: 0.7953 - val_loss: 2.3426 - val_acc: 0.4354
Epoch 7/20
 - 0s - loss: 0.3950 - acc: 0.8198 - val_loss: 2.9434 - val_acc: 0.4083
Epoch 8/20
 - 0s - loss: 0.3654 - acc: 0.8495 - val_loss: 3.2471 - val_acc: 0.4042
Epoch 9/20
 - 0s - loss: 0.3186 - acc: 0.8729 - val_loss: 3.9460 - val_acc: 0.3792
Epoch 10/20
 - 0s - loss: 0.2778 - acc: 0.8990 - val_loss: 3.4026 - val_acc: 0.4875
Epoch 11/20
 - 0s - loss: 0.2456 - acc: 0.9141 - val_loss: 3.7999 - val_acc: 0.4792
Epoch 12/20
 - 0s - loss: 0.2015 - acc: 0.9302 - val_loss: 4.8862 - val_acc: 0.3417
Epoch 13/20
 - 0s - loss: 0.1773 - acc: 0.9479 - val_loss: 5.0432 - val_acc: 0.3458
Epoch 14/20
 - 0s - loss: 0.1469 - acc: 0.9635 - val_loss: 4.6015 - val_acc: 0.4188
Epoch 15/20
 - 0s - loss: 0.1200 - acc: 0.9729 - val_loss: 4.2321 - val_acc: 0.4771
Epoch 16/20
 - 0s - loss: 0.1053 - acc: 0.9776 - val_loss: 4.9856 - val_acc: 0.4021
Epoch 17/20
 - 0s - loss: 0.0845 - acc: 0.9818 - val_loss: 5.3075 - val_acc: 0.3667
Epoch 18/20
 - 0s - loss: 0.0727 - acc: 0.9880 - val_loss: 5.1662 - val_acc: 0.3979
Epoch 19/20
 - 0s - loss: 0.0636 - acc: 0.9891 - val_loss: 5.1740 - val_acc: 0.4104
Epoch 20/20
 - 0s - loss: 0.0541 - acc: 0.9922 - val_loss: 5.3330 - val_acc: 0.4000
Tiempo de procesamiento (secs):  6.918715476989746
```



In [518]:
```
del nn_BoW_W2VTwitter_cu

import time
tic=time.time()

np.random.seed(1)

batch_size = 50
epochs = 6

nn_BoW_W2VTwitter_cu = Sequential()
nn_BoW_W2VTwitter_cu.add(Dense(512, activation='relu'))
nn_BoW_W2VTwitter_cu.add(Dropout(0.25))
nn_BoW_W2VTwitter_cu.add(Dense(sz_cu, activation='softmax'))
nn_BoW_W2VTwitter_cu.compile(loss='binary_crossentropy',
              optimizer='nadam',
              metrics=['accuracy'])

history_BoW_W2VTwitter_cu= nn_BoW_W2VTwitter_cu.fit(BoW_W2VTwitter_cu_train,
              y_train_BoW_W2VTwitter_cu,
              validation_split=.2,
              batch_size= batch_size,
              shuffle   =True,
              epochs=epochs,
              verbose=0)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
from keras.models import load_model
nn_BoW_W2VTwitter_cu.save('nn_BoW_W2VTwitter_cu')  # Guardar modelo
#nn_w2vtwit_cu = load_model('nn_cuba_w2vtwit') # Cargar modelo


y_pred_BoW_W2VTwitter_cu= nn_BoW_W2VTwitter_cu.predict(BoW_W2VTwitter_cu_test).squeez
y_test_label_BoW_W2VTwitter_cu = np.argmax(y_test_BoW_W2VTwitter_cu,1)
y_pred_label_BoW_W2VTwitter_cu = np.argmax(y_pred_BoW_W2VTwitter_cu,1)


print("F1 score", f1_score(y_test_label_BoW_W2VTwitter_cu,  y_pred_label_BoW_W2VTwit
print("F1 weighted", f1_score(y_test_label_BoW_W2VTwitter_cu,  y_pred_label_BoW_W2VT
print("Recall score", recall_score(y_test_label_BoW_W2VTwitter_cu,  y_pred_label_BoW_
print("Precision score", precision_score(y_test_label_BoW_W2VTwitter_cu,  y_pred_labe
```

```
Tiempo de procesamiento (secs):  4.555535554885864
F1 score 0.5816979962817599
F1 weighted 0.6337533567444742
Recall score 0.5800000000000001
Precision score 0.5857632933104631
```

25 Concatenar BoW TF-IDF + W2VGoogle + W2VTwitter

25.1 Clasificador SVM

25.1.1 México

```
In [342]: print(np.concatenate((x_train_tf_mx, mean_emb_train_w2vgoogle_mx,  mean_emb_train_w2v
          BoW_W2V_Twitter_Google_mx_train = np.concatenate((x_train_tf_mx, mean_emb_train_w2vg

          print(np.concatenate((x_test_tf_mx, mean_emb_test_w2vgoogle_mx,  mean_emb_test_w2vtw
          BoW_W2V_Twitter_Google_mx_test = np.concatenate((x_test_tf_mx, mean_emb_test_w2vgoog
```

```
(2400, 886)
(600, 886)
```

```
In [350]: from sklearn.pipeline import Pipeline
          from sklearn.svm import LinearSVC
          from sklearn.model_selection import GridSearchCV
          from sklearn.preprocessing import StandardScaler
          import time
          tic=time.time()

          SVCpipe = Pipeline([('SVC',LinearSVC(class_weight="balanced", random_state=1,verbose=

          # Gridsearch to determine the value of C
```

```
param_grid = {'SVC__C':np.arange(.01,2,.1)}
linearSVC = GridSearchCV(SVCpipe,param_grid,cv=5,return_train_score=True, verbose=0)
linearSVC.fit(BoW_W2V_Twitter_Google_mx_train, y_train.values)
print(linearSVC.best_params_)
#linearSVC.coef_
#linearSVC.intercept_

svc_BoW_W2V_Twitter_Google_mx = linearSVC.best_estimator_
svc_BoW_W2V_Twitter_Google_mx.fit(BoW_W2V_Twitter_Google_mx_train, y_train.values)
svc_BoW_W2V_Twitter_Google_mx.coef_ = svc_BoW_W2V_Twitter_Google_mx.named_steps['SVC
svc_BoW_W2V_Twitter_Google_mx.score(BoW_W2V_Twitter_Google_mx_train, y_train.values)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
{'SVC__C': 0.21000000000000002}
Tiempo de procesamiento (secs):  75.92161464691162
```

In [355]:
```
from joblib import dump, load
dump(svc_BoW_W2V_Twitter_Google_mx, 'svc_BoW_W2V_Twitter_Google_mx.joblib')
#svc_w2vtwit_cu = load('svc_w2vtwit_cu.joblib')
prediction_BoW_W2V_Twitter_Google_mx=svc_BoW_W2V_Twitter_Google_mx.predict(BoW_W2V_Tw
print("Acurracy Test",metrics.accuracy_score( y_test.values, prediction_BoW_W2V_Twitt
```

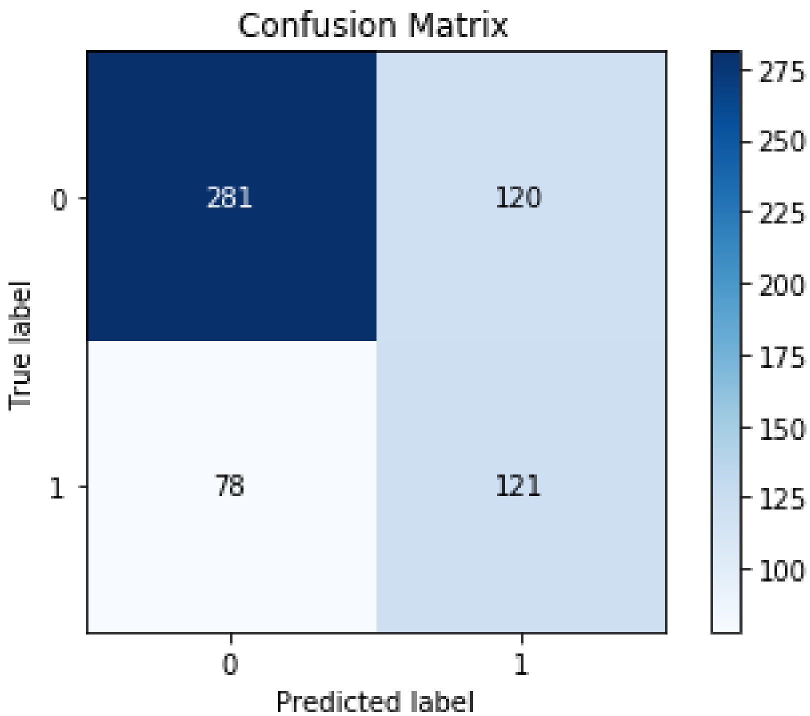
```
Acurracy Test 0.67
```

In [356]:
```
print('Accuracy score:', metrics.accuracy_score(y_test.values, prediction_BoW_W2V_Tw
print("F1 score", f1_score(y_test.values, prediction_BoW_W2V_Twitter_Google_mx,  aver
print("F1 weighted", f1_score(y_test.values, prediction_BoW_W2V_Twitter_Google_mx,  a
print("Recall score", recall_score(y_test.values, prediction_BoW_W2V_Twitter_Google_m
print("Precision score", precision_score(y_test.values, prediction_BoW_W2V_Twitter_Go


from sklearn.metrics import classification_report
print(classification_report( y_test.values, prediction_BoW_W2V_Twitter_Google_mx, ta

%matplotlib inline
import matplotlib.pyplot as plt
import scikitplot

scikitplot.metrics.plot_confusion_matrix(y_test.values, prediction_BoW_W2V_Twitter_Go
```

```
Accuracy score: 0.67
F1 score 0.6447368421052632
F1 weighted 0.6766315789473684
Recall score 0.6543941653404177
Precision score 0.642402246905304
              precision    recall  f1-score   support
```

```
   no-ironia       0.78      0.70      0.74       401
      ironia       0.50      0.61      0.55       199

   micro avg       0.67      0.67      0.67       600
   macro avg       0.64      0.65      0.64       600
weighted avg       0.69      0.67      0.68       600
```

```
Out[356]: <matplotlib.axes._subplots.AxesSubplot at 0x1ab76afceb8>
```



25.1.2 España

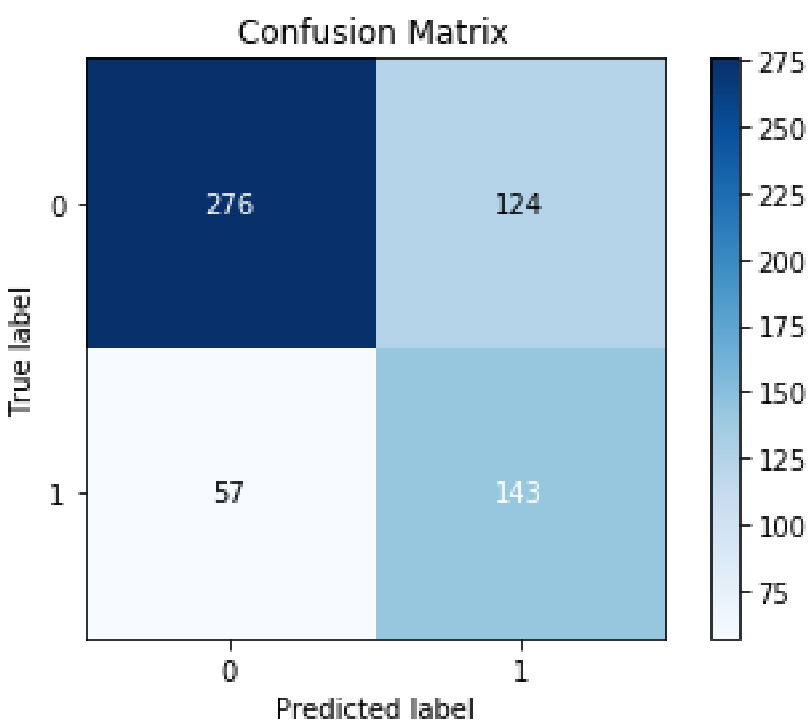
```
In [365]: print(np.concatenate((x_train_tf_es, mean_emb_train_w2vgoogle_es,  mean_emb_train_w2v
          BoW_W2V_Twitter_Google_es_train = np.concatenate((x_train_tf_es, mean_emb_train_w2vgo

          print(np.concatenate((x_test_tf_es, mean_emb_test_w2vgoogle_es,  mean_emb_test_w2vtwi
          BoW_W2V_Twitter_Google_es_test = np.concatenate((x_test_tf_es, mean_emb_test_w2vgoogl

