PROYECTO INTEGRADOR FINAL

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Deteccion de noticias falsas

La Deteccion de noticias en el mundo moderno han cambiado la forma en que las noticias son generadas, en las redes sociales se sumergen en campañas de desinformacion no legitimas en las cuales, publican cierta infromacion con veracidad dudosa que a sus lectores logra provocar incertidumbre sobre la lectura de dicha informacion, al recalar varia de esta informacion en las redes sociales y provocar varios conflictos sociales, se a comenzado a trabajar en varios detectores de noticias falsas para que asi la gente pueda notificarse solo de informacion original.

Importamos las librerias

Procedemos a importar las librerias que vamos a ocupar para el analisis de noticias falsas

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn import feature_extraction, linear_model, model_selection, preprocessing
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
```

Datos

Recogemos la informacion de las noticias de politica sobre los EEUU tanto originales en un dataset y en el otro son noticias falsas con relacion a las noticias originales, esta informacion la sacamos del siguiente link Abrir Kaggle

In [2]:
```
fake = pd.read_csv("data/Fake.csv")
true = pd.read_csv("data/True.csv")
```

In [3]:
```
fake.shape
```

Out[3]: (23481, 4)

In [4]:
```python
true.shape
```
Out[4]: (21417, 4)

Limpiamos la Data y Preparacion

Procedemos a preparar la data en esta seccion nosotros debemos limpiar la informacion relevante del dataset, y despues procedmos tambien a eliminar las columnas innecesarias, como tambien limpiar el texto, que sea solo en minusculas y eliminar los signos dentro del texto.

In [5]:
```python
fake['target'] = 'fake'
true['target'] = 'true'
```

In [6]:
```python
data = pd.concat([fake, true]).reset_index(drop = True)
data.shape
```
Out[6]: (44898, 5)

In [7]:
```python
from sklearn.utils import shuffle
data = shuffle(data)
data = data.reset_index(drop=True)
```

In [8]:
```python
data.head()
```
Out[8]:

	title	text	subject	date	target
0	'DEAD BROKE' HILLARY'S HAMPTONS VACATION WITH ...	Hillary s been campaigning so hard that she ne...	politics	Aug 16, 2015	fake
1	New fires ravage Rohingya villages in northwes...	YANGON (Reuters) - Up to eight villages were b...	worldnews	September 9, 2017	true
2	TOP NAVY COMMANDER RELEASED After Reportedly R...	Seven years ago, this story would ve seemed li...	left-news	Feb 1, 2016	fake
3	SHOCKING! EVIDENCE SHOWS WHY OBAMA IS HEART OF...	There will be no peace in America until white...	left-news	Sep 8, 2015	fake
4	AWESOME PRO-GUN AD Removed From Airport After ...	The rainbows and unicorn crowd decided they ju...	politics	Jul 9, 2016	fake

In [9]:
```python
data.drop(["date"],axis=1,inplace=True)
data.head()
```
Out[9]:

	title	text	subject	target
0	'DEAD BROKE' HILLARY'S HAMPTONS VACATION WITH ...	Hillary s been campaigning so hard that she ne...	politics	fake
1	New fires ravage Rohingya villages in northwes...	YANGON (Reuters) - Up to eight villages were b...	worldnews	true
2	TOP NAVY COMMANDER RELEASED After Reportedly R...	Seven years ago, this story would ve seemed li...	left-news	fake
3	SHOCKING! EVIDENCE SHOWS WHY OBAMA IS HEART OF...	There will be no peace in America until white...	left-news	fake
4	AWESOME PRO-GUN AD Removed From Airport After ...	The rainbows and unicorn crowd decided they ju...	politics	fake

In [10]:
```python
data.drop(["title"],axis=1,inplace=True)
data.head()
```
Out[10]:

	text	subject	target
0	Hillary s been campaigning so hard that she ne...	politics	fake
1	YANGON (Reuters) - Up to eight villages were b...	worldnews	true
2	Seven years ago, this story would ve seemed li...	left-news	fake
3	There will be no peace in America until white...	left-news	fake
4	The rainbows and unicorn crowd decided they ju...	politics	fake

In [11]:

```
data['text'] = data['text'].apply(lambda x: x.lower())
data.head()
```

Out[11]:

	text	subject	target
0	hillary s been campaigning so hard that she ne...	politics	fake
1	yangon (reuters) - up to eight villages were b...	worldnews	true
2	seven years ago, this story would ve seemed li...	left-news	fake
3	there will be no peace in america until white...	left-news	fake
4	the rainbows and unicorn crowd decided they ju...	politics	fake

In [12]:

