NLP - Ejercicio Final Integrador

Entrenar un clasificador binario para análisis de sentimiento de sentimiento utilizando diferentes técnicas de NLP.

1. Descargar el dataset del siguiente link.
2. Pre-procesar el texto de manera básica:
    - a. Eliminar tags html: por ejemplo
    - b. Eliminar puntuaciones
    - c. Eliminar stopwords
3. Entrenar un clasificador utilizando BOW.
    - a. Definir el tamaño del vocabulario.
    - b. (opcional) Agregar pesos utilizando TFIDF.
    - c. Transformar los textos en vectores.
    - d. Crear los datasets de train, validation y test.
    - e. (opcional) Aplicar PCA para reducir la dimensión de los vectores.
    - f. Entrenar una red neuronal (seleccionar arquitectura, loss y optimizador).
    - g. Medir AUC.
4. Entrenar un clasificador utilizando words embeddings (probar con GloVe y con FastText).
    - a. Calcular el embedding de cada texto como el promedio de los embeddings de las palabras.
    - b. Crear los datasets de train, validation y test.
    - c. Entrenar una red neuronal (seleccionar arquitectura, loss y optimizador).
    - d. Medir AUC.
    - e. Tratar de mejorar los embeddings de los textos con:
        - Agregar TFIDF como pesos a las palabras.
        - En lugar de tomar el promedio probar tomando el max o el min de cada componente de los embeddings de las palabras.
        - Probar diferentes tamaños de embeddings.
5. Entrenar un clasificador utilizando celdas LSTM.
    - a. Convertir secuencias de palabras a secuencias de números (indexer).
    - b. Agregar padding para que cada elemento de entrenamiento tenga la misma longitud.
    - c. Armar una red LSTM con las siguientes capas:
        - Capa de embedding que transforma un número (index) en un embedding.
        - Agregar uno dos layers LSTM para obtener el embedding de la secuencias.
        - Agregar un layer denso para entrenar el clasificador.

Desarrollo

```
# Para futura tabla comparativa (se agregó luego de entrenar y probar todos
# los modelos, por eso se incorporan manualmanete los resultados)
model_comparison_table = {}
```

1. Descarga y exploración de dataset.

1. Descargar el dataset del siguiente link.

```
!gdown --id 1zX2KM72Enhv8eWyJt1j4x6YZ75XwzHkm
!unzip "IMDB Dataset.csv.zip"
```

```
Downloading...
From: https://drive.google.com/uc?id=1zX2KM72Enhv8eWyJt1j4x6YZ75XwzHkm
To: /content/IMDB Dataset.csv.zip
27.0MB [00:00, 65.1MB/s]
Archive:  IMDB Dataset.csv.zip
  inflating: IMDB Dataset.csv
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
df = pd.read_csv("IMDB Dataset.csv")
df
```

```
df[df.isnull().any(axis=1)]
```

	review	sentiment
2	I thought this was a wonderful way to spend ti...	positive

```
df.sentiment.value_counts()
```

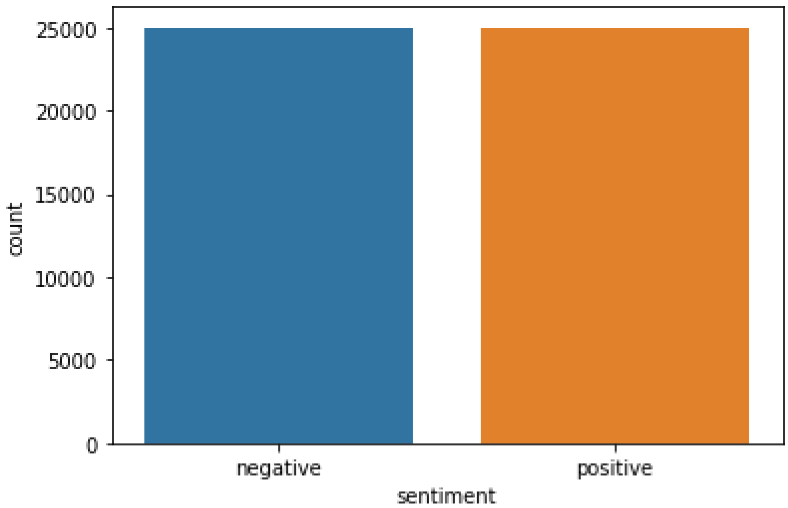
```
negative    25000
positive    25000
Name: sentiment, dtype: int64
```

```
df['sentiment'].unique()
```

```
['positive', 'negative']
Categories (2, object): ['positive', 'negative']
```

```
sns.countplot(x='sentiment', data=df)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff5fb006da0>
```



2. Preprocesamiento básico

Pre-procesar el texto de manera básica:

- a. Eliminar tags html: por ejemplo
.
- b. Eliminar puntuaciones.
- c. Eliminar stopwords.

```
import nltk
import re
```

Tags HTML.

```
tag_re = re.compile(r'<[^>]+>')
df['review'] = df['review'].apply(lambda x: tag_re.sub('',x) )
```

```
df.head()
```

	review	sentiment
0	One of the other reviewers has mentioned that ...	positive
1	A wonderful little production. The filming tec...	positive
2	I thought this was a wonderful way to spend ti...	positive
3	Basically there's a family where a little boy ...	negative
4	Petter Mattei's "Love in the Time of Money" is...	positive

Puntuación

```
df['review'] = df['review'].apply(lambda x: re.sub('[^a-zA-Z]', ' ', x ))
df.head()
```

	review	sentiment
0	One of the other reviewers has mentioned that ...	positive
1	A wonderful little production The filming tec...	positive
2	I thought this was a wonderful way to spend ti...	positive
3	Basically there s a family where a little boy ...	negative
4	Petter Mattei s Love in the Time of Money is...	positive

Stop Words

```
nltk.download('stopwords')
stopwords_re = re.compile(r'\b(' + r'|'.join(nltk.corpus.stopwords.words('engli
df['review'] = df['review'].apply(lambda x: stopwords_re.sub('',x) )
df.head()
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

	review	sentiment
0	One reviewers mentioned watching Oz episode ho...	positive
1	A wonderful little production The filming tec...	positive
2	I thought wonderful way spend time hot summer ...	positive
3	Basically family little boy Jake thinks zomb...	negative
4	Petter Mattei Love Time Money visually stunni...	positive

Lowercase

```
df['review'] = df['review'].apply(lambda x: " ".join(x.lower() for x in x.split
df.head()
```

	review	sentiment
0	one reviewers mentioned watching oz episode ho...	positive
1	a wonderful little production the filming tech...	positive
2	i thought wonderful way spend time hot summer ...	positive
3	basically family little boy jake thinks zombie...	negative
4	petter mattei love time money visually stunnin...	positive

Etiquetas.

```
df["sentiment"] = df["sentiment"].astype('category')
df["target"] = df["sentiment"].cat.codes
df.head()
```

	review	sentiment	target
0	one reviewers mentioned watching oz episode ho...	positive	1
1	a wonderful little production the filming tech...	positive	1
2	i thought wonderful way spend time hot summer ...	positive	1
3	basically family little boy jake thinks zombie...	negative	0
4	petter mattei love time money visually stunnin...	positive	1

3. Clasificador BOW con Red Neuronal

Entrenar un clasificador utilizando BOW.

- a. Definir el tamaño del vocabulario.
- b. (opcional) Agregar pesos utilizando TFIDF.
- c. Transformar los textos en vectores.
- d. Crear los datasets de train, validation y test.
- e. (opcional) Aplicar PCA para reducir la dimensión de los vectores.
- f. Entrenar una red neuronal (seleccionar arquitectura, loss y optimizador).
- g. Medir AUC.