(2400, 7644)
(600, 7644)
```

```
In [372]: from sklearn.pipeline import Pipeline
          from sklearn.svm import LinearSVC
          from sklearn.model_selection import GridSearchCV
          from sklearn.preprocessing import StandardScaler
          import time
          tic=time.time()

          SVCpipe = Pipeline([('SVC',LinearSVC(class_weight="balanced", random_state=1,verbose=

          # Gridsearch to determine the value of C
          param_grid = {'SVC__C':np.arange(.01,2,.1)}
          linearSVC = GridSearchCV(SVCpipe,param_grid,cv=5,return_train_score=True, verbose=0)
          linearSVC.fit(BoW_W2V_Twitter_Google_es_train, y_train_es.values)
          print(linearSVC.best_params_)
          #linearSVC.coef_
          #linearSVC.intercept_

          svc_BoW_W2V_Twitter_Google_es = linearSVC.best_estimator_
          svc_BoW_W2V_Twitter_Google_es.fit(BoW_W2V_Twitter_Google_es_train, y_train_es.values
          svc_BoW_W2V_Twitter_Google_es.coef_ = svc_BoW_W2V_Twitter_Google_es.named_steps['SVC
          svc_BoW_W2V_Twitter_Google_es.score(BoW_W2V_Twitter_Google_es_train, y_train_es.valu

          print('Tiempo de procesamiento (secs): ', time.time()-tic)

{'SVC__C': 0.01}
Tiempo de procesamiento (secs):  44.04638862609863


In [373]: from joblib import dump, load
          dump(svc_BoW_W2V_Twitter_Google_es, 'svc_BoW_W2V_Twitter_Google_es.joblib')
          #svc_w2vtwit_cu = load('svc_w2vtwit_cu.joblib')
          prediction_BoW_W2V_Twitter_Google_es=svc_BoW_W2V_Twitter_Google_es.predict(BoW_W2V_Tw
          print("Acurracy Test",metrics.accuracy_score( y_test_es.values, prediction_BoW_W2V_Tw

Acurracy Test 0.6983333333333334


In [374]: print('Accuracy score:', metrics.accuracy_score(y_test_es.values, prediction_BoW_W2V_
          print("F1 score", f1_score(y_test_es.values, prediction_BoW_W2V_Twitter_Google_es,  a
          print("F1 weighted", f1_score(y_test_es.values, prediction_BoW_W2V_Twitter_Google_es
          print("Recall score", recall_score(y_test_es.values, prediction_BoW_W2V_Twitter_Googl
          print("Precision score", precision_score(y_test_es.values, prediction_BoW_W2V_Twitte


          from sklearn.metrics import classification_report
          print(classification_report( y_test_es.values, prediction_BoW_W2V_Twitter_Google_es,

          %matplotlib inline
          import matplotlib.pyplot as plt
```

```python
import scikitplot
#0.6827446386473119
scikitplot.metrics.plot_confusion_matrix(y_test_es.values, prediction_BoW_W2V_Twitte
```

```
Accuracy score: 0.6983333333333334
F1 score 0.6827446386473119
F1 weighted 0.706186284791705
Recall score 0.7024999999999999
Precision score 0.682204676586699
              precision    recall  f1-score   support

   no-ironia       0.83      0.69      0.75       400
      ironia       0.54      0.71      0.61       200

   micro avg       0.70      0.70      0.70       600
   macro avg       0.68      0.70      0.68       600
weighted avg       0.73      0.70      0.71       600
```

Out[374]: <matplotlib.axes._subplots.AxesSubplot at 0x1ab941e0f60>



25.1.3 Cuba

```
In [375]: print(np.concatenate((x_train_tf_cu, mean_emb_train_w2vgoogle_cu,  mean_emb_train_w2v
          BoW_W2V_Twitter_Google_cu_train = np.concatenate((x_train_tf_cu, mean_emb_train_w2vgo

          print(np.concatenate((x_test_tf_cu, mean_emb_test_w2vgoogle_cu,  mean_emb_test_w2vtwi
          BoW_W2V_Twitter_Google_cu_test = np.concatenate((x_test_tf_cu, mean_emb_test_w2vgoogl
```

```
(2400, 991)
(600, 991)
```

```
In [380]: from sklearn.pipeline import Pipeline
          from sklearn.svm import LinearSVC
          from sklearn.model_selection import GridSearchCV
          from sklearn.preprocessing import StandardScaler
          import time
          tic=time.time()

          SVCpipe = Pipeline([('SVC',LinearSVC(class_weight="balanced", random_state=1,verbose=

          # Gridsearch to determine the value of C
          param_grid = {'SVC__C':np.arange(.001,1,.1)}
          linearSVC = GridSearchCV(SVCpipe,param_grid,cv=5,return_train_score=True, verbose=0)
          linearSVC.fit(BoW_W2V_Twitter_Google_cu_train, y_train_cu.values)
          print(linearSVC.best_params_)
          #linearSVC.coef_
          #linearSVC.intercept_

          svc_BoW_W2V_Twitter_Google_cu = linearSVC.best_estimator_
          svc_BoW_W2V_Twitter_Google_cu.fit(BoW_W2V_Twitter_Google_cu_train, y_train_cu.values)
          svc_BoW_W2V_Twitter_Google_cu.coef_ = svc_BoW_W2V_Twitter_Google_cu.named_steps['SVC
          svc_BoW_W2V_Twitter_Google_cu.score(BoW_W2V_Twitter_Google_cu_train, y_train_cu.value

          print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
{'SVC__C': 0.001}
Tiempo de procesamiento (secs):  22.981482982635498
```

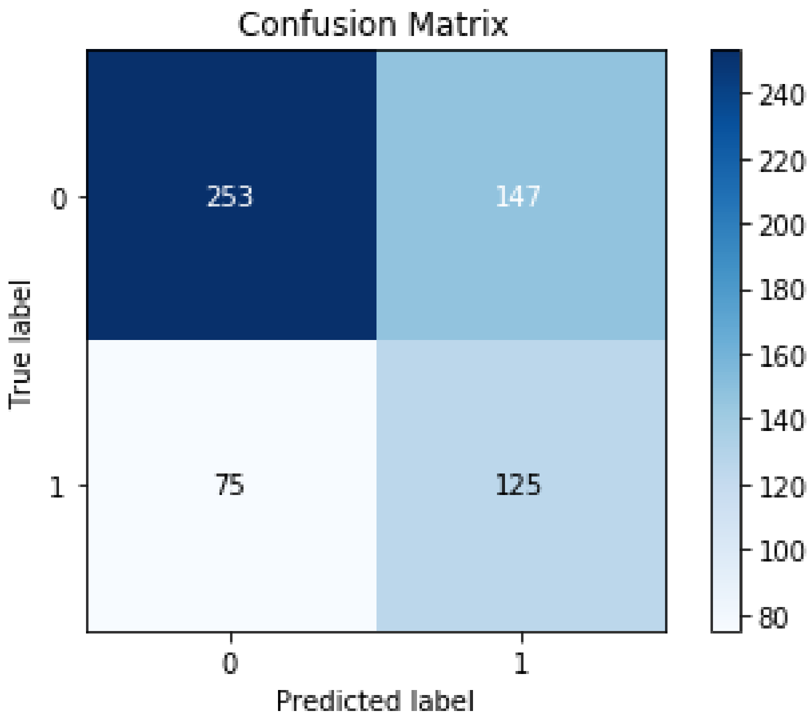
```
In [381]: from joblib import dump, load
          dump(svc_BoW_W2V_Twitter_Google_cu, 'svc_BoW_W2V_Twitter_Google_cu.joblib')
          #svc_w2vtwit_cu = load('svc_w2vtwit_cu.joblib')
          prediction_BoW_W2V_Twitter_Google_cu=svc_BoW_W2V_Twitter_Google_cu.predict(BoW_W2V_Tw
          print("Acurracy Test",metrics.accuracy_score( y_test_cu.values, prediction_BoW_W2V_Tw
```

```
Acurracy Test 0.63
```

```
In [382]: print('Accuracy score:', metrics.accuracy_score(y_test_cu.values, prediction_BoW_W2V_
          print("F1 score", f1_score(y_test_cu.values, prediction_BoW_W2V_Twitter_Google_cu,  a
          print("F1 weighted", f1_score(y_test_cu.values, prediction_BoW_W2V_Twitter_Google_cu
          print("Recall score", recall_score(y_test_cu.values, prediction_BoW_W2V_Twitter_Googl
          print("Precision score", precision_score(y_test_cu.values, prediction_BoW_W2V_Twitte


          from sklearn.metrics import classification_report
          print(classification_report( y_test_cu.values, prediction_BoW_W2V_Twitter_Google_cu,

          %matplotlib inline
          import matplotlib.pyplot as plt
          import scikitplot
          #0.6827446386473119
          scikitplot.metrics.plot_confusion_matrix(y_test_cu.values, prediction_BoW_W2V_Twitte
```

```
Accuracy score: 0.63
F1 score 0.6123579810020487
F1 weighted 0.6399236356863476
Recall score 0.6287499999999999
Precision score 0.615450143472023
              precision    recall  f1-score   support

   no-ironia       0.77      0.63      0.70       400
      ironia       0.46      0.62      0.53       200

   micro avg       0.63      0.63      0.63       600
   macro avg       0.62      0.63      0.61       600
weighted avg       0.67      0.63      0.64       600
```

```
Out[382]: <matplotlib.axes._subplots.AxesSubplot at 0x1ab947d2d68>
```



25.2 Clasificador NN

25.2.1 México

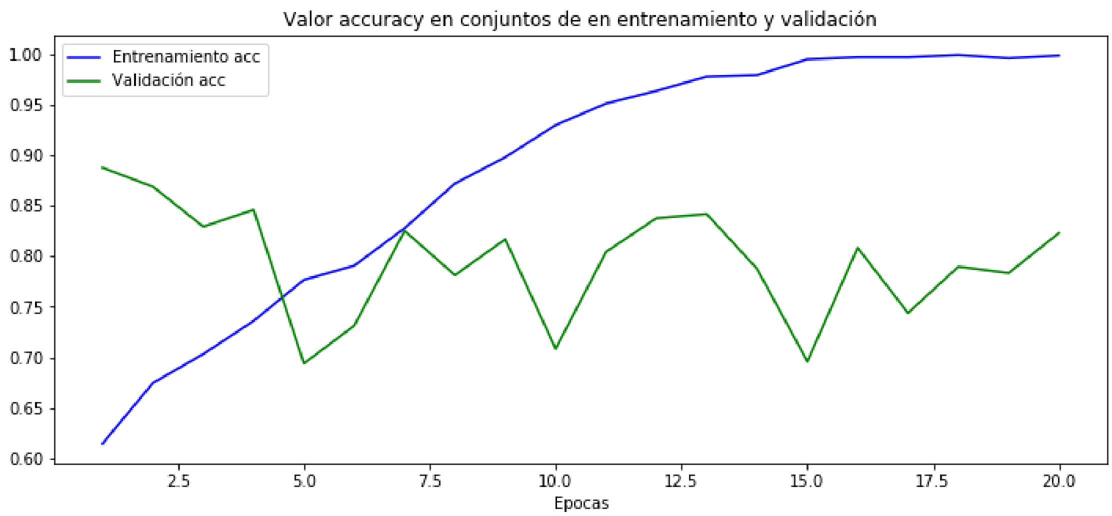
```
In [522]: del nn_Bow_W2V_Twitter_Google_mx
          # BoW_W2V_Twitter_Google_mx_train
```