```
import string

def punctuation_removal(text):
    all_list = [char for char in text if char not in string.punctuation]
    clean_str = ''.join(all_list)
    return clean_str

data['text'] = data['text'].apply(punctuation_removal)
```

Procedemos a remover las stopwords en ingles

Para el analisis de las noticias falsas procedemos a borrar la informacion que nos es inncesaria como lo son las stopwords, estas son las denominadas palabras vacias, que son los articulos, los pronombres, preposiciones, etc.

In [13]:

```
import nltk
nltk.download('stopwords')
from nltk.corpus import stopwords
stop = stopwords.words('english')

data['text'] = data['text'].apply(lambda x: ' '.join([word for word in x.split() if word not in (stop)]))
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\angel\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

In [14]:

```
data.head()
```

Out[14]:

	text	subject	target
0	hillary campaigning hard needs hamptons vacati...	politics	fake
1	yangon reuters eight villages burned friday pa...	worldnews	true
2	seven years ago story would seemed like someth...	left-news	fake
3	peace america whites begin hate whiteness reve...	left-news	fake
4	rainbows unicorn crowd decided complain gun ma...	politics	fake

Contador de Palabras mas frecuentes

Procedemos a generar el tokenizer, el contador de palabras mas frecuentes dentro del texto

In [15]:

```
from nltk import tokenize

token_space = tokenize.WhitespaceTokenizer()

def counter(text, column_text, quantity):
    all_words = ' '.join([text for text in text[column_text]])
    token_phrase = token_space.tokenize(all_words)
    frequency = nltk.FreqDist(token_phrase)
    df_frequency = pd.DataFrame({"Word": list(frequency.keys()),
                                 "Frequency": list(frequency.values())})
    df_frequency = df_frequency.nlargest(columns = "Frequency", n = quantity)
    plt.figure(figsize=(12,8))
    ax = sns.barplot(data = df_frequency, x = "Word", y = "Frequency", color = 'blue')
    ax.set(ylabel = "Count")
    plt.xticks(rotation='vertical')
```

```
    plt.show()
```

Modelo

In [16]:

```
from sklearn import metrics
import itertools

def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, cm[i, j],
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

Peparamos la data para el entrenamiento y la prueba

Para las pruebas vamos a realizar la separacion 80% y 20%, en la cual el 80% se va al entrenamiento y el 20% a las pruebas.

In [17]:

```
X_train,X_test,y_train,y_test = train_test_split(data['text'], data.target, test_size=0.2, random_state=42)
```

Modelos

Para la creacion de los modelos nosotros decidimos compararlo enre el modelo de regresion que es uno de los mas basicos, con el clasificador random forest, que nos da un mejor resultado

Modelo de regresion

In [18]:

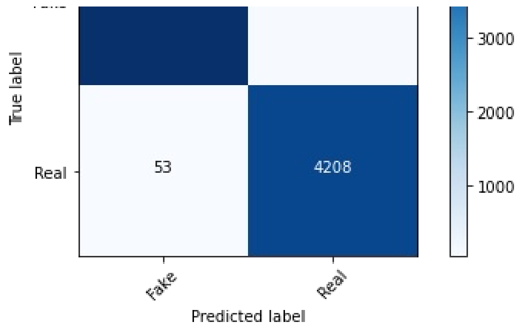
```
from sklearn.linear_model import LogisticRegression

pipe = Pipeline([('vect', CountVectorizer()),
                 ('tfidf', TfidfTransformer()),
                 ('model', LogisticRegression())])


model = pipe.fit(X_train, y_train)


prediction = model.predict(X_test)
print("accuracy: {}%".format(round(accuracy_score(y_test, prediction)*100,2)))
```

```
accuracy: 98.46%
```

In [19]:

```
cm = metrics.confusion_matrix(y_test, prediction)
plot_confusion_matrix(cm, classes=['Fake', 'Real'])
```