```
X = df.review
y = df.target
```

```
from sklearn.model_selection import train_test_split

TRAIN_TEST_SPLIT = 0.2
TRAIN_VAL_SPLIT = 0.25
```

```

X_train_set, X_test, y_train_set, y_test = train_test_split(X, y, test_size=TRA
X_train, X_val, y_train, y_val = train_test_split(X_train_set,y_train_set,test_

print("Test:",X_test.shape)
print("Train:",X_train.shape)
print("Val:",X_val.shape)
```

```
Test: (10000,)
Train: (30000,)
Val: (10000,)
```

```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer

VOCAB_SIZE = 200000
count_vectorizer = CountVectorizer(stop_words="english",max_features=VOCAB_SIZE
```

```
X_train = count_vectorizer.fit_transform(X_train)
X_val = count_vectorizer.transform(X_val)
```

```
tfidf_transformer = TfidfTransformer(smooth_idf=False)

X_train = tfidf_transformer.fit_transform(X_train)
X_val = tfidf_transformer.transform(X_val)
```

```
N_DIM_REDUC = 512

from sklearn.decomposition import TruncatedSVD

svd = TruncatedSVD(N_DIM_REDUC)

X_train = svd.fit_transform(X_train)
X_val = svd.transform(X_val)

X_train.shape,X_val.shape
```

```
((30000, 512), (10000, 512))
```

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

X_train = scaler.fit_transform(X_train)
X_val = scaler.transform(X_val)
```

```
import keras
from keras.models import Sequential
from keras.layers import Dense,Dropout
from keras.utils.vis_utils import plot_model

```

```

model = Sequential()
model.add(Dense(50, activation = "relu", input_shape=(N_DIM_REDUC, )))
model.add(Dropout(0.3, noise_shape=None, seed=None))
model.add(Dense(50, activation = "relu"))
model.add(Dropout(0.2, noise_shape=None, seed=None))
model.add(Dense(50, activation = "relu"))
model.add(Dense(1, activation = "sigmoid"))
model.summary()

plot_model(model, show_shapes=True, show_layer_names=True)
```

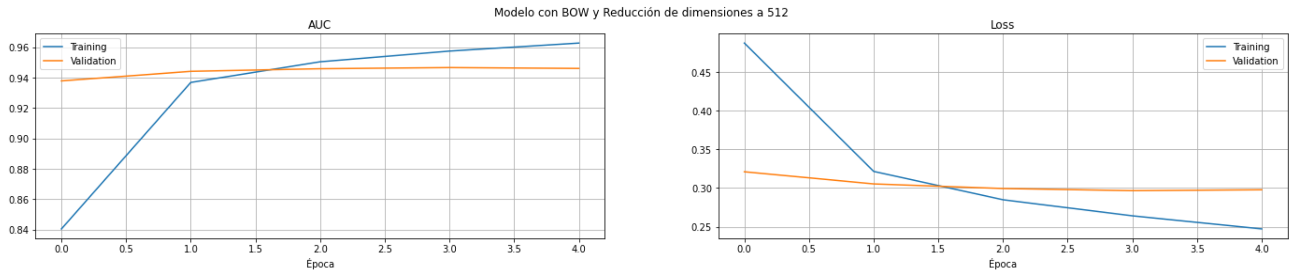
```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_12 (Dense)             (None, 50)                25650
_________________________________________________________________
dropout_6 (Dropout)          (None, 50)                0
_________________________________________________________________
dense_13 (Dense)             (None, 50)                2550
_________________________________________________________________
dropout_7 (Dropout)          (None, 50)                0
_________________________________________________________________
dense_14 (Dense)             (None, 50)                2550
_________________________________________________________________
dense_15 (Dense)             (None, 1)                 51
=================================================================
```

```python
model.compile(
 optimizer = "adam",
 loss = "binary_crossentropy",
 metrics = [keras.metrics.AUC(name="auc")]
)

NUM_EPOCHS = 5

history = model.fit( X_train, y_train,
            epochs= NUM_EPOCHS,
            batch_size = 32,
            validation_data = (X_val, y_val),
            verbose = True )
```

```
Epoch 1/5
938/938 [==============================] - 7s 5ms/step - loss: 0.5964 - auc:
Epoch 2/5
938/938 [==============================] - 4s 4ms/step - loss: 0.3231 - auc:
Epoch 3/5
938/938 [==============================] - 4s 4ms/step - loss: 0.2839 - auc:
Epoch 4/5
938/938 [==============================] - 4s 4ms/step - loss: 0.2537 - auc:
Epoch 5/5
938/938 [==============================] - 4s 4ms/step - loss: 0.2393 - auc:
```

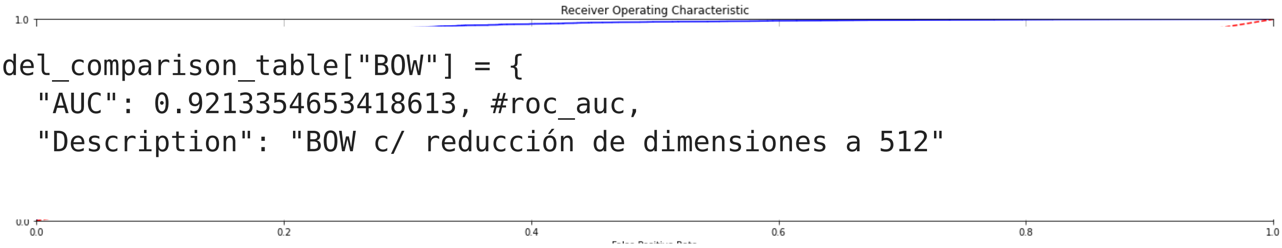
```python
fig,axes = plt.subplots(1,2,figsize=(24,4))
plt.suptitle("Modelo con BOW y Reducción de dimensiones a %d" % N_DIM_REDUC)
axes[0].set_title("AUC")
axes[0].plot(np.arange(NUM_EPOCHS),history.history['auc'])
axes[0].plot(np.arange(NUM_EPOCHS),history.history['val_auc'])
axes[0].legend(["Training","Validation"])
axes[0].grid(which="Both")
axes[0].set_xlabel("Época")
axes[1].set_title("Loss")
axes[1].plot(np.arange(NUM_EPOCHS),history.history['loss'])
axes[1].plot(np.arange(NUM_EPOCHS),history.history['val_loss'])
axes[1].legend(["Training","Validation"])
axes[1].grid(which="Both")
axes[1].set_xlabel("Época")
plt.show()
```

```
plt.show()
```




```
x_test_tx = count_vectorizer.transform(X_test)
x_test_tx = svd.transform(x_test_tx)
x_test_tx = scaler.transform(x_test_tx)
y_test_pred = model.predict(x_test_tx)
```

```
import sklearn
from sklearn.metrics import auc

fpr, tpr, thresholds = sklearn.metrics.roc_curve(y_test.values, y_test_pred)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(24,4))
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.grid(which="Both")
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()

print("AUC:",roc_auc)
```




```
model_comparison_table["BOW"] = {
    "AUC": 0.9213354653418613, #roc_auc,
    "Description": "BOW c/ reducción de dimensiones a 512"
}
```

4. Clasificador con Word Embeddings

- Entrenar un clasificador utilizando words embeddings (probar con GloVe y con FastText).
    - a. Calcular el embedding de cada texto como el promedio de los embeddings de las palabras.
    - b. Crear los datasets de train, validation y test.
    - c. Entrenar una red neuronal (seleccionar arquitectura, loss y optimizador).
    - d. Medir AUC.
    - e. Tratar de mejorar los embeddings de los textos con:
        - Agregar TFIDF como pesos a las palabras.
        - En lugar de tomar el promedio probar tomando el max o el min de cada componente de los embeddings de las palabras.
        - Probar diferentes tamaños de embeddings.