```
In [523]: from keras.utils import to_categorical

          y_train_Bow_W2V_Twitter_Google_mx = to_categorical(y_train)
          y_test_Bow_W2V_Twitter_Google_mx  = to_categorical(y_test)

          num_mx, sz_mx = y_train_Bow_W2V_Twitter_Google_mx.shape

          print(num_mx)
          print(sz_mx)


          import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 50
```

```python
epochs = 20

nn_Bow_W2V_Twitter_Google_mx = Sequential()
nn_Bow_W2V_Twitter_Google_mx.add(Dense(512, activation='relu'))
nn_Bow_W2V_Twitter_Google_mx.add(Dropout(0.25))
nn_Bow_W2V_Twitter_Google_mx.add(Dense(sz_mx, activation='softmax'))
nn_Bow_W2V_Twitter_Google_mx.compile(loss='binary_crossentropy',
              optimizer='nadam',
              metrics=['accuracy'])

history_Bow_W2V_Twitter_Google_mx = nn_Bow_W2V_Twitter_Google_mx.fit(BoW_W2V_Twitter_
              y_train_Bow_W2V_Twitter_Google_mx,
              validation_split=.2,
              batch_size= batch_size,
              shuffle   =True,
              epochs=epochs,
              verbose=2)

print('Tiempo de procesamiento (secs): ', time.time()-tic)

history_dict_Bow_W2V_Twitter_Google_mx = history_Bow_W2V_Twitter_Google_mx.history
dictkeys_Bow_W2V_Twitter_Google_mx=list(history_dict_Bow_W2V_Twitter_Google_mx.keys()
loss_values_Bow_W2V_Twitter_Google_mx = history_Bow_W2V_Twitter_Google_mx.history['ac
val_loss_values_Bow_W2V_Twitter_Google_mx = history_Bow_W2V_Twitter_Google_mx.history
epochs_Bow_W2V_Twitter_Google_mx = range(1, len(loss_values_Bow_W2V_Twitter_Google_mx



plt.figure(figsize=(12,5))
plt.plot(epochs_Bow_W2V_Twitter_Google_mx, loss_values_Bow_W2V_Twitter_Google_mx, 'b
plt.plot(epochs_Bow_W2V_Twitter_Google_mx, val_loss_values_Bow_W2V_Twitter_Google_mx
plt.title('Valor accuracy en conjuntos de en entrenamiento y validación')
plt.xlabel('Epocas')
plt.ylabel('')
plt.legend()

plt.show()
```

```
2400
2
Train on 1920 samples, validate on 480 samples
Epoch 1/20
 - 3s - loss: 0.6636 - acc: 0.6146 - val_loss: 0.4435 - val_acc: 0.8875
Epoch 2/20
 - 0s - loss: 0.5993 - acc: 0.6745 - val_loss: 0.4519 - val_acc: 0.8688
Epoch 3/20
 - 0s - loss: 0.5663 - acc: 0.7031 - val_loss: 0.4795 - val_acc: 0.8292
Epoch 4/20
```

```
 - 0s - loss: 0.5281 - acc: 0.7359 - val_loss: 0.4383 - val_acc: 0.8458
Epoch 5/20
 - 0s - loss: 0.4740 - acc: 0.7766 - val_loss: 0.5911 - val_acc: 0.6938
Epoch 6/20
 - 0s - loss: 0.4401 - acc: 0.7906 - val_loss: 0.5508 - val_acc: 0.7312
Epoch 7/20
 - 0s - loss: 0.3918 - acc: 0.8276 - val_loss: 0.4506 - val_acc: 0.8250
Epoch 8/20
 - 0s - loss: 0.3282 - acc: 0.8719 - val_loss: 0.5047 - val_acc: 0.7812
Epoch 9/20
 - 0s - loss: 0.2740 - acc: 0.8979 - val_loss: 0.4732 - val_acc: 0.8167
Epoch 10/20
 - 0s - loss: 0.2214 - acc: 0.9297 - val_loss: 0.6359 - val_acc: 0.7083
Epoch 11/20
 - 0s - loss: 0.1840 - acc: 0.9510 - val_loss: 0.5283 - val_acc: 0.8042
Epoch 12/20
 - 0s - loss: 0.1471 - acc: 0.9635 - val_loss: 0.5515 - val_acc: 0.8375
Epoch 13/20
 - 0s - loss: 0.1123 - acc: 0.9776 - val_loss: 0.5818 - val_acc: 0.8417
Epoch 14/20
 - 0s - loss: 0.0999 - acc: 0.9792 - val_loss: 0.6113 - val_acc: 0.7875
Epoch 15/20
 - 0s - loss: 0.0644 - acc: 0.9948 - val_loss: 0.8739 - val_acc: 0.6958
Epoch 16/20
 - 0s - loss: 0.0519 - acc: 0.9969 - val_loss: 0.6773 - val_acc: 0.8083
Epoch 17/20
 - 0s - loss: 0.0433 - acc: 0.9969 - val_loss: 0.7630 - val_acc: 0.7437
Epoch 18/20
 - 0s - loss: 0.0321 - acc: 0.9990 - val_loss: 0.7482 - val_acc: 0.7896
Epoch 19/20
 - 0s - loss: 0.0329 - acc: 0.9958 - val_loss: 0.7723 - val_acc: 0.7833
Epoch 20/20
 - 0s - loss: 0.0262 - acc: 0.9984 - val_loss: 0.7727 - val_acc: 0.8229
Tiempo de procesamiento (secs):  6.959745645523071
```



In [536]:
```
del nn_Bow_W2V_Twitter_Google_mx

import time
tic=time.time()

np.random.seed(1)

batch_size = 50
epochs = 6

nn_Bow_W2V_Twitter_Google_mx = Sequential()
nn_Bow_W2V_Twitter_Google_mx.add(Dense(512, activation='relu'))
nn_Bow_W2V_Twitter_Google_mx.add(Dropout(0.25))
nn_Bow_W2V_Twitter_Google_mx.add(Dense(sz_mx, activation='softmax'))
nn_Bow_W2V_Twitter_Google_mx.compile(loss='binary_crossentropy',
              optimizer='nadam',
              metrics=['accuracy'])

history_Bow_W2V_Twitter_Google_mx= nn_Bow_W2V_Twitter_Google_mx.fit(BoW_W2V_Twitter_(
              y_train_Bow_W2V_Twitter_Google_mx,
              validation_split=.2,
              batch_size= batch_size,
              shuffle   =True,
              epochs=epochs,
              verbose=0)

print('Tiempo de procesamiento (secs): ', time.time()-tic)


from keras.models import load_model
```

```
nn_Bow_W2V_Twitter_Google_mx.save('nn_Bow_W2V_Twitter_Google_mx')  # Guardar modelo
#nn_w2vtwit_cu = load_model('nn_cuba_w2vtwit') # Cargar modelo


y_pred_Bow_W2V_Twitter_Google_mx= nn_Bow_W2V_Twitter_Google_mx.predict(BoW_W2V_Twitte
y_test_label_Bow_W2V_Twitter_Google_mx = np.argmax(y_test_Bow_W2V_Twitter_Google_mx,1
y_pred_label_Bow_W2V_Twitter_Google_mx = np.argmax(y_pred_Bow_W2V_Twitter_Google_mx,1


print("F1 score", f1_score(y_test_label_Bow_W2V_Twitter_Google_mx,  y_pred_label_Bow_
print("F1 weighted", f1_score(y_test_label_Bow_W2V_Twitter_Google_mx,  y_pred_label_B
print("Recall score", recall_score(y_test_label_Bow_W2V_Twitter_Google_mx,  y_pred_la
print("Precision score", precision_score(y_test_label_Bow_W2V_Twitter_Google_mx,  y_p
```

```
Tiempo de procesamiento (secs):  4.4209911823272705
F1 score 0.6125683792443866
F1 weighted 0.6512641885663
Recall score 0.616686925901327
Precision score 0.6107575739553472
```

25.2.2 España

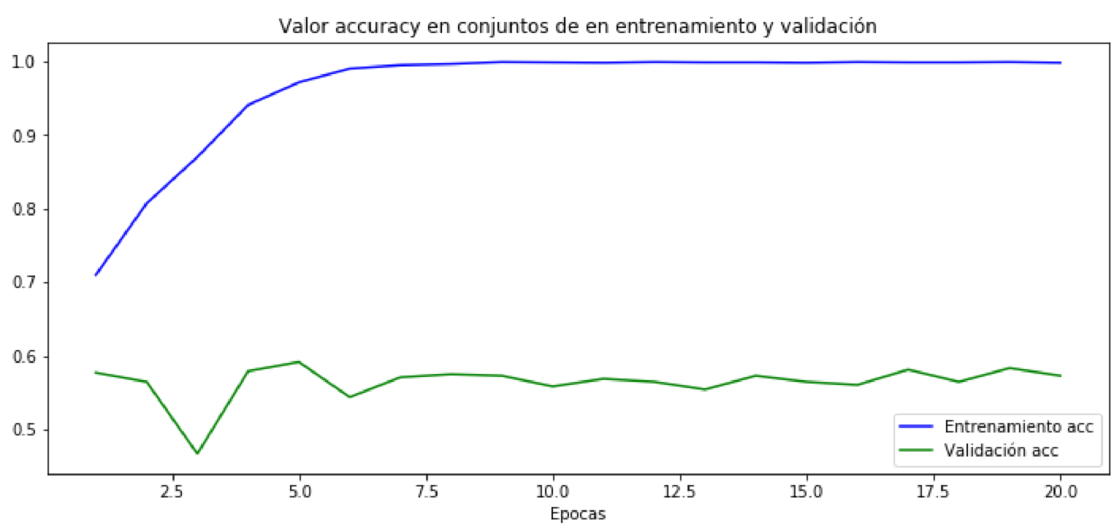
```
In [ ]: del nn_Bow_W2V_Twitter_Google_es
```

```
In [528]: from keras.utils import to_categorical

          y_train_Bow_W2V_Twitter_Google_es = to_categorical(y_train_es)
          y_test_Bow_W2V_Twitter_Google_es  = to_categorical(y_test_es)

          num_es, sz_es = y_train_Bow_W2V_Twitter_Google_es.shape

          print(num_es)
          print(sz_es)


          import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 50
          epochs = 20

          nn_Bow_W2V_Twitter_Google_es = Sequential()
          nn_Bow_W2V_Twitter_Google_es.add(Dense(512, activation='relu'))
          nn_Bow_W2V_Twitter_Google_es.add(Dropout(0.25))
          nn_Bow_W2V_Twitter_Google_es.add(Dense(sz_es, activation='softmax'))
```

```
nn_Bow_W2V_Twitter_Google_es.compile(loss='binary_crossentropy',
              optimizer='nadam',
              metrics=['accuracy'])

history_Bow_W2V_Twitter_Google_es = nn_Bow_W2V_Twitter_Google_es.fit(BoW_W2V_Twitter_
              y_train_Bow_W2V_Twitter_Google_es,
              validation_split=.2,
              batch_size= batch_size,
              shuffle   =True,
              epochs=epochs,
              verbose=2)

print('Tiempo de procesamiento (secs): ', time.time()-tic)

history_dict_Bow_W2V_Twitter_Google_es = history_Bow_W2V_Twitter_Google_es.history
dictkeys_Bow_W2V_Twitter_Google_es=list(history_dict_Bow_W2V_Twitter_Google_es.keys()
loss_values_Bow_W2V_Twitter_Google_es = history_Bow_W2V_Twitter_Google_es.history['ac
val_loss_values_Bow_W2V_Twitter_Google_es = history_Bow_W2V_Twitter_Google_es.history
epochs_Bow_W2V_Twitter_Google_es = range(1, len(loss_values_Bow_W2V_Twitter_Google_es



plt.figure(figsize=(12,5))
plt.plot(epochs_Bow_W2V_Twitter_Google_es, loss_values_Bow_W2V_Twitter_Google_es, 'b
plt.plot(epochs_Bow_W2V_Twitter_Google_es, val_loss_values_Bow_W2V_Twitter_Google_es
plt.title('Valor accuracy en conjuntos de en entrenamiento y validación')
plt.xlabel('Epocas')
plt.ylabel('')
plt.legend()

plt.show()
```

```
2400
2
Train on 1920 samples, validate on 480 samples
Epoch 1/20
 - 4s - loss: 0.5543 - acc: 0.7099 - val_loss: 0.6864 - val_acc: 0.5771
Epoch 2/20
 - 1s - loss: 0.4190 - acc: 0.8073 - val_loss: 0.7314 - val_acc: 0.5646
Epoch 3/20
 - 1s - loss: 0.3025 - acc: 0.8703 - val_loss: 1.0707 - val_acc: 0.4667
Epoch 4/20
 - 1s - loss: 0.1830 - acc: 0.9411 - val_loss: 0.8777 - val_acc: 0.5792
Epoch 5/20
 - 1s - loss: 0.1062 - acc: 0.9719 - val_loss: 0.9175 - val_acc: 0.5917
Epoch 6/20
 - 1s - loss: 0.0556 - acc: 0.9906 - val_loss: 1.1645 - val_acc: 0.5438
Epoch 7/20
```