```
Confusion matrix, without normalization
```



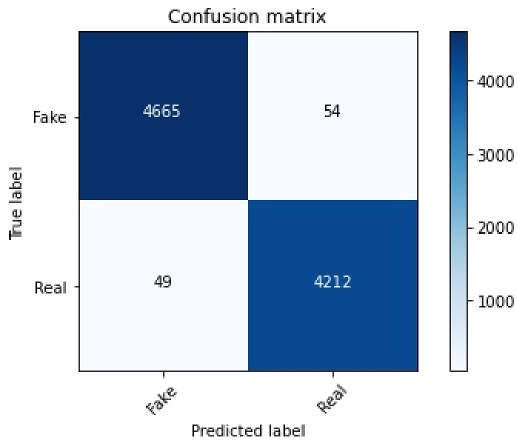
Random Forest Clasificador

In [20]:
```
from sklearn.ensemble import RandomForestClassifier

pipe = Pipeline([('vect', CountVectorizer()),
                 ('tfidf', TfidfTransformer()),
                 ('model', RandomForestClassifier(n_estimators=50, criterion="entropy"))])

model = pipe.fit(X_train, y_train)
prediction = model.predict(X_test)
print("accuracy: {}%".format(round(accuracy_score(y_test, prediction)*100,2)))
```

```
accuracy: 98.85%
```

In [21]:
```
cm = metrics.confusion_matrix(y_test, prediction)
plot_confusion_matrix(cm, classes=['Fake', 'Real'])
```

```
Confusion matrix, without normalization
```



Pruebas

Para las pruebas procedemos a realizar con dos noticias, una de ellas es una noticia original y la otra es falsa, despues procederemos a realizar el analisis de sentimientos.

In [22]:
```
data['text']
```

Out[22]:
```
0        hillary campaigning hard needs hamptons vacati...
1        yangon reuters eight villages burned friday pa...
2        seven years ago story would seemed like someth...
3        peace america whites begin hate whiteness reve...
4        rainbows unicorn crowd decided complain gun ma...
                               ...
44893    one time ann coulter thought donald trump grea...
44894    following mass exodus hispanic surrogates trum...
44895    msnbc casey hunt interviewing warhawk rino sen...
44896    donald trump fell face repeatedly sunday night...
44897    rome reuters united nations preparing deploy 1...
Name: text, Length: 44898, dtype: object
```

In [23]:
```
print(X_test.get(1))
```

```
yangon reuters eight villages burned friday part northwest myanmar large numbers muslim rohingya sheltering wave
violence engulfing area witness three sources briefed matter told reuters fires blazing ethnically mixed rathedau
ng township populations rohingya muslims rakhine buddhists live side side today around 4 pm saw smoke coming vill
ages burning saw chin village staying said villager area contacted reuters phone unclear set fire villages indepe
ndent journalists allowed area myanmar says security forces carrying clearance operations defend extremist terror
ists rights monitors fleeing rohingya say army rakhine vigilantes unleashed campaign arson aimed driving muslim p
opulation burning villages likely fuel exodus rohingya neighboring bangladesh nearly 270000 fled less two weeks c
reating humanitarian crisis myanmar leader aung san suu kyi said thursday government best protect everyone drawn
criticism around world failing speak violence muslim minority including calls revoke 1991 nobel peace prize rathe
daung site latest fires furthest rohingyainhabited area border bangladesh humanitarian workers concerned large nu
mber muslims trapped blazes confirmed sources including two monitors network informants ground local journalist b
ased nearby town buthidaung said among torched villages hamlets ah htet nan yar auk nan yar 65 km 40 miles north
sittwe capital rakhine state one source said camp internally displaced people area also went flames one sources s
aid 300 400 rohingya escaped burnings sheltering ah htet nan yar day fire broke escaped started source said quoti
ng eyewitness villagers hiding forest attempting perilous dayslong journey foot monsoon rain toward maungdaw regi
on west river naf separating myanmar bangladesh latest flight rohingya homes myanmar began two weeks ago rohingya
insurgents attacked several police posts rakhine triggered army counteroffensive least 400 people killed
```

In [24]:
```
prediction[1]
```

Out[24]: 'true'

In [25]:
```
print(X_test.get(7))
```