Descargar GloVe y FastText.

```
!wget http://nlp.stanford.edu/data/glove.twitter.27B.zip
!unzip glove.twitter.27B.zip
```

```
--2021-01-01 12:00:59--  http://nlp.stanford.edu/data/glove.twitter.27B.zip
Resolving nlp.stanford.edu (nlp.stanford.edu)... 171.64.67.140
Connecting to nlp.stanford.edu (nlp.stanford.edu)|171.64.67.140|:80... connec
HTTP request sent, awaiting response... 302 Found
Location: https://nlp.stanford.edu/data/glove.twitter.27B.zip [following]
--2021-01-01 12:00:59--  https://nlp.stanford.edu/data/glove.twitter.27B.zip
Connecting to nlp.stanford.edu (nlp.stanford.edu)|171.64.67.140|:443... conne
HTTP request sent, awaiting response... 301 Moved Permanently
Location: http://downloads.cs.stanford.edu/nlp/data/glove.twitter.27B.zip [fo
--2021-01-01 12:00:59--  http://downloads.cs.stanford.edu/nlp/data/glove.twit
Resolving downloads.cs.stanford.edu (downloads.cs.stanford.edu)... 171.64.64.
Connecting to downloads.cs.stanford.edu (downloads.cs.stanford.edu)|171.64.64
HTTP request sent, awaiting response... 200 OK
Length: 1520408563 (1.4G) [application/zip]
Saving to: ‘glove.twitter.27B.zip’

glove.twitter.27B.z 100%[===================>]   1.42G  1.97MB/s    in 11m 42

2021-01-01 12:12:42 (2.06 MB/s) - ‘glove.twitter.27B.zip’ saved [1520408563/1

Archive:  glove.twitter.27B.zip
  inflating: glove.twitter.27B.25d.txt
  inflating: glove.twitter.27B.50d.txt
  inflating: glove.twitter.27B.100d.txt
  inflating: glove.twitter.27B.200d.txt
```

```
!wget https://dl.fbaipublicfiles.com/fasttext/vectors-crawl/cc.en.300.vec.gz
!gunzip -k cc.en.300.vec.gz
```

```
--2021-01-01 22:21:09--  https://dl.fbaipublicfiles.com/fasttext/vectors-craw
Resolving dl.fbaipublicfiles.com (dl.fbaipublicfiles.com)... 104.22.74.142, 1
Connecting to dl.fbaipublicfiles.com (dl.fbaipublicfiles.com)|104.22.74.142|:
HTTP request sent, awaiting response... 200 OK
Length: 1325960915 (1.2G) [binary/octet-stream]
Saving to: ‘cc.en.300.vec.gz’

cc.en.300.vec.gz    100%[===================>]   1.23G  50.6MB/s    in 26s

2021-01-01 22:21:35 (48.6 MB/s) - ‘cc.en.300.vec.gz’ saved [1325960915/132596
```

El siguiente código fue copiado del ejemplo de:
https://github.com/ejesposito/ceai/blob/master/nlp/word2vec/pretrained.py

```
import logging
import os
from pathlib import Path
from io import StringIO
import pickle

logging.basicConfig(level=logging.INFO)

class WordsEmbeddings(object):
    logger = logging.getLogger(__name__)

    def __init__(self):
        # load the embeddings
        words_embedding_pkl = Path(self.PKL_PATH)
        if not words_embedding_pkl.is_file():
            words_embedding_txt = Path(self.WORD_TO_VEC_MODEL_TXT_PATH)
            assert words_embedding_txt.is_file(), 'Words embedding not availabl
            embeddings = self.convert_model_to_pickle()
        else:
            embeddings = self.load_model_from_pickle()
        self.embeddings = embeddings
        # build the vocabulary hashmap
        index = np.arange(self.embeddings.shape[0])
        self.word2idx = dict(zip(self.embeddings['word'], index))
        self.idx2word = dict(zip(index, self.embeddings['word']))

    def get_words_embeddings(self, words):
        words_idxs = self.words2idxs(words)
        return self.embeddings[words_idxs]['embedding']

    def words2idxs(self, words):
        return np.array([self.word2idx.get(word, -1) for word in words])

    def idxs2words(self, idxs):
```

```
    def idxs2words(self, idxs):
        return np.array([self.idx2word.get(idx, '-1') for idx in idxs])

    def load_model_from_pickle(self):
        self.logger.debug(
            'loading words embeddings from pickle {}'.format(
                self.PKL_PATH
            )
        )
        max_bytes = 2**28 - 1 # 256MB
        bytes_in = bytearray(0)
        input_size = os.path.getsize(self.PKL_PATH)
        with open(self.PKL_PATH, 'rb') as f_in:
            for _ in range(0, input_size, max_bytes):
                bytes_in += f_in.read(max_bytes)
        embeddings = pickle.loads(bytes_in)
        self.logger.debug('words embeddings loaded')
        return embeddings

    def convert_model_to_pickle(self):
        # create a numpy strctured array:
        # word     embedding
        # U50      np.float32[]
        # word_1   a, b, c
        # word_2   d, e, f
        # ...
        # word_n   g, h, i
        self.logger.debug(
            'converting and loading words embeddings from text file {}'.format(
                self.WORD_TO_VEC_MODEL_TXT_PATH
            )
        )
        structure = [('word', np.dtype('U' + str(self.WORD_MAX_SIZE))),
                     ('embedding', np.float32, (self.N_FEATURES,))]
        structure = np.dtype(structure)
        # load numpy array from disk using a generator
        with open(self.WORD_TO_VEC_MODEL_TXT_PATH, encoding="utf8") as words_em
            embeddings_gen = (
                (line.split()[0], line.split()[1:]) for line in words_embedding
                if len(line.split()[1:]) == self.N_FEATURES
            )
            embeddings = np.fromiter(embeddings_gen, structure)
        # add a null embedding
        null_embedding = np.array(
            [('null_embedding', np.zeros((self.N_FEATURES,), dtype=np.float32))
            dtype=structure
        )
        embeddings = np.concatenate([embeddings, null_embedding])
        # dump numpy array to disk using pickle
        max_bytes = 2**28 - 1 # # 256MB
        bytes_out = pickle.dumps(embeddings, protocol=pickle.HIGHEST_PROTOCOL)
        with open(self.PKL_PATH, 'wb') as f_out:
            for idx in range(0, len(bytes_out), max_bytes):
                f_out.write(bytes_out[idx:idx+max_bytes])
        self.logger.debug('words embeddings loaded')
        return embeddings
```

```
        return embeddings


class GloveEmbeddings(WordsEmbeddings):

    WORD_TO_VEC_MODEL_TXT_PATH = 'glove.twitter.27B.50d.txt'
    PKL_PATH = 'gloveembedding.pkl'
    N_FEATURES = 50
    WORD_MAX_SIZE = 60


class FasttextEmbeddings(WordsEmbeddings):

    WORD_TO_VEC_MODEL_TXT_PATH = 'cc.en.300.vec'
    PKL_PATH = 'fasttext.pkl'
    N_FEATURES = 300
    WORD_MAX_SIZE = 60
```

a. Calcular el embedding de cada texto como el promedio de los embeddings de las palabras.

```
X = df.review
y = df.target
```

```
nltk.download('punkt')
from nltk.tokenize import word_tokenize
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
```

```
embedder_model = FasttextEmbeddings()
```

```
def embed_corpus_average(corpus,embedder_model):
  X_emb = np.zeros(shape=(len(corpus),embedder_model.N_FEATURES))
  for i in range(len(corpus)):
      X_emb[i] = np.average(
          embedder_model.get_words_embeddings(
              word_tokenize(corpus[i])
          ),axis=0)
  return X_emb
```

```
X_emb = embed_corpus_average(X,embedder_model)
```

```
X_emb.shape
```

```
(50000, 300)
```

b. Crear los datasets de train, validation y test.

```
def split_dataset(X,y):
  TRAIN_TEST_SPLIT = 0.2
```

```
  TRAIN_TEST_SPLIT = 0.2
  TRAIN_VAL_SPLIT = 0.25
  X_train_set, X_test, y_train_set, y_test = train_test_split(X, y, test_size=T
  X_train, X_val, y_train, y_val = train_test_split(X_train_set,y_train_set,tes
  print("Test:",X_test.shape)
  print("Train:",X_train.shape)
  print("Val:",X_val.shape)
  return X_train_set, X_test, y_train_set, y_test,X_train, X_val, y_train, y_va

X_train_set, X_test, y_train_set, y_test,X_train, X_val, y_train, y_val = split
```

```
Test: (10000, 300)
Train: (30000, 300)
Val: (10000, 300)
```

- c. Entrenar una red neuronal (seleccionar arquitectura, loss y optimizador).
- d. Obtener AUC.