```
 - 1s - loss: 0.0325 - acc: 0.9953 - val_loss: 1.0694 - val_acc: 0.5708
Epoch 8/20
 - 1s - loss: 0.0212 - acc: 0.9969 - val_loss: 1.0469 - val_acc: 0.5750
Epoch 9/20
 - 1s - loss: 0.0134 - acc: 0.9995 - val_loss: 1.1023 - val_acc: 0.5729
Epoch 10/20
 - 1s - loss: 0.0111 - acc: 0.9990 - val_loss: 1.2673 - val_acc: 0.5583
Epoch 11/20
 - 1s - loss: 0.0103 - acc: 0.9984 - val_loss: 1.1845 - val_acc: 0.5688
Epoch 12/20
 - 1s - loss: 0.0069 - acc: 0.9995 - val_loss: 1.2789 - val_acc: 0.5646
Epoch 13/20
 - 1s - loss: 0.0051 - acc: 0.9990 - val_loss: 1.3791 - val_acc: 0.5542
Epoch 14/20
 - 1s - loss: 0.0055 - acc: 0.9990 - val_loss: 1.2744 - val_acc: 0.5729
Epoch 15/20
 - 1s - loss: 0.0069 - acc: 0.9984 - val_loss: 1.2597 - val_acc: 0.5646
Epoch 16/20
 - 1s - loss: 0.0039 - acc: 0.9995 - val_loss: 1.3029 - val_acc: 0.5604
Epoch 17/20
 - 1s - loss: 0.0062 - acc: 0.9990 - val_loss: 1.3711 - val_acc: 0.5813
Epoch 18/20
 - 1s - loss: 0.0041 - acc: 0.9990 - val_loss: 1.3230 - val_acc: 0.5646
Epoch 19/20
 - 1s - loss: 0.0042 - acc: 0.9995 - val_loss: 1.3878 - val_acc: 0.5833
Epoch 20/20
 - 1s - loss: 0.0066 - acc: 0.9984 - val_loss: 1.5369 - val_acc: 0.5729
Tiempo de procesamiento (secs):  16.42751383781433
```



```
In [534]: del nn_Bow_W2V_Twitter_Google_es

          import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 50
          epochs = 7

          nn_Bow_W2V_Twitter_Google_es = Sequential()
          nn_Bow_W2V_Twitter_Google_es.add(Dense(512, activation='relu'))
          nn_Bow_W2V_Twitter_Google_es.add(Dropout(0.25))
          nn_Bow_W2V_Twitter_Google_es.add(Dense(sz_es, activation='softmax'))
          nn_Bow_W2V_Twitter_Google_es.compile(loss='binary_crossentropy',
                        optimizer='nadam',
                        metrics=['accuracy'])

          history_Bow_W2V_Twitter_Google_es= nn_Bow_W2V_Twitter_Google_es.fit(BoW_W2V_Twitter_(
                        y_train_Bow_W2V_Twitter_Google_es,
                        validation_split=.2,
                        batch_size= batch_size,
                        shuffle   =True,
                        epochs=epochs,
                        verbose=0)

          print('Tiempo de procesamiento (secs): ', time.time()-tic)


          from keras.models import load_model
          nn_Bow_W2V_Twitter_Google_es.save('nn_Bow_W2V_Twitter_Google_es')  # Guardar modelo
          #nn_w2vtwit_cu = load_model('nn_cuba_w2vtwit') # Cargar modelo


          y_pred_Bow_W2V_Twitter_Google_es= nn_Bow_W2V_Twitter_Google_es.predict(BoW_W2V_Twitte
          y_test_label_Bow_W2V_Twitter_Google_es = np.argmax(y_test_Bow_W2V_Twitter_Google_es,1
          y_pred_label_Bow_W2V_Twitter_Google_es = np.argmax(y_pred_Bow_W2V_Twitter_Google_es,1


          print("F1 score", f1_score(y_test_label_Bow_W2V_Twitter_Google_es,  y_pred_label_Bow_
          print("F1 weighted", f1_score(y_test_label_Bow_W2V_Twitter_Google_es,  y_pred_label_I
          print("Recall score", recall_score(y_test_label_Bow_W2V_Twitter_Google_es,  y_pred_la
          print("Precision score", precision_score(y_test_label_Bow_W2V_Twitter_Google_es,  y_p

Tiempo de procesamiento (secs):  7.712883710861206
F1 score 0.6703246105440872
F1 weighted 0.7042079144603893
Recall score 0.67375
```

```
Precision score 0.6679250981576563
```

25.2.3 Cuba

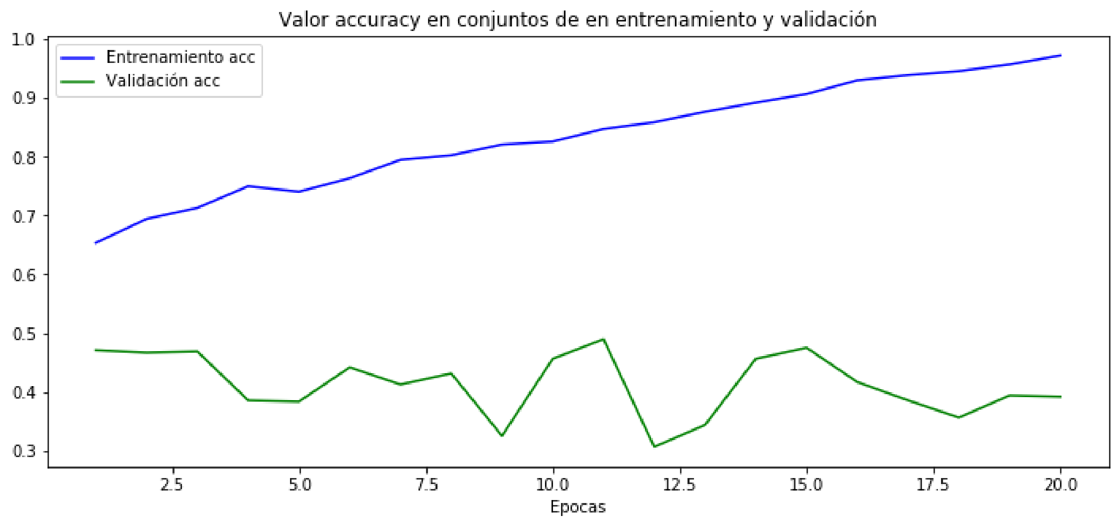
```
In [ ]: del nn_Bow_W2V_Twitter_Google_cu
```

```
In [537]: from keras.utils import to_categorical

          y_train_Bow_W2V_Twitter_Google_cu = to_categorical(y_train_cu)
          y_test_Bow_W2V_Twitter_Google_cu  = to_categorical(y_test_cu)

          num_cu, sz_cu = y_train_Bow_W2V_Twitter_Google_cu.shape

          print(num_cu)
          print(sz_cu)


          import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 50
          epochs = 20

          nn_Bow_W2V_Twitter_Google_cu = Sequential()
          nn_Bow_W2V_Twitter_Google_cu.add(Dense(512, activation='relu'))
          nn_Bow_W2V_Twitter_Google_cu.add(Dropout(0.25))
          nn_Bow_W2V_Twitter_Google_cu.add(Dense(sz_cu, activation='softmax'))
          nn_Bow_W2V_Twitter_Google_cu.compile(loss='binary_crossentropy',
                        optimizer='nadam',
                        metrics=['accuracy'])

          history_Bow_W2V_Twitter_Google_cu = nn_Bow_W2V_Twitter_Google_cu.fit(BoW_W2V_Twitter_
                        y_train_Bow_W2V_Twitter_Google_cu,
                        validation_split=.2,
                        batch_size= batch_size,
                        shuffle   =True,
                        epochs=epochs,
                        verbose=2)

          print('Tiempo de procesamiento (secs): ', time.time()-tic)

          history_dict_Bow_W2V_Twitter_Google_cu = history_Bow_W2V_Twitter_Google_cu.history
          dictkeys_Bow_W2V_Twitter_Google_cu=list(history_dict_Bow_W2V_Twitter_Google_cu.keys()
          loss_values_Bow_W2V_Twitter_Google_cu = history_Bow_W2V_Twitter_Google_cu.history['ac
          val_loss_values_Bow_W2V_Twitter_Google_cu = history_Bow_W2V_Twitter_Google_cu.history
```

```python
epochs_Bow_W2V_Twitter_Google_cu = range(1, len(loss_values_Bow_W2V_Twitter_Google_cu



plt.figure(figsize=(12,5))
plt.plot(epochs_Bow_W2V_Twitter_Google_cu, loss_values_Bow_W2V_Twitter_Google_cu, 'b
plt.plot(epochs_Bow_W2V_Twitter_Google_cu, val_loss_values_Bow_W2V_Twitter_Google_cu
plt.title('Valor accuracy en conjuntos de en entrenamiento y validación')
plt.xlabel('Epocas')
plt.ylabel('')
plt.legend()

plt.show()
```

```
2400
2
Train on 1920 samples, validate on 480 samples
Epoch 1/20
 - 4s - loss: 0.6351 - acc: 0.6536 - val_loss: 0.7986 - val_acc: 0.4708
Epoch 2/20
 - 0s - loss: 0.5793 - acc: 0.6943 - val_loss: 1.1715 - val_acc: 0.4667
Epoch 3/20
 - 0s - loss: 0.5557 - acc: 0.7130 - val_loss: 1.0885 - val_acc: 0.4687
Epoch 4/20
 - 0s - loss: 0.5173 - acc: 0.7500 - val_loss: 1.8124 - val_acc: 0.3854
Epoch 5/20
 - 0s - loss: 0.5074 - acc: 0.7406 - val_loss: 1.8658 - val_acc: 0.3833
Epoch 6/20
 - 0s - loss: 0.4862 - acc: 0.7635 - val_loss: 1.7185 - val_acc: 0.4417
Epoch 7/20
 - 0s - loss: 0.4468 - acc: 0.7948 - val_loss: 2.2587 - val_acc: 0.4125
Epoch 8/20
 - 0s - loss: 0.4397 - acc: 0.8026 - val_loss: 2.1612 - val_acc: 0.4312
Epoch 9/20
 - 0s - loss: 0.3995 - acc: 0.8208 - val_loss: 2.9903 - val_acc: 0.3250
Epoch 10/20
 - 0s - loss: 0.3814 - acc: 0.8260 - val_loss: 2.3818 - val_acc: 0.4563
Epoch 11/20
 - 0s - loss: 0.3648 - acc: 0.8474 - val_loss: 2.4952 - val_acc: 0.4896
Epoch 12/20
 - 0s - loss: 0.3359 - acc: 0.8589 - val_loss: 4.1163 - val_acc: 0.3063
Epoch 13/20
 - 0s - loss: 0.3008 - acc: 0.8766 - val_loss: 4.0380 - val_acc: 0.3438
Epoch 14/20
 - 0s - loss: 0.2738 - acc: 0.8922 - val_loss: 3.1168 - val_acc: 0.4563
Epoch 15/20
 - 0s - loss: 0.2430 - acc: 0.9068 - val_loss: 2.2357 - val_acc: 0.4750
Epoch 16/20
```

```
 - 0s - loss: 0.2288 - acc: 0.9302 - val_loss: 3.8607 - val_acc: 0.4167
Epoch 17/20
 - 0s - loss: 0.1917 - acc: 0.9391 - val_loss: 4.0045 - val_acc: 0.3854
Epoch 18/20
 - 0s - loss: 0.1755 - acc: 0.9458 - val_loss: 4.4066 - val_acc: 0.3562
Epoch 19/20
 - 0s - loss: 0.1564 - acc: 0.9573 - val_loss: 4.3285 - val_acc: 0.3938
Epoch 20/20
 - 0s - loss: 0.1259 - acc: 0.9724 - val_loss: 4.4865 - val_acc: 0.3917
Tiempo de procesamiento (secs):  8.18939733505249
```




```
In [543]: del nn_Bow_W2V_Twitter_Google_cu

          import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 50
          epochs = 6

          nn_Bow_W2V_Twitter_Google_cu = Sequential()
          nn_Bow_W2V_Twitter_Google_cu.add(Dense(512, activation='relu'))
          nn_Bow_W2V_Twitter_Google_cu.add(Dropout(0.25))
          nn_Bow_W2V_Twitter_Google_cu.add(Dense(sz_cu, activation='softmax'))
          nn_Bow_W2V_Twitter_Google_cu.compile(loss='binary_crossentropy',
                        optimizer='nadam',
                        metrics=['accuracy'])
```