```
welcome big leagues kiddonald trump supreme court justice made senate confirmation republicans changed rules coul
d complete robbery seat president obama pick merrick garlandneil gorsuch sits high court first day monday course
like trump embarrassed getgogorsuch first case involved census bureau worker dismissed filed lawsuit itthe former
government employee lawyers want entire case allowed move forward instead part heard federal appeals courts rathe
r keep mouth shut learn gorsuch apparently decided try prove belonged thereand waste time gorsuch argumentative s
pent lots time wording words looks like gorsuch going asshole judge going base every decision makes exact wording
interpretation words going nitpick decide cases technicalitiesbut gorsuch decided go even changing decorum court
channeling trump gorsuch literally accused attorney chris landau lying open courtaccording bloomberglandau asked
court let man entire suit go forward federal district court rather waiting part case addressed first federal appe
als court landau said asking court break new ground gorsuch gave pointed response continue make gorsuch saidbut l
andau correct bloomberg points plenty precedent supreme court allowing lawsuits move forward entirety landau real
ly asking high court anything different asking uphold precedent something gorsuch clearly interest regardless law
saysbut justice elena kagan quick put gorsuch place humiliated process would kind revolution began mean extent re
volution kind case room laughed everyone recognized good supreme court burnso like donald trump gorsuch embarrass
mentfrankly trump impeached gorsuch impeached well belong position currently holds clear respect supreme court de
corum make partisan decisions regardless precedent law republicans ones blame chose trump leader forced gorsuch u
pon supreme court democrats fix embarrassments soon take back control congressfeatured image win mcnameegetty ima
ges
```

In [26]:
```
prediction[7]
```

Out[26]: 'true'

Analisis de sentimiento

Con el analisis de sentimiento podemos observar el patron de comportamiento de las noticias verdaderas y falsa, ademas si somos una empresa que utilice la data de noticias podremos obtener mejores conclusiones de la misma.

Importación de librerias

In [27]:
```
from collections import Counter
import numpy as np
import time
import sys
import numpy as np
from collections import Counter
```

Importacion de datos

Se importan los datasets que se ultizaran para obtener todos los datos necesarios

In [29]:

```
def review_and_label(i):
    print(labels[i] + "\t:\t" + reviews[i][:80] + "...")

g = open('./data/reviews.txt','r')
reviews = list(map(lambda x:x[:-1],g.readlines()))
g.close()

g = open('./data/labels.txt','r')
labels = list(map(lambda x:x[:-1].upper(),g.readlines()))
g.close()
```

Variables

Count para almacenar conteos positivos, negativos y totales

In [30]:

```
positive_counts = Counter()
negative_counts = Counter()
total_counts = Counter()

counter = 0
for review in reviews:
    words = review.split(' ')
    if labels[counter] == 'POSITIVE':
        positive_counts.update(words)
    else:
        negative_counts.update(words)
    total_counts.update(words)
    counter += 1
```

Muestra

Los 20 primeros recuentos de las palabras más comunes en las revisiones positivas

In [31]:

```
positive_counts.most_common()[:20]
```

Out[31]:

```
[('', 550468),
 ('the', 173324),
 ('.', 159654),
 ('and', 89722),
 ('a', 83688),
 ('of', 76855),
 ('to', 66746),
 ('is', 57245),
 ('in', 50215),
 ('br', 49235),
 ('it', 48025),
 ('i', 40743),
 ('that', 35630),
 ('this', 35080),
 ('s', 33815),
 ('as', 26308),
 ('with', 23247),
 ('for', 22416),
 ('was', 21917),
 ('film', 20937)]
```

Muestra

Los 20 primeros recuentos de las palabras más comunes en las revisiones negativas

In [32]:

```
negative_counts.most_common()[:20]
```

Out[32]:

```
[('', 561462),
 ('.', 167538),
```

```
 ('the', 163389),
 ('a', 79321),
 ('and', 74385),
 ('of', 69009),
 ('to', 68974),
 ('br', 52637),
 ('is', 50083),
 ('it', 48327),
 ('i', 46880),
 ('in', 43753),
 ('this', 40920),
 ('that', 37615),
 ('s', 31546),
 ('was', 26291),
 ('movie', 24965),
 ('for', 21927),
 ('but', 21781),
 ('with', 20878)]
```

Analisis

Las proporciones nos dicen qué palabras se usan con más frecuencia en las revisiones positivas o positivas, pero los valores específicos que hemos calculado son un poco difíciles de trabajar. Una palabra muy positiva como "amazing" tiene un valor superior a 4, mientras que una palabra muy negativa como "terrible" tiene un valor de alrededor de 0.18. Para solucionar estos problemas, convertiremos todas nuestras proporciones en nuevos valores utilizando logaritmos.

In [33]:

```
pos_neg_ratios = Counter()
for word in total_counts.elements():
    if total_counts[word] >= 100:
        pos_neg_ratios[word] = positive_counts[word] / float(negative_counts[word] + 1)

print("Pos-to-neg ratio para 'the' = {}".format(pos_neg_ratios["the"]))
print("Pos-to-neg ratio para 'amazing' = {}".format(pos_neg_ratios["amazing"]))
print("Pos-to-neg ratio para 'terrible' = {}".format(pos_neg_ratios["terrible"]))
```

```
Pos-to-neg ratio para 'the' = 1.0607993145235326
Pos-to-neg ratio para 'amazing' = 4.022813688212928
Pos-to-neg ratio para 'terrible' = 0.17744252873563218
```

Analisis

Examinamos las nuevas proporciones que hemos calculado para las mismas palabras de antes:

In [34]:

```
for word in pos_neg_ratios:
    ratio = pos_neg_ratios[word]
    pos_neg_ratios[word] = np.log(ratio)

print("Pos-to-neg ratio para 'the' = {}".format(pos_neg_ratios["the"]))
print("Pos-to-neg ratio para 'amazing' = {}".format(pos_neg_ratios["amazing"]))
print("Pos-to-neg ratio para 'terrible' = {}".format(pos_neg_ratios["terrible"]))
```

```
Pos-to-neg ratio para 'the' = 0.05902269426102881
Pos-to-neg ratio para 'amazing' = 1.3919815802404802
Pos-to-neg ratio para 'terrible' = -1.7291085042663878
```

In [35]:

```
pos_neg_ratios.most_common()[:20]
```

Out[35]:

```
[('edie', 4.6913478822291435),
 ('paulie', 4.07753744390572),
 ('felix', 3.152736022363656),
 ('polanski', 2.8233610476132043),
 ('matthau', 2.80672172860924),
 ('victoria', 2.681021528714291),
 ('mildred', 2.6026896854443837),
 ('gandhi', 2.538973871058276),
 ('flawless', 2.451005098112319),
 ('superbly', 2.26002547857525),
 ('perfection', 2.159484249353372),
 ('astaire', 2.1400661634962708),
```

```
 ('captures', 2.038619547159581),
 ('voight', 2.030170492673053),
 ('wonderfully', 2.0218960560332353),
 ('powell', 1.978345424808467),
 ('brosnan', 1.9547990964725592),
 ('lily', 1.9203768470501485),
 ('bakshi', 1.9029851043382795),
 ('lincoln', 1.9014583864844796)]
```

Analisis

Analizamos palabras que se ven con mayor frecuencia en una revisión con una etiqueta "NEGATIVA"

In [36]:

```
list(reversed(pos_neg_ratios.most_common()))[0:20]
```

Out[36]:

```
[('boll', -4.969813299576001),
 ('uwe', -4.624972813284271),
 ('seagal', -3.644143560272545),
 ('unwatchable', -3.258096538021482),
 ('stinker', -3.2088254890146994),
 ('mst', -2.9502698994772336),
 ('incoherent', -2.9368917735310576),
 ('unfunny', -2.6922395950755678),
 ('waste', -2.6193845640165536),
 ('blah', -2.5704288232261625),
 ('horrid', -2.4849066497880004),
 ('pointless', -2.4553061800117097),
 ('atrocious', -2.4259083090260445),
 ('redeeming', -2.3682390632154826),
 ('prom', -2.3608540011180215),
 ('drivel', -2.3470368555648795),
 ('lousy', -2.307572634505085),
 ('worst', -2.286987896180378),
 ('laughable', -2.264363880173848),
 ('awful', -2.227194247027435)]
```

Creacion de datos de entrada/salida

Creamos un conjunto denominado vocab que contenga cada palabra en el vocabulario.

In [37]:

```
vocab = set(total_counts)
vocab_size = len(vocab)
print(vocab_size)
layer_0 = np.zeros((1, vocab_size))
layer_0.shape
```

```
74074
```

Out[37]:

```
(1, 74074)
```

Creacion de un diccionario

Creamos un diccionario de palabras en el vocabulario asignado a las posiciones de índice

In [38]:

```
word2index = {}
for i,word in enumerate(vocab):
    word2index[word] = i

c = 0
for w in word2index:
    if c < 20:
        print(w, end="")
        print(' : ', end="")
        print(word2index[w])
    c = c + 1
```