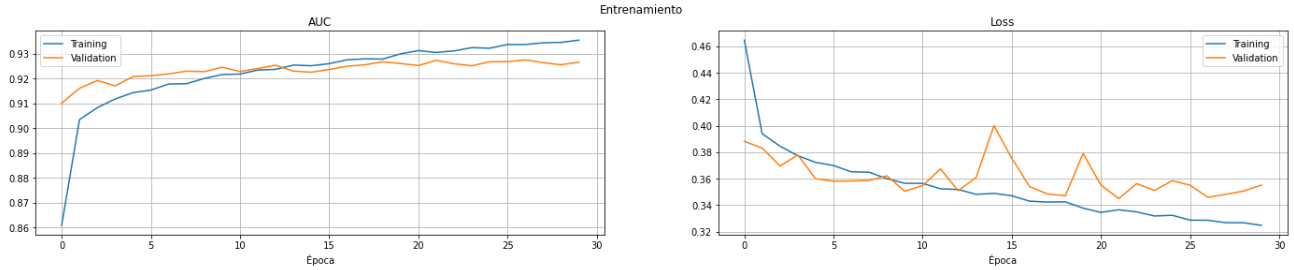
```
import sklearn
from sklearn.metrics import auc

def create_model(n_features):
  model = Sequential()
  model.add(Dense(50, activation = "relu", input_shape=(embedder_model.N_FEATUR
  model.add(Dropout(0.3, noise_shape=None, seed=None))
  model.add(Dense(50, activation = "relu"))
  model.add(Dropout(0.2, noise_shape=None, seed=None))
  model.add(Dense(50, activation = "relu"))
  model.add(Dense(1, activation = "sigmoid"))
  model.summary()
  plot_model(model, show_shapes=True, show_layer_names=True)
  return model

def train_and_evaluate_model(model):
  model_metrics = [
    keras.metrics.AUC(name="auc")
  ]

  # compiling the model
  model.compile(
  optimizer = "adam",
  loss = "binary_crossentropy",
  metrics = model_metrics
  )

  NUM_EPOCHS = 30

  history = model.fit( X_train, y_train,
              epochs= NUM_EPOCHS,
              batch_size = 32,
              validation_data = (X_val, y_val),
              verbose = True )

  fig,axes = plt.subplots(1,2,figsize=(24,4))
```

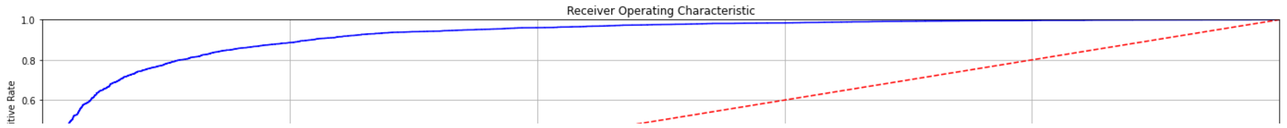
```
  plt.suptitle("Entrenamiento")
  axes[0].set_title("AUC")
  axes[0].plot(np.arange(NUM_EPOCHS),history.history['auc'])
  axes[0].plot(np.arange(NUM_EPOCHS),history.history['val_auc'])
  axes[0].legend(["Training","Validation"])
  axes[0].grid(which="Both")
  axes[0].set_xlabel("Época")
  axes[1].set_title("Loss")
  axes[1].plot(np.arange(NUM_EPOCHS),history.history['loss'])
  axes[1].plot(np.arange(NUM_EPOCHS),history.history['val_loss'])
  axes[1].legend(["Training","Validation"])
  axes[1].grid(which="Both")
  axes[1].set_xlabel("Época")
  plt.show()

  y_test_pred = model.predict(X_test)

  fpr, tpr, thresholds = sklearn.metrics.roc_curve(y_test.values, y_test_pred)
  roc_auc = auc(fpr, tpr)

  plt.figure(figsize=(24,4))
  plt.title('Receiver Operating Characteristic')
  plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
  plt.legend(loc = 'lower right')
  plt.plot([0, 1], [0, 1],'r--')
  plt.xlim([0, 1])
  plt.ylim([0, 1])
  plt.grid(which="Both")
  plt.ylabel('True Positive Rate')
  plt.xlabel('False Positive Rate')
  plt.show()

  print("AUC:",roc_auc)
  return roc_auc
```

```
model = create_model(n_features=embedder_model.N_FEATURES)
roc_auc = train_and_evaluate_model(model)
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_4 (Dense)              (None, 50)                15050     
_________________________________________________________________
dropout_2 (Dropout)          (None, 50)                0         
_________________________________________________________________
dense_5 (Dense)              (None, 50)                2550      
_________________________________________________________________
dropout_3 (Dropout)          (None, 50)                0         
_________________________________________________________________
dense_6 (Dense)              (None, 50)                2550      
_________________________________________________________________
dense_7 (Dense)              (None, 1)                 51        
=================================================================
Total params: 20,201
Trainable params: 20,201
Non-trainable params: 0
_________________________________________________________________
Epoch 1/30
938/938 [==============================] - 5s 4ms/step - loss: 0.5453 - auc:
Epoch 2/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3921 - auc:
Epoch 3/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3893 - auc:
Epoch 4/30
938/938 [==============================] - 4s 5ms/step - loss: 0.3785 - auc:
Epoch 5/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3750 - auc:
Epoch 6/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3692 - auc:
Epoch 7/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3649 - auc:
Epoch 8/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3623 - auc:
Epoch 9/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3596 - auc:
Epoch 10/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3528 - auc:
Epoch 11/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3569 - auc:
Epoch 12/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3529 - auc:
Epoch 13/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3540 - auc:
Epoch 14/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3530 - auc:
Epoch 15/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3506 - auc:
Epoch 16/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3428 - auc:
Epoch 17/30
938/938 [==============================] - 4s 5ms/step - loss: 0.3390 - auc:
Epoch 18/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3434 - auc:
Epoch 19/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3510 - auc:
Epoch 20/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3411 - auc:
Epoch 21/30
```

```
938/938 [==============================] - 4s 4ms/step - loss: 0.3390 - auc:
Epoch 22/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3348 - auc:
Epoch 23/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3346 - auc:
Epoch 24/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3277 - auc:
Epoch 25/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3318 - auc:
Epoch 26/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3302 - auc:
Epoch 27/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3286 - auc:
Epoch 28/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3250 - auc:
Epoch 29/30
938/938 [==============================] - 4s 5ms/step - loss: 0.3259 - auc:
Epoch 30/30
938/938 [==============================] - 4s 4ms/step - loss: 0.3241 - auc:
```






```
model_comparison_table["FastText (Average)"] = {
    "AUC": 0.9237549829902969, #roc_auc,
    "Description": "FastText 300 (cc.en.300.vec.gz)"
}
```

e. Tratar de mejorar los embeddings de los textos con:

- Agregar TFIDF como pesos a las palabras.

```
X = df.review.values
y = df.target.values
X_train_set, X_test, y_train_set, y_test,X_train, X_val, y_train, y_val =  spli
```

```
Test: (10000,)
Train: (30000,)
Val: (10000,)
```

```
from sklearn.feature_extraction.text import TfidfVectorizer
tfidf_vectorizer = TfidfVectorizer(tokenizer=word_tokenize)
```

Entrenar el TF-IDF Vectorizer con el Train set y obtener los pesos para el corpus.

```
X_train_tfidf = tfidf_vectorizer.fit_transform(X_train)
```

```
X_val_tfidf = tfidf_vectorizer.transform(X_val)
X_test_tfidf = tfidf_vectorizer.transform(X_test)
feature_names = tfidf_vectorizer.get_feature_names()
inverse_feature_names = { v:k for k, v in enumerate(feature_names)}
len(feature_names)
```

```
82157
```

La siguiente función devuelve los pesos de las palabras de un documento.

```
def doc_to_weights(doc_idx,doc_matrix, tfidf_doc_matrix):
  """
    doc_idx: índice del documento en ambas matrices
    doc_matrix: matriz con documentos (texto)
    tfidf_doc_matrix: matriz TF-IDF
  """
  tokenized_doc = word_tokenize(doc_matrix[doc_idx])
  indexed_terms = []
  for term in tokenized_doc:
    indexed_terms.append(inverse_feature_names[term] if term in inverse_feature
  doc_weights = [tfidf_doc_matrix[doc_idx].toarray()[:,token_index][0] for toke
  return np.array(doc_weights)

x0_w = doc_to_weights(1,X_train,X_train_tfidf).reshape(-1,1)
x0_w.shape
```

```
(43, 1)
```