```
history_Bow_W2V_Twitter_Google_cu= nn_Bow_W2V_Twitter_Google_cu.fit(BoW_W2V_Twitter_(
              y_train_Bow_W2V_Twitter_Google_cu,
              validation_split=.2,
              batch_size= batch_size,
              shuffle   =True,
              epochs=epochs,
              verbose=0)

print('Tiempo de procesamiento (secs): ', time.time()-tic)


from keras.models import load_model
nn_Bow_W2V_Twitter_Google_cu.save('nn_Bow_W2V_Twitter_Google_cu')  # Guardar modelo
#nn_w2vtwit_cu = load_model('nn_cuba_w2vtwit') # Cargar modelo


y_pred_Bow_W2V_Twitter_Google_cu= nn_Bow_W2V_Twitter_Google_cu.predict(BoW_W2V_Twitte
y_test_label_Bow_W2V_Twitter_Google_cu = np.argmax(y_test_Bow_W2V_Twitter_Google_cu,
y_pred_label_Bow_W2V_Twitter_Google_cu = np.argmax(y_pred_Bow_W2V_Twitter_Google_cu,


print("F1 score", f1_score(y_test_label_Bow_W2V_Twitter_Google_cu,  y_pred_label_Bow
print("F1 weighted", f1_score(y_test_label_Bow_W2V_Twitter_Google_cu,  y_pred_label_
print("Recall score", recall_score(y_test_label_Bow_W2V_Twitter_Google_cu,  y_pred_la
print("Precision score", precision_score(y_test_label_Bow_W2V_Twitter_Google_cu,  y_p
```

```
Tiempo de procesamiento (secs):  4.980557918548584
F1 score 0.5946150737522732
F1 weighted 0.6414595541186773
Recall score 0.59375
Precision score 0.5957414215686274
```

26 Concatenar W2VGoogle + W2VTwitter

26.0.1 México

```
In [360]: print(np.concatenate((mean_emb_train_w2vgoogle_mx,  mean_emb_train_w2vtwit_mx),axis=
          Twitter_Google_mx_train = np.concatenate((mean_emb_train_w2vgoogle_mx,  mean_emb_trai


          print(np.concatenate((mean_emb_test_w2vgoogle_mx,  mean_emb_test_w2vtwit_mx),axis=1)
          Twitter_Google_mx_test = np.concatenate((mean_emb_test_w2vgoogle_mx,  mean_emb_test_
```

```
(2400, 700)
(600, 700)
```

```
In [362]: from sklearn.pipeline import Pipeline
          from sklearn.svm import LinearSVC
          from sklearn.model_selection import GridSearchCV
          from sklearn.preprocessing import StandardScaler
          import time
          tic=time.time()

          SVCpipe = Pipeline([('SVC',LinearSVC(class_weight="balanced", random_state=1,verbose=

          # Gridsearch to determine the value of C
          param_grid = {'SVC__C':np.arange(.01,2,.1)}
          linearSVC = GridSearchCV(SVCpipe,param_grid,cv=5,return_train_score=True, verbose=0)
          linearSVC.fit(Twitter_Google_mx_train, y_train.values)
          print(linearSVC.best_params_)
          #linearSVC.coef_
          #linearSVC.intercept_

          svc_W2V_Twitter_Google_mx = linearSVC.best_estimator_
          svc_W2V_Twitter_Google_mx.fit(Twitter_Google_mx_train, y_train.values)
          svc_W2V_Twitter_Google_mx.coef_ = svc_W2V_Twitter_Google_mx.named_steps['SVC'].coef_
          svc_W2V_Twitter_Google_mx.score(Twitter_Google_mx_train, y_train.values)

          print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
{'SVC__C': 1.9100000000000001}
Tiempo de procesamiento (secs):  100.54076671600342
```

```
In [363]: from joblib import dump, load
          dump(svc_W2V_Twitter_Google_mx, 'svc_W2V_Twitter_Google_mx.joblib')
          #svc_w2vtwit_cu = load('svc_w2vtwit_cu.joblib')
          prediction_Twitter_Google_mx=svc_W2V_Twitter_Google_mx.predict(Twitter_Google_mx_tes
          print("Acurracy Test",metrics.accuracy_score( y_test.values, prediction_Twitter_Googl
```

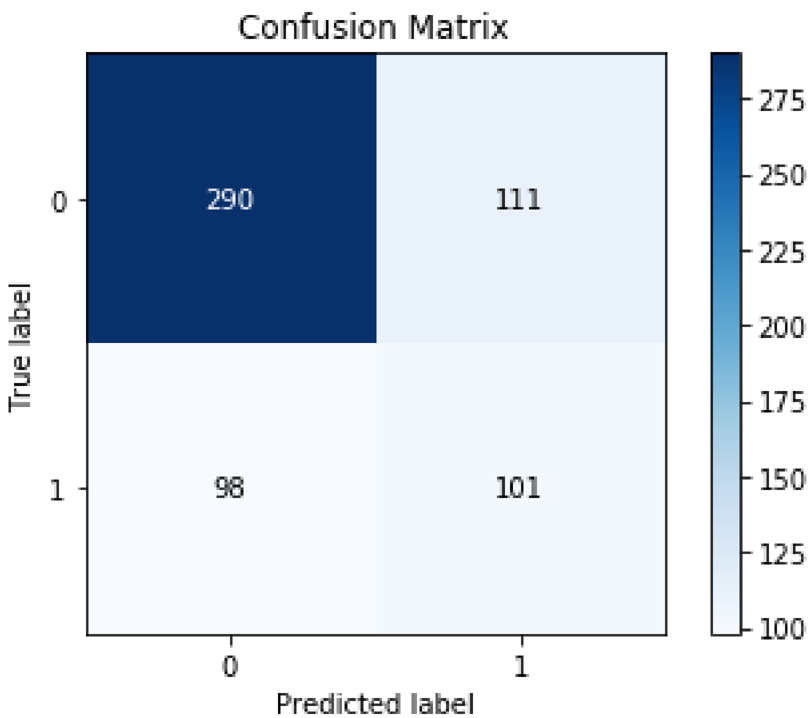
```
Acurracy Test 0.6516666666666666
```

```
In [364]: print('Accuracy score:', metrics.accuracy_score(y_test.values, prediction_Twitter_Goo
          print("F1 score", f1_score(y_test.values, prediction_Twitter_Google_mx,  average='mac
          print("F1 weighted", f1_score(y_test.values, prediction_Twitter_Google_mx,  average=
          print("Recall score", recall_score(y_test.values, prediction_Twitter_Google_mx,  aver
          print("Precision score", precision_score(y_test.values, prediction_Twitter_Google_mx


          from sklearn.metrics import classification_report
          print(classification_report( y_test.values, prediction_Twitter_Google_mx, target_name

          %matplotlib inline
          import matplotlib.pyplot as plt
```

```python
import scikitplot

scikitplot.metrics.plot_confusion_matrix(y_test.values, prediction_Twitter_Google_mx)
```

```
Accuracy score: 0.6516666666666666
F1 score 0.6132959581101459
F1 weighted 0.654305921752565
Recall score 0.6153648541961678
Precision score 0.6119188873759969
              precision    recall  f1-score   support

   no-ironia       0.75      0.72      0.74       401
      ironia       0.48      0.51      0.49       199

   micro avg       0.65      0.65      0.65       600
   macro avg       0.61      0.62      0.61       600
weighted avg       0.66      0.65      0.65       600
```

Out[364]: <matplotlib.axes._subplots.AxesSubplot at 0x1ab76b83908>



26.0.2 España

```
In [383]: print(np.concatenate((mean_emb_train_w2vgoogle_es,  mean_emb_train_w2vtwit_es),axis=
          Twitter_Google_es_train = np.concatenate((mean_emb_train_w2vgoogle_es,  mean_emb_trai


          print(np.concatenate((mean_emb_test_w2vgoogle_es,  mean_emb_test_w2vtwit_es),axis=1)
          Twitter_Google_es_test = np.concatenate((mean_emb_test_w2vgoogle_es,  mean_emb_test_
```

```
(2400, 700)
(600, 700)
```

```
In [390]: from sklearn.pipeline import Pipeline
          from sklearn.svm import LinearSVC
          from sklearn.model_selection import GridSearchCV
          from sklearn.preprocessing import StandardScaler
          import time
          tic=time.time()

          SVCpipe = Pipeline([('SVC',LinearSVC(class_weight="balanced", random_state=1,verbose

          # Gridsearch to determine the value of C
          param_grid = {'SVC__C':np.arange(.01,2,.1)}
          linearSVC = GridSearchCV(SVCpipe,param_grid,cv=5,return_train_score=True, verbose=0)
          linearSVC.fit(Twitter_Google_es_train, y_train_es.values)
          print(linearSVC.best_params_)
          #linearSVC.coef_
          #linearSVC.intercept_

          svc_W2V_Twitter_Google_es = linearSVC.best_estimator_
          svc_W2V_Twitter_Google_es.fit(Twitter_Google_es_train, y_train_es.values)
          svc_W2V_Twitter_Google_es.coef_ = svc_W2V_Twitter_Google_es.named_steps['SVC'].coef_
          svc_W2V_Twitter_Google_es.score(Twitter_Google_es_train, y_train_es.values)

          print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
{'SVC__C': 0.01}
Tiempo de procesamiento (secs):  57.703532695770264
```

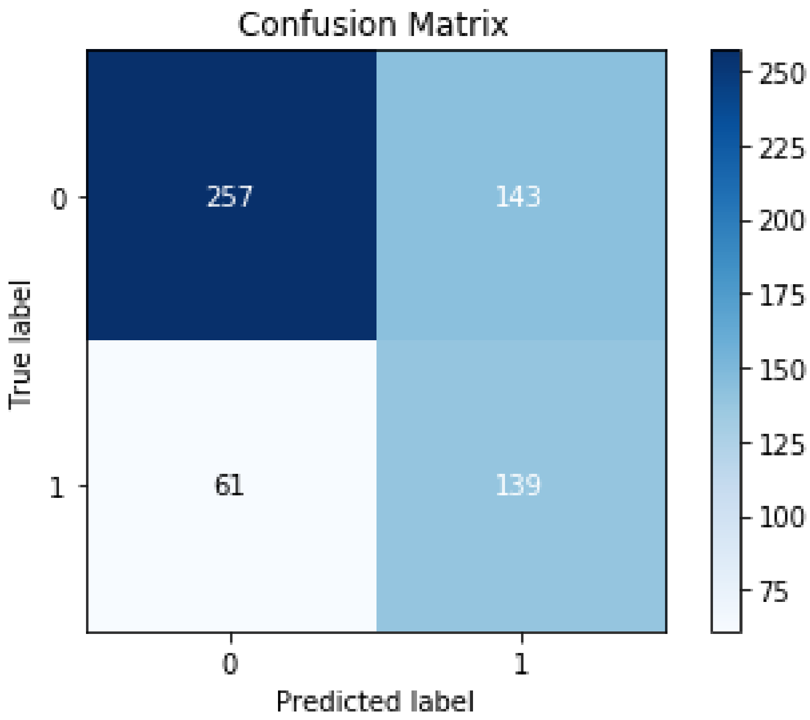
```
In [391]: from joblib import dump, load
          dump(svc_W2V_Twitter_Google_es, 'svc_W2V_Twitter_Google_es.joblib')
          #svc_w2vtwit_cu = load('svc_w2vtwit_cu.joblib')
          prediction_Twitter_Google_es=svc_W2V_Twitter_Google_es.predict(Twitter_Google_es_tes
          print("Acurracy Test",metrics.accuracy_score( y_test_es.values, prediction_Twitter_Go
```

```
Acurracy Test 0.66
```

```
In [392]: print('Accuracy score:', metrics.accuracy_score(y_test_es.values, prediction_Twitter_
          print("F1 score", f1_score(y_test_es.values, prediction_Twitter_Google_es,  average=
          print("F1 weighted", f1_score(y_test_es.values, prediction_Twitter_Google_es,  averag
          print("Recall score", recall_score(y_test_es.values, prediction_Twitter_Google_es,  a
          print("Precision score", precision_score(y_test_es.values, prediction_Twitter_Google_


          from sklearn.metrics import classification_report
          print(classification_report( y_test_es.values, prediction_Twitter_Google_es, target_n

          %matplotlib inline
          import matplotlib.pyplot as plt
          import scikitplot

          scikitplot.metrics.plot_confusion_matrix(y_test_es.values, prediction_Twitter_Google_
```

```
Accuracy score: 0.66
F1 score 0.6463204614015419
F1 weighted 0.6695061200429964
Recall score 0.66875
Precision score 0.6505419510236853
              precision    recall  f1-score   support

   no-ironia       0.81      0.64      0.72       400
      ironia       0.49      0.69      0.58       200

   micro avg       0.66      0.66      0.66       600
   macro avg       0.65      0.67      0.65       600
weighted avg       0.70      0.66      0.67       600
```