```
 : 0
pokey : 1
christianty : 2
brattiness : 3
rapacious : 4
excuses : 5
platitudinous : 6
truffle : 7
dethman : 8
thrill : 9
oblige : 10
marischka : 11
cusp : 12
quatermain : 13
clment : 14
grayscale : 15
investigator : 16
borrows : 17
earthlings : 18
begrudgingly : 19
```

Funciones

Debe contar cuántas veces se usa cada palabra en la revisión dada, y luego almacenar esos conteos en los índices apropiados dentro de layer_0.

In [39]:

```
def update_input_layer(review):
    global layer_0
    layer_0 *= 0
    for word in review.split(" "):
        layer_0[0][word2index[word]] += 1

update_input_layer(reviews[0])
layer_0

def get_target_for_label(label):
    if (label=="POSITIVE"):
        return 1
    else:
        return 0
```

Red Neuronal

Se utiliza una clase llamada SentimentNetwork. Los pasos a seguir son los siguientes:

- Crear una red neuronal básica como las redes con una capa de entrada, una capa oculta y una capa de salida.
- No agregamos una non-linearity en la capa oculta. Es decir, no usa una función de activación cuando calcule las salidas de la capa oculta.
- Implementamos la función pre_process_data para crear el vocabulario de nuestras funciones de generación de datos de capacitación
- Asegurar que se entrene sobre todo el corpus

In [40]:

```
class SentimentNetwork:

    def __init__(self, reviews,labels,min_count = 10,polarity_cutoff = 0.1,hidden_nodes = 10, learning_rate = 0.1
        """Creamos SentimenNetwork con la configuración dada
         Args:
             revisiones (lista) - Lista de revisiones usadas para entrenamiento
             labels (list) - Lista de etiquetas POSITIVAS / NEGATIVAS asociadas con las revisiones dadas
             min_count (int) - Las palabras solo deben agregarse al vocabulario
                                si ocurren más que esto muchas veces
             polarity_cutoff (float) - El valor absoluto de la palabra positiva a negativa
                                         la proporción debe ser al menos tan grande como para ser considerada.
             hidden_nodes (int) - Número de nodos para crear en la capa oculta
             learning_rate (float) - Tasa de aprendizaje para usar durante el entrenamiento

        """
        # Asignar una semilla a nuestro generador de números aleatorios para asegurarnos de obtener resultados re
        np.random.seed(1)

        # procesar las revisiones y sus etiquetas asociadas para que todo está listo para el entrenamiento
        self.pre_process_data(reviews, labels, polarity_cutoff, min_count)

        # Construye la red para tener la cantidad de nodos ocultos y la velocidad de aprendizaje que se pasaron a
        self.init_network(len(self.review_vocab),hidden_nodes, 1, learning_rate)
```

```
    def pre_process_data(self, reviews, labels, polarity_cutoff, min_count):

        positive_counts = Counter()
        negative_counts = Counter()
        total_counts = Counter()

        for i in range(len(reviews)):
            if(labels[i] == 'POSITIVE'):
                for word in reviews[i].split(" "):
                    positive_counts[word] += 1
                    total_counts[word] += 1
            else:
                for word in reviews[i].split(" "):
                    negative_counts[word] += 1
                    total_counts[word] += 1

        pos_neg_ratios = Counter()

        for term,cnt in list(total_counts.most_common()):
            if(cnt >= 50):
                pos_neg_ratio = positive_counts[term] / float(negative_counts[term]+1)
                pos_neg_ratios[term] = pos_neg_ratio

        for word,ratio in pos_neg_ratios.most_common():
            if(ratio > 1):
                pos_neg_ratios[word] = np.log(ratio)
            else:
                pos_neg_ratios[word] = -np.log((1 / (ratio + 0.01)))

        # poblar review_vocab con todas las palabras en las revisiones dadas
        review_vocab = set()
        for review in reviews:
            for word in review.split(" "):
                if(total_counts[word] > min_count):
                    if(word in pos_neg_ratios.keys()):
                        if((pos_neg_ratios[word] >= polarity_cutoff) or (pos_neg_ratios[word] <= -polarity_cutoff
                            review_vocab.add(word)
                    else:
                        review_vocab.add(word)

        # Convertir el conjunto de vocabulario en una lista para que podamos acceder a las palabras a través de i
        self.review_vocab = list(review_vocab)

        # poblar etiqueta_vocab con todas las palabras en las etiquetas dadas.
        label_vocab = set()
        for label in labels:
            label_vocab.add(label)

        # Convertir el conjunto de vocabulario de la etiqueta en una lista para que podamos acceder a las etiquet
        self.label_vocab = list(label_vocab)