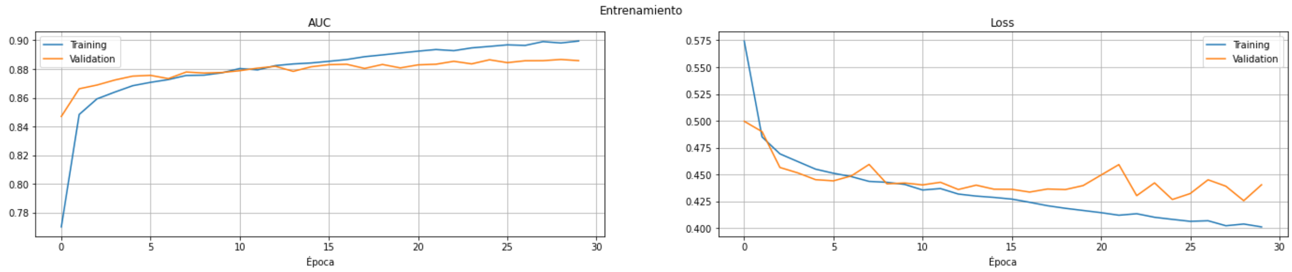
```
def embed_corpus_tfidf_weight(corpus,corpus_tfidf,embedder_model):
  X_emb = np.zeros(shape=(len(corpus),embedder_model.N_FEATURES))
  for i in range(len(corpus)):
      x_w = doc_to_weights(i,corpus,corpus_tfidf).reshape(-1,1)
      x_e = embedder_model.get_words_embeddings(  word_tokenize(corpus[i]))
      X_emb[i] = np.sum(x_e*x_w,axis=0)/x_w.shape[0]
  return X_emb

X_train =  embed_corpus_tfidf_weight(X_train,X_train_tfidf,embedder_model)
X_val =  embed_corpus_tfidf_weight(X_val,X_val_tfidf,embedder_model)
X_test =  embed_corpus_tfidf_weight(X_test,X_test_tfidf,embedder_model)
```

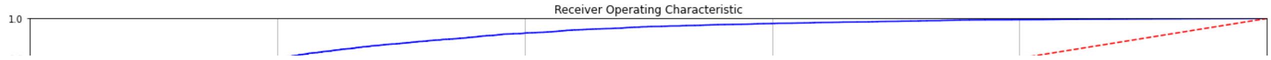
```
model = create_model(n_features=embedder_model.N_FEATURES)
model.compile(
  optimizer = "adam",
  loss = "binary_crossentropy",
  metrics = [ keras.metrics.AUC(name="auc")]
)

NUM_EPOCHS = 30

history = model.fit( X_train, y_train,
              epochs= NUM_EPOCHS,
              batch_size = 32,
              validation_data = (X_val, y_val)
```

```
              validation_data = (X_val, y_val),
              verbose = True )
```

```
938/938 [==============================] - 5s 5ms/step - loss: 0.6355 - auc
Epoch 2/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4897 - auc
Epoch 3/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4710 - auc
Epoch 4/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4639 - auc
Epoch 5/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4564 - auc
Epoch 6/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4546 - auc
Epoch 7/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4499 - auc
Epoch 8/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4443 - auc
Epoch 9/30
938/938 [==============================] - 4s 5ms/step - loss: 0.4441 - auc
Epoch 10/30
938/938 [==============================] - 4s 5ms/step - loss: 0.4412 - auc
Epoch 11/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4328 - auc
Epoch 12/30
938/938 [==============================] - 4s 5ms/step - loss: 0.4401 - auc
Epoch 13/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4285 - auc
Epoch 14/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4331 - auc
Epoch 15/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4313 - auc
Epoch 16/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4255 - auc
Epoch 17/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4210 - auc
Epoch 18/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4187 - auc
Epoch 19/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4203 - auc

Epoch 20/30
938/938 [==============================] - 4s 5ms/step - loss: 0.4114 - auc
Epoch 21/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4093 - auc
Epoch 22/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4164 - auc
Epoch 23/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4140 - auc
Epoch 24/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4097 - auc
Epoch 25/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4058 - auc
Epoch 26/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4032 - auc
Epoch 27/30
938/938 [==============================] - 4s 5ms/step - loss: 0.4059 - auc
Epoch 28/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4036 - auc
Epoch 29/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4043 - auc
Epoch 30/30
```

```
fig,axes = plt.subplots(1,2,figsize=(24,4))
plt.suptitle("Entrenamiento")
axes[0].set_title("AUC")
axes[0].plot(np.arange(NUM_EPOCHS),history.history['auc'])
axes[0].plot(np.arange(NUM_EPOCHS),history.history['val_auc'])
axes[0].legend(["Training","Validation"])
axes[0].grid(which="Both")
axes[0].set_xlabel("Época")
axes[1].set_title("Loss")
axes[1].plot(np.arange(NUM_EPOCHS),history.history['loss'])
axes[1].plot(np.arange(NUM_EPOCHS),history.history['val_loss'])
axes[1].legend(["Training","Validation"])
axes[1].grid(which="Both")
axes[1].set_xlabel("Época")
plt.show()

y_test_pred = model.predict(X_test)

fpr, tpr, thresholds = sklearn.metrics.roc_curve(y_test, y_test_pred)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(24,4))
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.grid(which="Both")
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()

print("AUC:",roc_auc)
```






```python
model_comparison_table["FastText (TF-IDF)"] = {
    "AUC": 0.8834895915067472, # roc_auc,
    "Description": "FastText 300 (cc.en.300.vec.gz)"
}
```

AUC: 0.8834895915067472

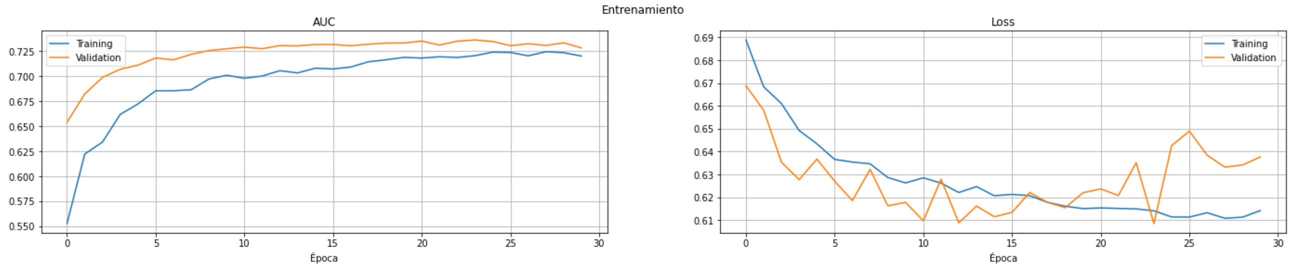
- En lugar de tomar el promedio probar tomando el max o el min de cada componente de los embeddings de las palabras.

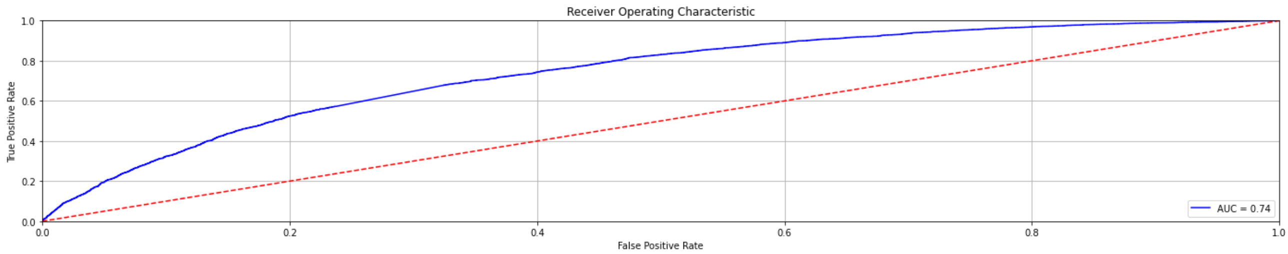
```python
def embed_corpus_max(corpus,embedder_model):
  X_emb = np.zeros(shape=(len(corpus),embedder_model.N_FEATURES))
  for i in range(len(corpus)):
      X_emb[i] = np.max(
          embedder_model.get_words_embeddings(
              word_tokenize(corpus[i])
          ),axis=0)
  return X_emb

def embed_corpus_min(corpus,embedder_model):
  X_emb = np.zeros(shape=(len(corpus),embedder_model.N_FEATURES))
  for i in range(len(corpus)):
      X_emb[i] = np.min(
          embedder_model.get_words_embeddings(
              word_tokenize(corpus[i])
          ),axis=0)
  return X_emb
```

```python
X_emb = embed_corpus_max(X,embedder_model)
X_train_set, X_test, y_train_set, y_test,X_train, X_val, y_train, y_val =  spli
model = create_model(n_features=embedder_model.N_FEATURES)
roc_auc = train_and_evaluate_model(model)
```

```
Test: (10000, 300)
Train: (30000, 300)
Val: (10000, 300)
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_8 (Dense)              (None, 50)                15050     
_________________________________________________________________
dropout_4 (Dropout)          (None, 50)                0         
_________________________________________________________________
dense_9 (Dense)              (None, 50)                2550      
_________________________________________________________________
dropout_5 (Dropout)          (None, 50)                0         
_________________________________________________________________
dense_10 (Dense)             (None, 50)                2550      
_________________________________________________________________
dense_11 (Dense)             (None, 1)                 51        
=================================================================
Total params: 20,201
Trainable params: 20,201
Non-trainable params: 0
_________________________________________________________________
Epoch 1/30
938/938 [==============================] - 5s 4ms/step - loss: 0.6926 - auc:
Epoch 2/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6733 - auc:
Epoch 3/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6614 - auc:
Epoch 4/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6516 - auc:
Epoch 5/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6438 - auc:
Epoch 6/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6348 - auc:
Epoch 7/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6365 - auc:
Epoch 8/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6339 - auc:
Epoch 9/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6324 - auc:
Epoch 10/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6303 - auc:
Epoch 11/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6281 - auc:
Epoch 12/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6221 - auc:
Epoch 13/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6189 - auc:
Epoch 14/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6259 - auc:
Epoch 15/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6185 - auc:
Epoch 16/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6221 - auc:
Epoch 17/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6212 - auc:
Epoch 18/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6210 - auc:
Epoch 19/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6175 - auc:
```

```
Epoch 20/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6143 - auc:
Epoch 21/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6138 - auc:
Epoch 22/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6148 - auc:
Epoch 23/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6150 - auc:
Epoch 24/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6142 - auc:
Epoch 25/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6085 - auc:
Epoch 26/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6114 - auc:
Epoch 27/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6143 - auc:
Epoch 28/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6110 - auc:
Epoch 29/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6116 - auc:
Epoch 30/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6161 - auc:
```