```
Out[392]: <matplotlib.axes._subplots.AxesSubplot at 0x1ab948df3c8>
```



26.0.3 Cuba

In [393]:
```
print(np.concatenate((mean_emb_train_w2vgoogle_cu,  mean_emb_train_w2vtwit_cu),axis=
Twitter_Google_cu_train = np.concatenate((mean_emb_train_w2vgoogle_cu,  mean_emb_trai


print(np.concatenate((mean_emb_test_w2vgoogle_cu,  mean_emb_test_w2vtwit_cu),axis=1)
Twitter_Google_cu_test = np.concatenate((mean_emb_test_w2vgoogle_cu,  mean_emb_test_
```

```
(2400, 700)
(600, 700)
```

In [397]:
```
from sklearn.pipeline import Pipeline
from sklearn.svm import LinearSVC
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
import time
tic=time.time()

SVCpipe = Pipeline([('SVC',LinearSVC(class_weight="balanced", random_state=1,verbose=

# Gridsearch to determine the value of C
param_grid = {'SVC__C':np.arange(.001,1,.01)}
```

```
linearSVC = GridSearchCV(SVCpipe,param_grid,cv=5,return_train_score=True, verbose=0)
linearSVC.fit(Twitter_Google_cu_train, y_train_cu.values)
print(linearSVC.best_params_)
#linearSVC.coef_
#linearSVC.intercept_

svc_W2V_Twitter_Google_cu = linearSVC.best_estimator_
svc_W2V_Twitter_Google_cu.fit(Twitter_Google_cu_train, y_train_cu.values)
svc_W2V_Twitter_Google_cu.coef_ = svc_W2V_Twitter_Google_cu.named_steps['SVC'].coef_
svc_W2V_Twitter_Google_cu.score(Twitter_Google_cu_train, y_train_cu.values)

print('Tiempo de procesamiento (secs): ', time.time()-tic)
```

```
{'SVC__C': 0.001}
Tiempo de procesamiento (secs):  251.3999924659729
```

```
In [398]: from joblib import dump, load
          dump(svc_W2V_Twitter_Google_cu, 'svc_W2V_Twitter_Google_cu.joblib')
          #svc_w2vtwit_cu = load('svc_w2vtwit_cu.joblib')
          prediction_Twitter_Google_cu=svc_W2V_Twitter_Google_cu.predict(Twitter_Google_cu_tes
          print("Acurracy Test",metrics.accuracy_score( y_test_cu.values, prediction_Twitter_Go
```

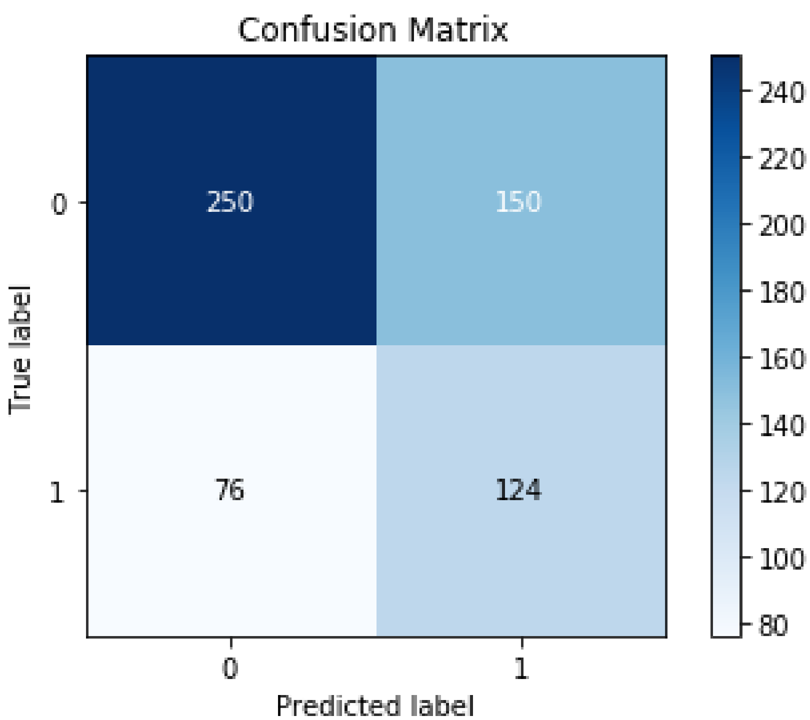
```
Acurracy Test 0.6233333333333333
```

```
In [399]: print('Accuracy score:', metrics.accuracy_score(y_test_cu.values, prediction_Twitter_
          print("F1 score", f1_score(y_test_cu.values, prediction_Twitter_Google_cu,  average=
          print("F1 weighted", f1_score(y_test_cu.values, prediction_Twitter_Google_cu,  averag
          print("Recall score", recall_score(y_test_cu.values, prediction_Twitter_Google_cu,  a
          print("Precision score", precision_score(y_test_cu.values, prediction_Twitter_Google_


          from sklearn.metrics import classification_report
          print(classification_report( y_test_cu.values, prediction_Twitter_Google_cu, target_n

          %matplotlib inline
          import matplotlib.pyplot as plt
          import scikitplot

          scikitplot.metrics.plot_confusion_matrix(y_test_cu.values, prediction_Twitter_Google_
```

```
Accuracy score: 0.6233333333333333
F1 score 0.6059559926073159
F1 weighted 0.6335390731248038
Recall score 0.6225
Precision score 0.6097129550848597
              precision    recall  f1-score   support
```

```
  no-ironia       0.77      0.62      0.69       400
     ironia       0.45      0.62      0.52       200

  micro avg       0.62      0.62      0.62       600
  macro avg       0.61      0.62      0.61       600
weighted avg      0.66      0.62      0.63       600
```

```
Out[399]: <matplotlib.axes._subplots.AxesSubplot at 0x1ab949f0630>
```



26.1 Clasificador NN

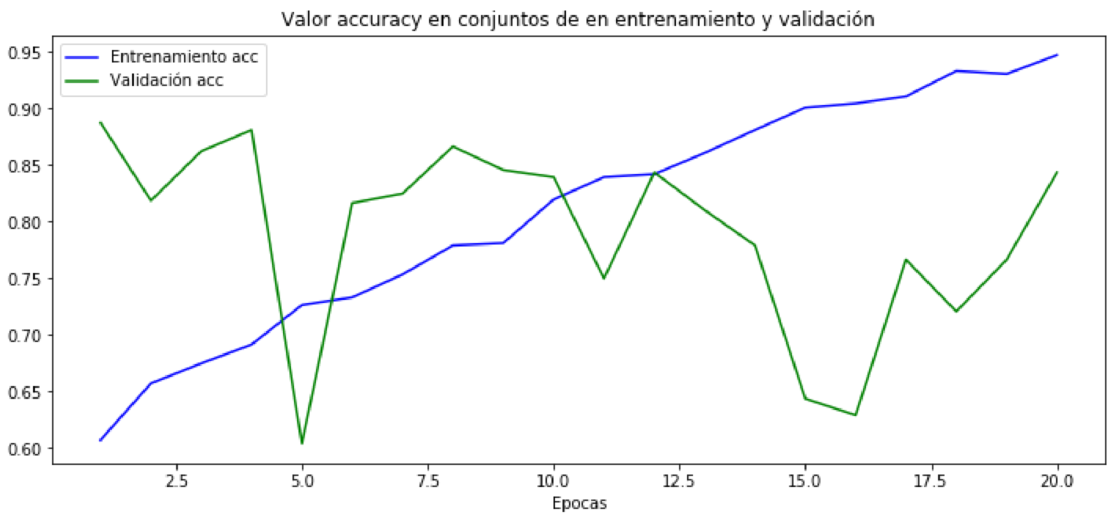
26.1.1 México

```
In [ ]: del nn_W2V_Twitter_Google_mx
        # Twitter_Google_mx_train
```

```
In [544]: from keras.utils import to_categorical

          y_train_W2V_Twitter_Google_mx = to_categorical(y_train)
          y_test_W2V_Twitter_Google_mx  = to_categorical(y_test)

          num_mx, sz_mx = y_train_W2V_Twitter_Google_mx.shape
```

```
print(num_mx)
print(sz_mx)


import time
tic=time.time()

np.random.seed(1)

batch_size = 50
epochs = 20

nn_W2V_Twitter_Google_mx = Sequential()
nn_W2V_Twitter_Google_mx.add(Dense(512, activation='relu'))
nn_W2V_Twitter_Google_mx.add(Dropout(0.25))
nn_W2V_Twitter_Google_mx.add(Dense(sz_mx, activation='softmax'))
nn_W2V_Twitter_Google_mx.compile(loss='binary_crossentropy',
              optimizer='nadam',
              metrics=['accuracy'])

history_W2V_Twitter_Google_mx = nn_W2V_Twitter_Google_mx.fit(Twitter_Google_mx_train
              y_train_W2V_Twitter_Google_mx,
              validation_split=.2,
              batch_size= batch_size,
              shuffle   =True,
              epochs=epochs,
              verbose=2)

print('Tiempo de procesamiento (secs): ', time.time()-tic)

history_dict_W2V_Twitter_Google_mx = history_W2V_Twitter_Google_mx.history
dictkeys_W2V_Twitter_Google_mx=list(history_dict_W2V_Twitter_Google_mx.keys())
loss_values_W2V_Twitter_Google_mx = history_W2V_Twitter_Google_mx.history['acc']
val_loss_values_W2V_Twitter_Google_mx = history_W2V_Twitter_Google_mx.history['val_ac
epochs_W2V_Twitter_Google_mx = range(1, len(loss_values_W2V_Twitter_Google_mx) + 1)



plt.figure(figsize=(12,5))
plt.plot(epochs_W2V_Twitter_Google_mx, loss_values_W2V_Twitter_Google_mx, 'b', label=
plt.plot(epochs_W2V_Twitter_Google_mx, val_loss_values_W2V_Twitter_Google_mx, 'g', la
plt.title('Valor accuracy en conjuntos de en entrenamiento y validación')
plt.xlabel('Epocas')
plt.ylabel('')
plt.legend()

plt.show()
```

```
2400
2
Train on 1920 samples, validate on 480 samples
Epoch 1/20
 - 4s - loss: 0.6724 - acc: 0.6073 - val_loss: 0.4581 - val_acc: 0.8875
Epoch 2/20
 - 0s - loss: 0.6282 - acc: 0.6573 - val_loss: 0.4813 - val_acc: 0.8188
Epoch 3/20
 - 0s - loss: 0.6075 - acc: 0.6750 - val_loss: 0.4875 - val_acc: 0.8625
Epoch 4/20
 - 0s - loss: 0.5788 - acc: 0.6917 - val_loss: 0.4307 - val_acc: 0.8813
Epoch 5/20
 - 0s - loss: 0.5411 - acc: 0.7266 - val_loss: 0.6587 - val_acc: 0.6042
Epoch 6/20
 - 0s - loss: 0.5301 - acc: 0.7333 - val_loss: 0.4989 - val_acc: 0.8167
Epoch 7/20
 - 0s - loss: 0.5097 - acc: 0.7536 - val_loss: 0.4821 - val_acc: 0.8250
Epoch 8/20
 - 0s - loss: 0.4622 - acc: 0.7792 - val_loss: 0.3873 - val_acc: 0.8667
Epoch 9/20
 - 0s - loss: 0.4409 - acc: 0.7812 - val_loss: 0.4385 - val_acc: 0.8458
Epoch 10/20
 - 0s - loss: 0.4088 - acc: 0.8198 - val_loss: 0.4515 - val_acc: 0.8396
Epoch 11/20
 - 0s - loss: 0.3731 - acc: 0.8396 - val_loss: 0.5093 - val_acc: 0.7500
Epoch 12/20
 - 0s - loss: 0.3499 - acc: 0.8422 - val_loss: 0.4300 - val_acc: 0.8437
Epoch 13/20
 - 0s - loss: 0.3176 - acc: 0.8609 - val_loss: 0.4582 - val_acc: 0.8104
Epoch 14/20
 - 0s - loss: 0.3007 - acc: 0.8812 - val_loss: 0.5092 - val_acc: 0.7792
Epoch 15/20
 - 0s - loss: 0.2624 - acc: 0.9010 - val_loss: 0.7153 - val_acc: 0.6438
Epoch 16/20
 - 0s - loss: 0.2551 - acc: 0.9047 - val_loss: 0.6734 - val_acc: 0.6292
Epoch 17/20
 - 0s - loss: 0.2349 - acc: 0.9109 - val_loss: 0.5475 - val_acc: 0.7667
Epoch 18/20
 - 0s - loss: 0.1956 - acc: 0.9333 - val_loss: 0.6415 - val_acc: 0.7208
Epoch 19/20
 - 0s - loss: 0.2044 - acc: 0.9307 - val_loss: 0.5269 - val_acc: 0.7667
Epoch 20/20
 - 0s - loss: 0.1718 - acc: 0.9474 - val_loss: 0.4978 - val_acc: 0.8437
Tiempo de procesamiento (secs):  8.682274103164673
```