        # Almacenar los tamaños de los vocabularios de revisión y etiqueta.
        self.review_vocab_size = len(self.review_vocab)
        self.label_vocab_size = len(self.label_vocab)

        # Crear un diccionario de palabras en el vocabulario asignado a las posiciones de índice
        self.word2index = {}
        for i, word in enumerate(self.review_vocab):
            self.word2index[word] = i

        # Crear un diccionario de etiquetas mapeadas a posiciones de índice
        self.label2index = {}
        for i, label in enumerate(self.label_vocab):
            self.label2index[label] = i

    def init_network(self, input_nodes, hidden_nodes, output_nodes, learning_rate):
        # Establecer el número de nodos en las capas de entrada, ocultas y de salida.
        self.input_nodes = input_nodes
        self.hidden_nodes = hidden_nodes
        self.output_nodes = output_nodes

        # Almacenar la tasa de aprendizaje
        self.learning_rate = learning_rate

        # Inicializar los pesos Estos son los pesos entre la capa de entrada y la capa oculta.
        self.weights_0_1 = np.zeros((self.input_nodes,self.hidden_nodes))

        # Estos son los pesos entre la capa oculta y la capa de salida.
        self.weights_1_2 = np.random.normal(0.0, self.output_nodes**-0.5,
                                                (self.hidden_nodes, self.output_nodes))

        # La capa de entrada, una matriz bidimensional con forma 1 x hidden_nodes
        self.layer_1 = np.zeros((1,hidden_nodes))

    def get_target_for_label(self,label):
        if(label == 'POSITIVE'):
            return 1
        else:
            return 0
```

```
    def sigmoid(self,x):
        return 1 / (1 + np.exp(-x))

    def sigmoid_output_2_derivative(self,output):
        return output * (1 - output)

    def train(self, training_reviews_raw, training_labels):

        ## Preprocesamiento de las evaluaciones de capacitación para que podamos tratar directamente con los índi
        training_reviews = list()
        for review in training_reviews_raw:
            indices = set()
            for word in review.split(" "):
                if(word in self.word2index.keys()):
                    indices.add(self.word2index[word])
            training_reviews.append(list(indices))

        # asegúrate de que tenemos un número coincidente de reseñas y etiquetas
        assert(len(training_reviews) == len(training_labels))

        # Realizar un seguimiento de las predicciones correctas para mostrar la precisión durante el entrenamient
        correct_so_far = 0

        # Recuerda cuando comenzamos a imprimir las estadísticas de tiempo
        start = time.time()

        # recorrer todas las evaluaciones dadas y ejecutar un pase hacia adelante y hacia atrás, actualización de
        for i in range(len(training_reviews)):

            # Obtener la siguiente revisión y su etiqueta correcta
            review = training_reviews[i]
            label = training_labels[i]
            self.layer_1 *= 0
            for index in review:
                self.layer_1 += self.weights_0_1[index]

            # Output layer
            layer_2 = self.sigmoid(self.layer_1.dot(self.weights_1_2))

            # Output error
            layer_2_error = layer_2 - self.get_target_for_label(label) # El error de la capa de salida es la dife
            layer_2_delta = layer_2_error * self.sigmoid_output_2_derivative(layer_2)

            # Backpropagated error
            layer_1_error = layer_2_delta.dot(self.weights_1_2.T) # errores propagados a la capa oculta
            layer_1_delta = layer_1_error # gradientes de capas ocultas, sin falta de linealidad, es el mismo que

            # Actualiza los pesos
            self.weights_1_2 -= self.layer_1.T.dot(layer_2_delta) * self.learning_rate # actualizar pesos ocultos

            for index in review:
                self.weights_0_1[index] -= layer_1_delta[0] * self.learning_rate # actualizar pesos de entrada a

            # Manten un registro de las predicciones correctas.
            if(layer_2 >= 0.5 and label == 'POSITIVE'):
                correct_so_far += 1
            elif(layer_2 < 0.5 and label == 'NEGATIVE'):
                correct_so_far += 1