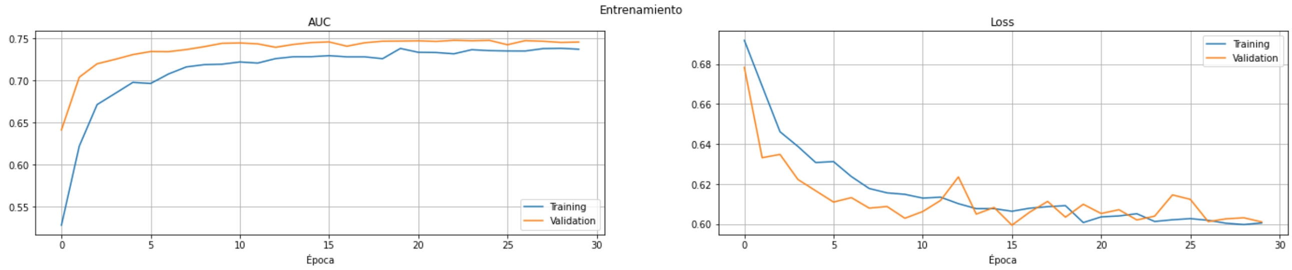

```
AUC: 0.7392006923537724
```

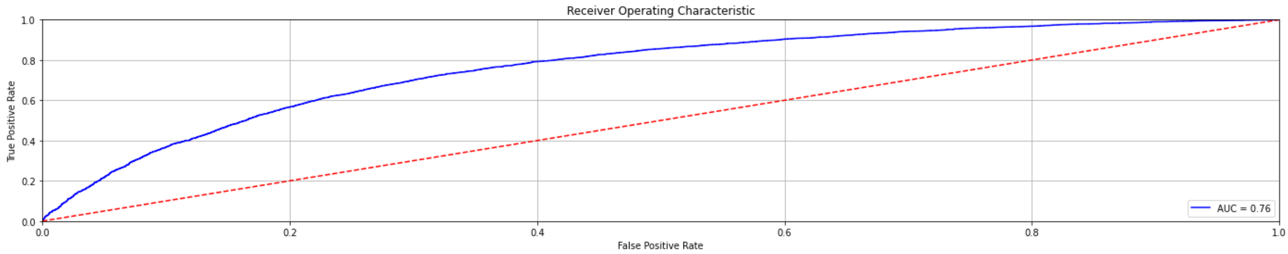
```
model_comparison_table["FastText (Max)"] = {
    "AUC": 0.7392006923537724, #roc_auc
    "Description": "FastText 300 (cc.en.300.vec.gz)"
}
```

```
X_emb = embed_corpus_min(X,embedder_model)
X_train_set, X_test, y_train_set, y_test,X_train, X_val, y_train, y_val =  spli
model = create_model(n_features=embedder_model.N_FEATURES)
roc_auc = train_and_evaluate_model(model)
```

```
Test: (10000, 300)
Train: (30000, 300)
Val: (10000, 300)
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_12 (Dense)             (None, 50)                15050
_________________________________________________________________
dropout_6 (Dropout)          (None, 50)                0
_________________________________________________________________
dense_13 (Dense)             (None, 50)                2550
_________________________________________________________________
dropout_7 (Dropout)          (None, 50)                0
_________________________________________________________________
dense_14 (Dense)             (None, 50)                2550
_________________________________________________________________
dense_15 (Dense)             (None, 1)                 51
=================================================================
Total params: 20,201
Trainable params: 20,201
Non-trainable params: 0
_________________________________________________________________
Epoch 1/30
938/938 [==============================] - 5s 4ms/step - loss: 0.6940 - auc:
Epoch 2/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6767 - auc:
Epoch 3/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6466 - auc:
Epoch 4/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6416 - auc:
Epoch 5/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6305 - auc:
Epoch 6/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6355 - auc:
Epoch 7/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6295 - auc:
Epoch 8/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6162 - auc:
Epoch 9/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6158 - auc:
Epoch 10/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6161 - auc:
Epoch 11/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6126 - auc:
Epoch 12/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6105 - auc:
Epoch 13/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6082 - auc:
Epoch 14/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6082 - auc:
Epoch 15/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6071 - auc:
Epoch 16/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6040 - auc:
Epoch 17/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6105 - auc:
Epoch 18/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6125 - auc:
Epoch 19/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6151 - auc:
```

```
Epoch 20/30
938/938 [==============================] - 4s 4ms/step - loss: 0.5981 - auc:
Epoch 21/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6060 - auc:
Epoch 22/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6057 - auc:
Epoch 23/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6066 - auc:
Epoch 24/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6012 - auc:
Epoch 25/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6052 - auc:
Epoch 26/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6002 - auc:
Epoch 27/30
938/938 [==============================] - 4s 4ms/step - loss: 0.5980 - auc:
Epoch 28/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6036 - auc:
Epoch 29/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6026 - auc:
Epoch 30/30
938/938 [==============================] - 4s 4ms/step - loss: 0.6023 - auc:
```






```
AUC: 0.7621117737390766
```

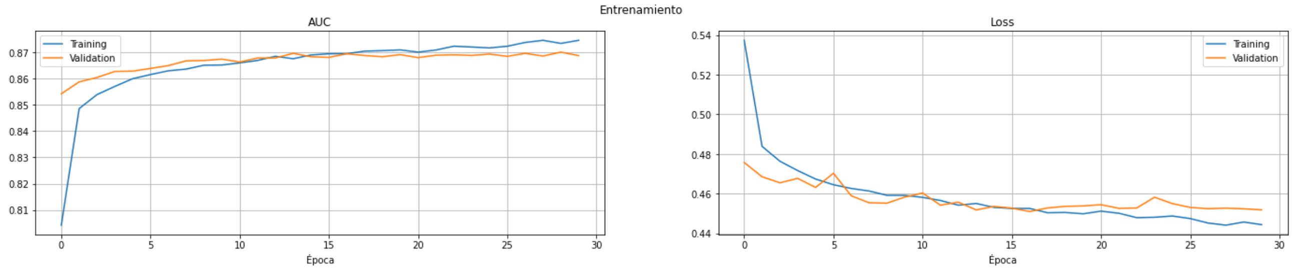
```
model_comparison_table["FastText (Min)"] = {
    "AUC": 0.7621117737390766, #roc_auc,
    "Description": "FastText 300 (cc.en.300.vec.gz)"
}
```