```
In [550]: del nn_W2V_Twitter_Google_mx

          import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 50
          epochs = 7

          nn_W2V_Twitter_Google_mx = Sequential()
          nn_W2V_Twitter_Google_mx.add(Dense(512, activation='relu'))
          nn_W2V_Twitter_Google_mx.add(Dropout(0.25))
          nn_W2V_Twitter_Google_mx.add(Dense(sz_mx, activation='softmax'))
          nn_W2V_Twitter_Google_mx.compile(loss='binary_crossentropy',
                        optimizer='nadam',
                        metrics=['accuracy'])

          history_W2V_Twitter_Google_mx= nn_W2V_Twitter_Google_mx.fit(Twitter_Google_mx_train,
                        y_train_W2V_Twitter_Google_mx,
                        validation_split=.2,
                        batch_size= batch_size,
                        shuffle   =True,
                        epochs=epochs,
                        verbose=0)

          print('Tiempo de procesamiento (secs): ', time.time()-tic)


          from keras.models import load_model
```

```
nn_W2V_Twitter_Google_mx.save('nn_W2V_Twitter_Google_mx')  # Guardar modelo
#nn_w2vtwit_cu = load_model('nn_cuba_w2vtwit') # Cargar modelo


y_pred_W2V_Twitter_Google_mx= nn_W2V_Twitter_Google_mx.predict(Twitter_Google_mx_tes
y_test_label_W2V_Twitter_Google_mx = np.argmax(y_test_W2V_Twitter_Google_mx,1)
y_pred_label_W2V_Twitter_Google_mx = np.argmax(y_pred_W2V_Twitter_Google_mx,1)


print("F1 score", f1_score(y_test_label_W2V_Twitter_Google_mx,  y_pred_label_W2V_Twi
print("F1 weighted", f1_score(y_test_label_W2V_Twitter_Google_mx,  y_pred_label_W2V_
print("Recall score", recall_score(y_test_label_W2V_Twitter_Google_mx,  y_pred_label_
print("Precision score", precision_score(y_test_label_W2V_Twitter_Google_mx,  y_pred_
```

```
Tiempo de procesamiento (secs):  8.264517784118652
F1 score 0.6182031774446184
F1 weighted 0.6764738569404042
Recall score 0.6135916490181581
Precision score 0.649187774650669
```

26.1.2 España

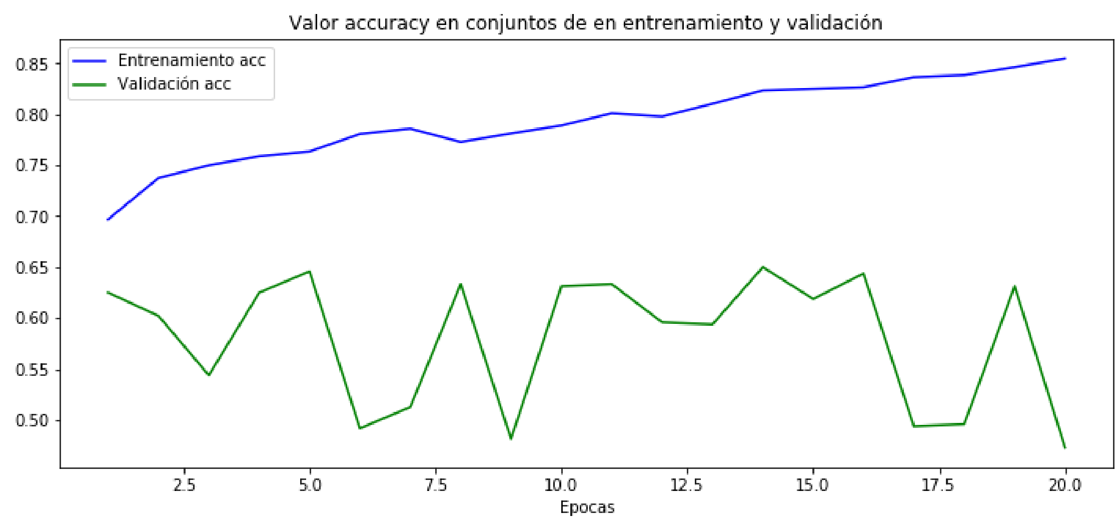
In [ ]:
```
del nn_W2V_Twitter_Google_es
```

In [551]:
```
from keras.utils import to_categorical

y_train_W2V_Twitter_Google_es = to_categorical(y_train_es)
y_test_W2V_Twitter_Google_es  = to_categorical(y_test_es)

num_es, sz_es = y_train_W2V_Twitter_Google_es.shape

print(num_es)
print(sz_es)


import time
tic=time.time()

np.random.seed(1)

batch_size = 50
epochs = 20

nn_W2V_Twitter_Google_es = Sequential()
nn_W2V_Twitter_Google_es.add(Dense(512, activation='relu'))
nn_W2V_Twitter_Google_es.add(Dropout(0.25))
nn_W2V_Twitter_Google_es.add(Dense(sz_es, activation='softmax'))
```

```
nn_W2V_Twitter_Google_es.compile(loss='binary_crossentropy',
              optimizer='nadam',
              metrics=['accuracy'])

history_W2V_Twitter_Google_es = nn_W2V_Twitter_Google_es.fit(Twitter_Google_es_train
              y_train_W2V_Twitter_Google_es,
              validation_split=.2,
              batch_size= batch_size,
              shuffle   =True,
              epochs=epochs,
              verbose=2)

print('Tiempo de procesamiento (secs): ', time.time()-tic)

history_dict_W2V_Twitter_Google_es = history_W2V_Twitter_Google_es.history
dictkeys_W2V_Twitter_Google_es=list(history_dict_W2V_Twitter_Google_es.keys())
loss_values_W2V_Twitter_Google_es = history_W2V_Twitter_Google_es.history['acc']
val_loss_values_W2V_Twitter_Google_es = history_W2V_Twitter_Google_es.history['val_ac
epochs_W2V_Twitter_Google_es = range(1, len(loss_values_W2V_Twitter_Google_es) + 1)



plt.figure(figsize=(12,5))
plt.plot(epochs_W2V_Twitter_Google_es, loss_values_W2V_Twitter_Google_es, 'b', label=
plt.plot(epochs_W2V_Twitter_Google_es, val_loss_values_W2V_Twitter_Google_es, 'g', la
plt.title('Valor accuracy en conjuntos de en entrenamiento y validación')
plt.xlabel('Epocas')
plt.ylabel('')
plt.legend()

plt.show()
```

```
2400
2
Train on 1920 samples, validate on 480 samples
Epoch 1/20
 - 8s - loss: 0.5788 - acc: 0.6969 - val_loss: 0.6795 - val_acc: 0.6250
Epoch 2/20
 - 0s - loss: 0.5477 - acc: 0.7375 - val_loss: 0.6837 - val_acc: 0.6021
Epoch 3/20
 - 0s - loss: 0.5214 - acc: 0.7500 - val_loss: 0.7942 - val_acc: 0.5437
Epoch 4/20
 - 0s - loss: 0.5080 - acc: 0.7589 - val_loss: 0.7110 - val_acc: 0.6250
Epoch 5/20
 - 0s - loss: 0.4946 - acc: 0.7635 - val_loss: 0.8013 - val_acc: 0.6458
Epoch 6/20
 - 0s - loss: 0.4800 - acc: 0.7807 - val_loss: 0.8210 - val_acc: 0.4917
Epoch 7/20
```

```
 - 0s - loss: 0.4641 - acc: 0.7859 - val_loss: 0.7942 - val_acc: 0.5125
Epoch 8/20
 - 0s - loss: 0.4688 - acc: 0.7729 - val_loss: 0.7372 - val_acc: 0.6333
Epoch 9/20
 - 0s - loss: 0.4549 - acc: 0.7812 - val_loss: 1.0074 - val_acc: 0.4813
Epoch 10/20
 - 0s - loss: 0.4417 - acc: 0.7891 - val_loss: 0.7719 - val_acc: 0.6312
Epoch 11/20
 - 0s - loss: 0.4287 - acc: 0.8010 - val_loss: 0.7563 - val_acc: 0.6333
Epoch 12/20
 - 0s - loss: 0.4151 - acc: 0.7979 - val_loss: 0.8047 - val_acc: 0.5958
Epoch 13/20
 - 0s - loss: 0.4100 - acc: 0.8104 - val_loss: 0.7677 - val_acc: 0.5938
Epoch 14/20
 - 0s - loss: 0.3968 - acc: 0.8234 - val_loss: 0.8997 - val_acc: 0.6500
Epoch 15/20
 - 0s - loss: 0.3879 - acc: 0.8250 - val_loss: 0.8435 - val_acc: 0.6188
Epoch 16/20
 - 0s - loss: 0.3849 - acc: 0.8266 - val_loss: 0.8704 - val_acc: 0.6438
Epoch 17/20
 - 0s - loss: 0.3580 - acc: 0.8365 - val_loss: 0.9825 - val_acc: 0.4937
Epoch 18/20
 - 0s - loss: 0.3626 - acc: 0.8385 - val_loss: 1.2186 - val_acc: 0.4958
Epoch 19/20
 - 0s - loss: 0.3419 - acc: 0.8464 - val_loss: 0.9033 - val_acc: 0.6313
Epoch 20/20
 - 0s - loss: 0.3341 - acc: 0.8547 - val_loss: 1.1043 - val_acc: 0.4729
Tiempo de procesamiento (secs):  15.610360860824585
```



```
In [555]: del nn_W2V_Twitter_Google_es

          import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 50
          epochs = 7


          nn_W2V_Twitter_Google_es = Sequential()
          nn_W2V_Twitter_Google_es.add(Dense(512, activation='relu'))
          nn_W2V_Twitter_Google_es.add(Dropout(0.25))
          nn_W2V_Twitter_Google_es.add(Dense(sz_es, activation='softmax'))
          nn_W2V_Twitter_Google_es.compile(loss='binary_crossentropy',
                        optimizer='nadam',
                        metrics=['accuracy'])

          history_W2V_Twitter_Google_es= nn_W2V_Twitter_Google_es.fit(Twitter_Google_es_train,
                        y_train_W2V_Twitter_Google_es,
                        validation_split=.2,
                        batch_size= batch_size,
                        shuffle   =True,
                        epochs=epochs,
                        verbose=0)

          print('Tiempo de procesamiento (secs): ', time.time()-tic)


          from keras.models import load_model
          nn_W2V_Twitter_Google_es.save('nn_W2V_Twitter_Google_es')  # Guardar modelo
          #nn_w2vtwit_cu = load_model('nn_cuba_w2vtwit') # Cargar modelo


          y_pred_W2V_Twitter_Google_es= nn_W2V_Twitter_Google_es.predict(Twitter_Google_es_test
          y_test_label_W2V_Twitter_Google_es = np.argmax(y_test_W2V_Twitter_Google_es,1)
          y_pred_label_W2V_Twitter_Google_es = np.argmax(y_pred_W2V_Twitter_Google_es,1)


          print("F1 score", f1_score(y_test_label_W2V_Twitter_Google_es,  y_pred_label_W2V_Twi
          print("F1 weighted", f1_score(y_test_label_W2V_Twitter_Google_es,  y_pred_label_W2V_
          print("Recall score", recall_score(y_test_label_W2V_Twitter_Google_es,  y_pred_label_
          print("Precision score", precision_score(y_test_label_W2V_Twitter_Google_es,  y_pred_

Tiempo de procesamiento (secs):  8.27528977394104
F1 score 0.6574389400690286
F1 weighted 0.6778022919649253
```