            # Para depuración, imprime nuestra precisión y velocidad de predicción a lo largo del proceso de capa
            elapsed_time = float(time.time() - start)
            reviews_per_second = i / elapsed_time if elapsed_time > 0 else 0

            sys.stdout.write("\rProgress:" + str(100 * i/float(len(training_reviews)))[:4] \
                             + "% Speed(reviews/sec):" + str(reviews_per_second)[0:5] \
                             + " #Correct:" + str(correct_so_far) + " #Trained:" + str(i+1) \
                             + " Training Accuracy:" + str(correct_so_far * 100 / float(i+1))[:4] + "%")
            if(i % 2500 == 0):
                print("")

    def test(self, testing_reviews, testing_labels):
        """
        Intenta predecir las etiquetas para las evaluaciones de prueba dadas,
         y usa test_labels para calcular la precisión de esas predicciones.
        """

        # realizar un seguimiento de la cantidad de predicciones correctas que hacemos
        correct = 0

        # vamos a cronometrar cuántas predicciones por segundo hacemos
        start = time.time()

        # Pasa por cada una de las revisiones dadas y ejecuta la llamada para predecir su etiqueta.
        for i in range(len(testing_reviews)):
            pred = self.run(testing_reviews[i])
            if(pred == testing_labels[i]):
                correct += 1
```

```
            # Para depuración, imprima nuestra precisión y velocidad de predicción durante todo el proceso de pre

            elapsed_time = float(time.time() - start)
            reviews_per_second = i / elapsed_time if elapsed_time > 0 else 0

            sys.stdout.write("\rProgress:" + str(100 * i/float(len(testing_reviews)))[:4] \
                             + "% Speed(reviews/sec):" + str(reviews_per_second)[0:5] \
                             + " #Correct:" + str(correct) + " #Tested:" + str(i+1) \
                             + " Testing Accuracy:" + str(correct * 100 / float(i+1))[:4] + "%")

    def run(self, review):
        """
        Devuelve una predicción POSITIVA o NEGATIVA para la revisión dada.
        """
        ## Hidden layer
        self.layer_1 *= 0
        unique_indices = set()
        for word in review.lower().split(" "):
            if word in self.word2index.keys():
                unique_indices.add(self.word2index[word])
        for index in unique_indices:
            self.layer_1 += self.weights_0_1[index]

        ## Output layer
        layer_2 = self.sigmoid(self.layer_1.dot(self.weights_1_2))

        # Devuelve POSITIVO para valores superiores a mayor que o igual a 0.5 en la capa de salida; devuelve NEGA
        if(layer_2[0] >= 0.5):
            return "POSITIVE"
        else:
            return "NEGATIVE"
```

Entrenamiento

In [41]:

```
mlp_full = SentimentNetwork(reviews[:-1000],labels[:-1000],min_count=0,polarity_cutoff=0,learning_rate=0.01)
mlp_full.train(reviews[:-1000],labels[:-1000])
```

```
Progress:0.0% Speed(reviews/sec):0.0 #Correct:1 #Trained:1 Training Accuracy:100.%
Progress:10.4% Speed(reviews/sec):2021. #Correct:1962 #Trained:2501 Training Accuracy:78.4%
Progress:20.8% Speed(reviews/sec):1996. #Correct:4002 #Trained:5001 Training Accuracy:80.0%
Progress:31.2% Speed(reviews/sec):2025. #Correct:6120 #Trained:7501 Training Accuracy:81.5%
Progress:41.6% Speed(reviews/sec):2041. #Correct:8271 #Trained:10001 Training Accuracy:82.7%
Progress:52.0% Speed(reviews/sec):2048. #Correct:10431 #Trained:12501 Training Accuracy:83.4%
Progress:62.5% Speed(reviews/sec):2042. #Correct:12565 #Trained:15001 Training Accuracy:83.7%
Progress:72.9% Speed(reviews/sec):2034. #Correct:14670 #Trained:17501 Training Accuracy:83.8%
Progress:83.3% Speed(reviews/sec):2022. #Correct:16833 #Trained:20001 Training Accuracy:84.1%
Progress:93.7% Speed(reviews/sec):2020. #Correct:19015 #Trained:22501 Training Accuracy:84.5%
Progress:99.9% Speed(reviews/sec):2021. #Correct:20335 #Trained:24000 Training Accuracy:84.7%
```

Pruebas

Con las noticias que comprobamos anteriormente analizamos el sentimiento de las mismas.

In [42]:

```
mlp_full.run("front page news every major media outletrussian intelligence targeted hillary clinton became secret
```

Out[42]: 'POSITIVE'

In [43]:

```
mlp_full.run("berlin reuters european union chief brexit negotiator michel barnier said wednesday bloc united dea
```

Out[43]: 'NEGATIVE'