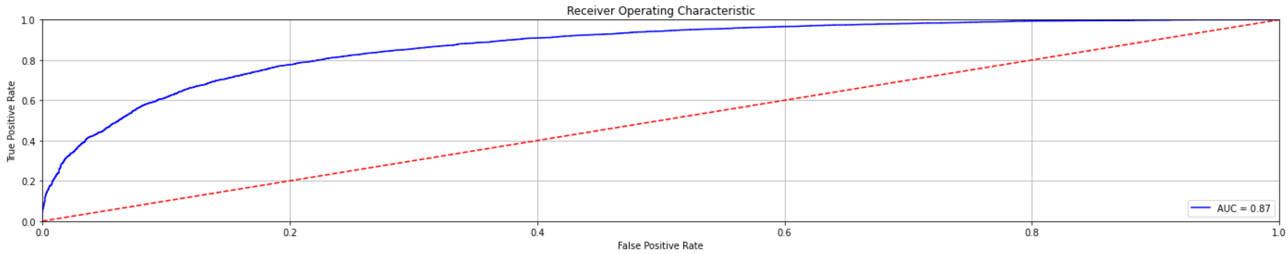
- Probar diferentes tamaños de embeddings.

```
embedder_model = GloveEmbeddings()
X_emb = embed_corpus_average(X,embedder_model)
X_train_set, X_test, y_train_set, y_test,X_train, X_val, y_train, y_val =  spli
model = create_model(n_features=embedder_model.N_FEATURES)
roc_auc = train_and_evaluate_model(model)
```

```
Test: (10000, 50)
Train: (30000, 50)
Val: (10000, 50)
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_16 (Dense)             (None, 50)                2550      
_________________________________________________________________
dropout_8 (Dropout)          (None, 50)                0         
_________________________________________________________________
dense_17 (Dense)             (None, 50)                2550      
_________________________________________________________________
dropout_9 (Dropout)          (None, 50)                0         
_________________________________________________________________
dense_18 (Dense)             (None, 50)                2550      
_________________________________________________________________
dense_19 (Dense)             (None, 1)                 51        
=================================================================
Total params: 7,701
Trainable params: 7,701
Non-trainable params: 0
_________________________________________________________________
Epoch 1/30
938/938 [==============================] - 5s 5ms/step - loss: 0.5966 - auc:
Epoch 2/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4832 - auc:
Epoch 3/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4755 - auc:
Epoch 4/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4736 - auc:
Epoch 5/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4654 - auc:
Epoch 6/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4645 - auc:
Epoch 7/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4577 - auc:
Epoch 8/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4599 - auc:
Epoch 9/30
938/938 [==============================] - 4s 5ms/step - loss: 0.4550 - auc:
Epoch 10/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4577 - auc:
Epoch 11/30
938/938 [==============================] - 4s 5ms/step - loss: 0.4530 - auc:
Epoch 12/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4597 - auc:
Epoch 13/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4492 - auc:
Epoch 14/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4550 - auc:
Epoch 15/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4536 - auc:
Epoch 16/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4516 - auc:
Epoch 17/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4560 - auc:
Epoch 18/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4532 - auc:
Epoch 19/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4567 - auc:
```

```
Epoch 20/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4485 - auc:
Epoch 21/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4478 - auc:
Epoch 22/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4498 - auc:
Epoch 23/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4515 - auc:
Epoch 24/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4514 - auc:
Epoch 25/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4468 - auc:
Epoch 26/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4421 - auc:
Epoch 27/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4455 - auc:
Epoch 28/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4500 - auc:
Epoch 29/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4464 - auc:
Epoch 30/30
938/938 [==============================] - 4s 4ms/step - loss: 0.4459 - auc:
```






```
AUC: 0.8682643656506908
```

```
model_comparison_table["GloVE"] = {
    "AUC": 0.8682643656506908, #roc_auc,
    "Description": "GloVE 50 (glove.twitter.27B.zip)"
}
```

5. Clasificador con LSTM

Entrenar un clasificador utilizando celdas LSTM.

- a. Convertir secuencias de palabras a secuencias de números (indexer).

- b. Agregar padding para que cada elemento de entrenamiento tenga la misma longitud.
- c. Armar una red LSTM con las siguientes capas:
    - Capa de embedding que transforma un número (index) en un embedding.
    - Agregar uno dos layers LSTM para obtener el embedding de la secuencias.
    - Agregar un layer denso para entrenar el clasificador.

```
X = df.review
y = df.target
```

```
from sklearn.model_selection import train_test_split

TRAIN_TEST_SPLIT = 0.2
TRAIN_VAL_SPLIT = 0.25

X_train_set, X_test, y_train_set, y_test = train_test_split(X, y, test_size=TRA
X_train, X_val, y_train, y_val = train_test_split(X_train_set,y_train_set,test_

print("Test:",X_test.shape)
print("Train:",X_train.shape)
print("Val:",X_val.shape)
```

```
Test: (10000,)
Train: (30000,)
Val: (10000,)
```

```
NUM_WORDS = 20000
EMBEDDING_DIM = 300
SEQ_LENGTH = 200
PADDING_TYPE='post'
TRUNC_TYPE='post'
```

```
from keras.preprocessing.text import Tokenizer
from keras.preprocessing.sequence import pad_sequences

tokenizer = Tokenizer(num_words=NUM_WORDS)
tokenizer.fit_on_texts(X_train)
```

```
X_train_seq = tokenizer.texts_to_sequences(X_train.values)
len(X_train_seq)
```

```
30000
```

```
X_val_seq = tokenizer.texts_to_sequences(X_val.values)
len(X_val_seq)
```

```
10000
```

```
X_train_padded = pad_sequences(X_train_seq,maxlen=SEQ_LENGTH,padding=PADDING_TY
X_train_padded[0]
```

```
array([    2,  1457,    45,    20,  1849,  8669,   108,    19,    20,
         975,    20,  1133,  1596,    20, 14595,    20,  2817,   107,
         432,  3899, 12386,   103,   730,  1894,  2921,  1023,  1495,
        4065,  2870,  4213,  2165, 10568,  3617,  3175,    55,    13,
         571,   370,  2234,    45,   690,  1067,  9428,  4647,    55,
          13,  2294,  1270,     1,     6,    14,  1397,  1825,  2119,
        1379,   190,  5526,  1379,  1849,  3110,  8669,   306,   519,
         255,  5031,   367,  1468,    64,    89,  1240,   838,     6,
        1002,  3155,  1044,  2772,   109,   679, 11510,  1497,  6063,
           0,     0,     0,     0,     0,     0,     0,     0,     0,
           0,     0,     0,     0,     0,     0,     0,     0,     0,
           0,     0,     0,     0,     0,     0,     0,     0,     0,
           0,     0,     0,     0,     0,     0,     0,     0,     0,
           0,     0,     0,     0,     0,     0,     0,     0,     0,
           0,     0,     0,     0,     0,     0,     0,     0,     0,
           0,     0,     0,     0,     0,     0,     0,     0,     0,
           0,     0,     0,     0,     0,     0,     0,     0,     0,
           0,     0,     0,     0,     0,     0,     0,     0,     0,
           0,     0,     0,     0,     0,     0,     0,     0,     0,
           0,     0,     0,     0,     0,     0,     0,     0,     0,
           0,     0,     0,     0,     0,     0,     0,     0,     0,
           0,     0,     0,     0,     0,     0,     0,     0,     0,
           0,     0], dtype=int32)
```

```
X_val_padded = pad_sequences(X_val_seq,maxlen=SEQ_LENGTH,padding=PADDING_TYPE,
X_val_padded[0]
```

```
array([    1,   237,  5663,  5361,   292,  2382,    62,  1394,    35,
          83,     4,   624,   148,    23,    10,  5361,  4153,     4,
        5088,  1085,  1150,     1,    23,   120,    14,   717,  5361,
        4065,  2870,  1676,   772,  6718,  1922,   916,     2,     5,
         158,   409,  3617,   120,  2927, 15458,     1,  8782,  5676,
       10622,  3468,   541,   845,   707,   314,    23,   714,   592,
         739, 16495,   420,  1597,  2709,   135,    34,  7040,   314,
         714,    83,  6040,   138,    38,  4678,  2615,    34,   221,
        1005,   120,  1286,    49,   558,    34,    24,    13,    20,
        1259,  8057,  4866,  4647,  1258, 10622,   115,    30,  4678,
        2988, 16495,  1625,  1686,  2140,  5937,   572,  2688,   297,
         253,    62, 15244,  2775,   615,   100,  3124,   245,  4409,
         253,  2080,   115,   669,   605,  3674,  1205,  1491,  7765,
         236,  2878,  9673,  2937,    32,     2,   174,   132, 16635,
           2,  4678,  8913,  2614,   355,  8039,  1952,  3843,   572,
        1113,   187,   212,   381,     1,   716,   825,  1492, 11700,
        6192,     5,    10,     1,  1777,     2,  3416,     9,     1,
         716,     1,   330,    51,   551,     2,     1,   284,   147,
          14,     2,  1306,   481, 19059,    39,     1,  5514,  2384,
           0,     0,     0,     0,     0,     0,     0,     0,     0,
           0,     0,     0,     0,     0,     0,     0,     0,     0,
           0,     0,     0,     0,     0,     0,     0,     0,     0,
           0,     0], dtype=int32)
```