```
Recall score 0.685
Precision score 0.6645340240797768
```

26.1.3 Cuba

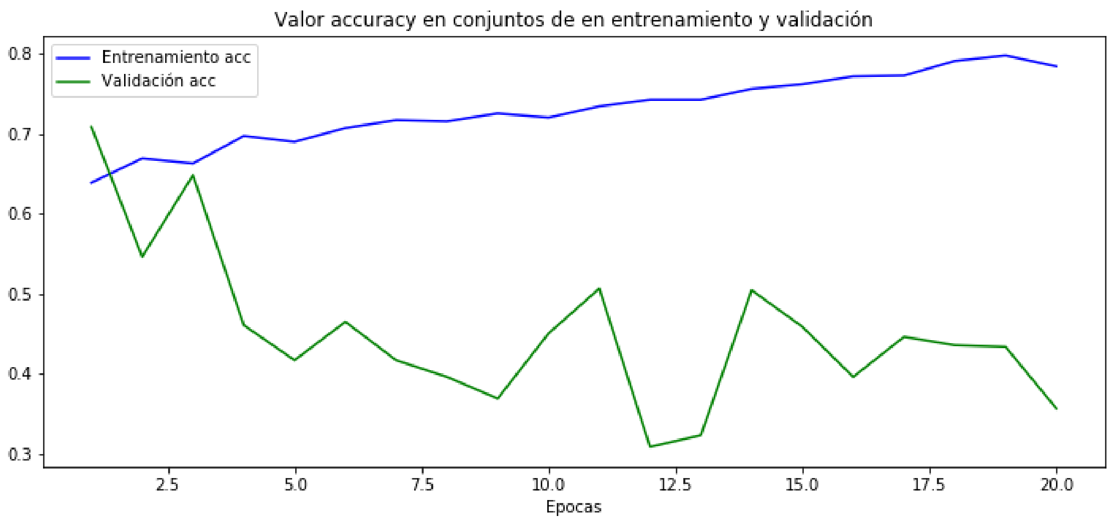
```
In [ ]: del nn_W2V_Twitter_Google_cu
```

```
In [556]: from keras.utils import to_categorical

          y_train_W2V_Twitter_Google_cu = to_categorical(y_train_cu)
          y_test_W2V_Twitter_Google_cu  = to_categorical(y_test_cu)

          num_cu, sz_cu = y_train_W2V_Twitter_Google_cu.shape

          print(num_cu)
          print(sz_cu)


          import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 50
          epochs = 20

          nn_W2V_Twitter_Google_cu = Sequential()
          nn_W2V_Twitter_Google_cu.add(Dense(512, activation='relu'))
          nn_W2V_Twitter_Google_cu.add(Dropout(0.25))
          nn_W2V_Twitter_Google_cu.add(Dense(sz_cu, activation='softmax'))
          nn_W2V_Twitter_Google_cu.compile(loss='binary_crossentropy',
                        optimizer='nadam',
                        metrics=['accuracy'])

          history_W2V_Twitter_Google_cu = nn_W2V_Twitter_Google_cu.fit(Twitter_Google_cu_train
                        y_train_W2V_Twitter_Google_cu,
                        validation_split=.2,
                        batch_size= batch_size,
                        shuffle   =True,
                        epochs=epochs,
                        verbose=2)

          print('Tiempo de procesamiento (secs): ', time.time()-tic)

          history_dict_W2V_Twitter_Google_cu = history_W2V_Twitter_Google_cu.history
          dictkeys_W2V_Twitter_Google_cu=list(history_dict_W2V_Twitter_Google_cu.keys())
          loss_values_W2V_Twitter_Google_cu = history_W2V_Twitter_Google_cu.history['acc']
```

```
val_loss_values_W2V_Twitter_Google_cu = history_W2V_Twitter_Google_cu.history['val_ac
epochs_W2V_Twitter_Google_cu = range(1, len(loss_values_W2V_Twitter_Google_cu) + 1)



plt.figure(figsize=(12,5))
plt.plot(epochs_W2V_Twitter_Google_cu, loss_values_W2V_Twitter_Google_cu, 'b', label=
plt.plot(epochs_W2V_Twitter_Google_cu, val_loss_values_W2V_Twitter_Google_cu, 'g', la
plt.title('Valor accuracy en conjuntos de en entrenamiento y validación')
plt.xlabel('Epocas')
plt.ylabel('')
plt.legend()

plt.show()
```

```
2400
2
Train on 1920 samples, validate on 480 samples
Epoch 1/20
 - 6s - loss: 0.6484 - acc: 0.6385 - val_loss: 0.6211 - val_acc: 0.7083
Epoch 2/20
 - 0s - loss: 0.6235 - acc: 0.6688 - val_loss: 0.7267 - val_acc: 0.5458
Epoch 3/20
 - 0s - loss: 0.6188 - acc: 0.6625 - val_loss: 0.6797 - val_acc: 0.6479
Epoch 4/20
 - 0s - loss: 0.5939 - acc: 0.6969 - val_loss: 0.8582 - val_acc: 0.4604
Epoch 5/20
 - 0s - loss: 0.5946 - acc: 0.6896 - val_loss: 1.0079 - val_acc: 0.4167
Epoch 6/20
 - 0s - loss: 0.5805 - acc: 0.7068 - val_loss: 0.9797 - val_acc: 0.4646
Epoch 7/20
 - 0s - loss: 0.5601 - acc: 0.7167 - val_loss: 1.1870 - val_acc: 0.4167
Epoch 8/20
 - 0s - loss: 0.5591 - acc: 0.7151 - val_loss: 1.2351 - val_acc: 0.3958
Epoch 9/20
 - 0s - loss: 0.5429 - acc: 0.7250 - val_loss: 1.4618 - val_acc: 0.3687
Epoch 10/20
 - 0s - loss: 0.5425 - acc: 0.7198 - val_loss: 1.2641 - val_acc: 0.4500
Epoch 11/20
 - 0s - loss: 0.5347 - acc: 0.7339 - val_loss: 1.1154 - val_acc: 0.5062
Epoch 12/20
 - 0s - loss: 0.5126 - acc: 0.7422 - val_loss: 1.8900 - val_acc: 0.3083
Epoch 13/20
 - 0s - loss: 0.5140 - acc: 0.7422 - val_loss: 2.0131 - val_acc: 0.3229
Epoch 14/20
 - 0s - loss: 0.5007 - acc: 0.7557 - val_loss: 1.2503 - val_acc: 0.5042
Epoch 15/20
 - 0s - loss: 0.4951 - acc: 0.7615 - val_loss: 1.3007 - val_acc: 0.4583
```

```
Epoch 16/20
 - 0s - loss: 0.4708 - acc: 0.7714 - val_loss: 1.8793 - val_acc: 0.3958
Epoch 17/20
 - 0s - loss: 0.4660 - acc: 0.7724 - val_loss: 1.7277 - val_acc: 0.4458
Epoch 18/20
 - 0s - loss: 0.4500 - acc: 0.7906 - val_loss: 1.6773 - val_acc: 0.4354
Epoch 19/20
 - 0s - loss: 0.4475 - acc: 0.7974 - val_loss: 1.8215 - val_acc: 0.4333
Epoch 20/20
 - 0s - loss: 0.4383 - acc: 0.7839 - val_loss: 2.3482 - val_acc: 0.3562
Tiempo de procesamiento (secs):  13.983967542648315
```




```
In [559]: del nn_W2V_Twitter_Google_cu

          import time
          tic=time.time()

          np.random.seed(1)

          batch_size = 50
          epochs = 7


          nn_W2V_Twitter_Google_cu = Sequential()
          nn_W2V_Twitter_Google_cu.add(Dense(512, activation='relu'))
          nn_W2V_Twitter_Google_cu.add(Dropout(0.25))
          nn_W2V_Twitter_Google_cu.add(Dense(sz_cu, activation='softmax'))
          nn_W2V_Twitter_Google_cu.compile(loss='binary_crossentropy',
                        optimizer='nadam',
```

```
                  metrics=['accuracy'])

history_W2V_Twitter_Google_cu= nn_W2V_Twitter_Google_cu.fit(Twitter_Google_cu_train,
                  y_train_W2V_Twitter_Google_cu,
                  validation_split=.2,
                  batch_size= batch_size,
                  shuffle   =True,
                  epochs=epochs,
                  verbose=0)

print('Tiempo de procesamiento (secs): ', time.time()-tic)


from keras.models import load_model
nn_W2V_Twitter_Google_cu.save('nn_W2V_Twitter_Google_cu')  # Guardar modelo
#nn_w2vtwit_cu = load_model('nn_cuba_w2vtwit') # Cargar modelo


y_pred_W2V_Twitter_Google_cu= nn_W2V_Twitter_Google_cu.predict(Twitter_Google_cu_tes
y_test_label_W2V_Twitter_Google_cu = np.argmax(y_test_W2V_Twitter_Google_cu,1)
y_pred_label_W2V_Twitter_Google_cu = np.argmax(y_pred_W2V_Twitter_Google_cu,1)


print("F1 score", f1_score(y_test_label_W2V_Twitter_Google_cu,  y_pred_label_W2V_Twi
print("F1 weighted", f1_score(y_test_label_W2V_Twitter_Google_cu,  y_pred_label_W2V_
print("Recall score", recall_score(y_test_label_W2V_Twitter_Google_cu,  y_pred_label
print("Precision score", precision_score(y_test_label_W2V_Twitter_Google_cu,  y_pred
```

```
Tiempo de procesamiento (secs):  8.909281492233276
F1 score 0.5376496867267744
F1 weighted 0.5964709210265347
Recall score 0.5375
Precision score 0.540894777736883
```

27 F1 SCORE

27.0.1 SVM

```
In [562]: # SVM
          Tabla = {'País':['México', 'España', 'Cuba'],
                  'BoW TF-IDF + W2V Google':[f1_score(y_test.values, prediction_BoW_W2VGoogle_m
                                 f1_score(y_test_es.values, prediction_BoW_W2VGoogle_es,  averag
                                 f1_score(y_test_cu.values, prediction_BoW_W2VGoogle_cu,  averag
                  'BoW TF-IDF + W2V Twitter':[f1_score(y_test.values, prediction_BoW_W2VTwitte
                                 f1_score(y_test_es.values, prediction_BoW_W2VTwitter_es,  avera
                                 f1_score(y_test_cu.values, prediction_BoW_W2VTwitter_cu,  avera
                  'BoW TF-IDF + W2V Google + W2V Twitter':[f1_score(y_test.values, prediction_
```

```
                     f1_score(y_test_es.values, prediction_BoW_W2V_Twitter_Google_es
                      f1_score(y_test_cu.values, prediction_BoW_W2V_Twitter_Google_cu
        'W2V Google + W2V Twitter':[f1_score(y_test.values, prediction_Twitter_Googl
                     f1_score(y_test_es.values, prediction_Twitter_Google_es,  averag
                     f1_score(y_test_cu.values, prediction_Twitter_Google_cu,  averag

# Create DataFrame
Tabla = pd.DataFrame(Tabla)
Tabla
```

Out[562]:

```
     País  BoW TF-IDF + W2V Google  BoW TF-IDF + W2V Twitter  \
0  México                 0.654038                  0.635878
1  España                 0.697746                  0.676872
2    Cuba                 0.618873                  0.621502

   BoW TF-IDF + W2V Google + W2V Twitter  W2V Google + W2V Twitter
0                               0.644737                  0.613296
1                               0.682745                  0.646320
2                               0.612358                  0.605956
```

27.0.2 NN

In [572]:

```
# SVM
Tabla2 = {'País':['México', 'España', 'Cuba'],
        'BoW TF-IDF + W2V Google':[f1_score(y_test_label_BoW_W2VGoogle_mx,  y_pred_la
                      f1_score(y_test_label_BoW_W2VGoogle_es,  y_pred_label_BoW_W2VGo
                     f1_score(y_test_label_BoW_W2VGoogle_cu,  y_pred_label_BoW_W2VGoo
        'BoW TF-IDF + W2V Twitter':[f1_score(y_test_label_BoW_W2VTwitter_mx,  y_pred_
                      f1_score(y_test_label_BoW_W2VTwitter_es,  y_pred_label_BoW_W2VT
                      f1_score(y_test_label_BoW_W2VTwitter_cu,  y_pred_label_BoW_W2VT
        'BoW TF-IDF + W2V Google + W2V Twitter':[f1_score(y_test_label_Bow_W2V_Twitte
                     f1_score(y_test_label_Bow_W2V_Twitter_Google_es,  y_pred_label_B
                     f1_score(y_test_label_Bow_W2V_Twitter_Google_cu,  y_pred_label_B
        'W2V Google + W2V Twitter':[f1_score(y_test_label_W2V_Twitter_Google_mx,  y_p
                     f1_score(y_test_label_W2V_Twitter_Google_es,  y_pred_label_W2V_T
                     f1_score(y_test_label_W2V_Twitter_Google_cu,  y_pred_label_W2V_T

# Create DataFrame
Tabla2 = pd.DataFrame(Tabla2)
Tabla2
```

Out[572]:

```
     País  BoW TF-IDF + W2V Google  BoW TF-IDF + W2V Twitter  \
0  México                 0.625342                  0.622533
1  España                 0.633245                  0.653650
2    Cuba                 0.545360                  0.581698

   BoW TF-IDF + W2V Google + W2V Twitter  W2V Google + W2V Twitter
0                               0.612568                  0.618203
```

1	0.670325	0.657439
2	0.594615	0.537650