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, LSTM, Dropout, Activation,

def create_model(vocab_size,embedding_dim):
  model = Sequential()

  model.add(Embedding(vocab_size,embedding_dim))
```

```
  model.add(Dropout(0.5))
  model.add(Bidirectional(LSTM(embedding_dim)))
  model.add(Dense(1,activation='sigmoid'))
  return model


model = create_model(NUM_WORDS,EMBEDDING_DIM)
model.summary()
```

```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, None, 300)         6000000
_________________________________________________________________
dropout_10 (Dropout)         (None, None, 300)         0
_________________________________________________________________
bidirectional (Bidirectional (None, 600)               1442400
_________________________________________________________________
dense_20 (Dense)             (None, 1)                 601
=================================================================
Total params: 7,443,001
Trainable params: 7,443,001
Non-trainable params: 0
_________________________________________________________________
```

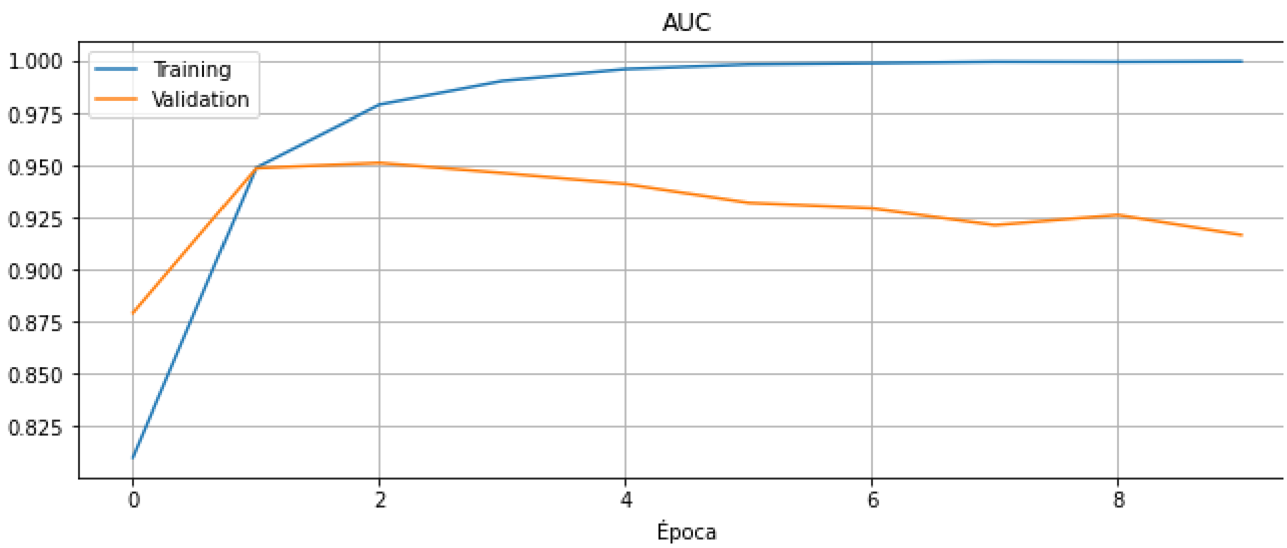
```
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.metrics import AUC

model.compile(
    loss='binary_crossentropy',
    optimizer=Adam(lr=0.001, decay=1e-6),
    metrics=[AUC(name="auc")],
)
```

```
NUM_EPOCHS = 10
history = model.fit(
    X_train_padded,
    y_train,
    epochs=NUM_EPOCHS,
    validation_data=(X_val_padded, y_val),
    verbose=True)
```

```
Epoch 1/10
938/938 [==============================] - 121s 120ms/step - loss: 0.6030 - a
Epoch 2/10
938/938 [==============================] - 112s 120ms/step - loss: 0.3128 - a
Epoch 3/10
938/938 [==============================] - 112s 120ms/step - loss: 0.1767 - a
Epoch 4/10
938/938 [==============================] - 112s 120ms/step - loss: 0.1043 - a
Epoch 5/10
938/938 [==============================] - 112s 119ms/step - loss: 0.0632 - a
Epoch 6/10
938/938 [==============================] - 112s 119ms/step - loss: 0.0357 - a
Epoch 7/10
```

```
938/938 [==============================] - 113s 120ms/step - loss: 0.0272 - a
Epoch 8/10
938/938 [==============================] - 112s 120ms/step - loss: 0.0154 - a
Epoch 9/10
938/938 [==============================] - 112s 120ms/step - loss: 0.0111 - a
Epoch 10/10
938/938 [==============================] - 112s 119ms/step - loss: 0.0077 - a
```

```
fig,axes = plt.subplots(1,2,figsize=(24,4))
plt.suptitle("LSTM")
axes[0].set_title("AUC")
axes[0].plot(np.arange(NUM_EPOCHS),history.history['auc'])
axes[0].plot(np.arange(NUM_EPOCHS),history.history['val_auc'])
axes[0].legend(["Training","Validation"])
axes[0].grid(which="Both")
axes[0].set_xlabel("Época")
axes[1].set_title("Loss")
axes[1].plot(np.arange(NUM_EPOCHS),history.history['loss'])
axes[1].plot(np.arange(NUM_EPOCHS),history.history['val_loss'])
axes[1].legend(["Training","Validation"])
axes[1].grid(which="Both")
axes[1].set_xlabel("Época")
plt.show()
```



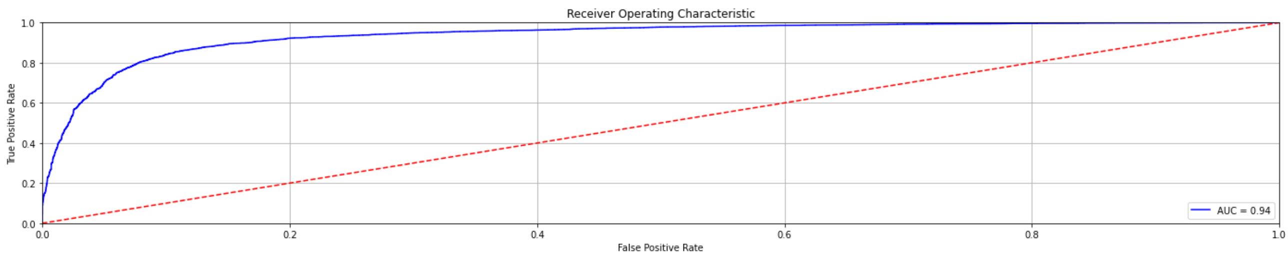
Se reentrena con una época para obtener el mejor modelo.

```
NUM_EPOCHS = 1
model = create_model(NUM_WORDS,EMBEDDING_DIM)
model.compile(loss='binary_crossentropy',optimizer=Adam(lr=0.001, decay=1e-6),
              metrics=[AUC(name="auc")])
history = model.fit(X_train_padded, y_train, epochs=NUM_EPOCHS,
                    validation_data=(X_val_padded, y_val), verbose=True)
```

```
938/938 [==============================] - 95s 99ms/step - loss: 0.5153 - auc
```

```
X_test_seq = tokenizer.texts_to_sequences(X_test.values)
X_test_padded = pad_sequences(X_test_seq,maxlen=SEQ_LENGTH,padding=PADDING_TYPE
y_test_pred = model.predict(X_test_padded)
```

```
import sklearn
from sklearn.metrics import auc

fpr, tpr, thresholds = sklearn.metrics.roc_curve(y_test.values, y_test_pred)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(24,4))
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.grid(which="Both")
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()

print("AUC:",roc_auc)
```




```
AUC: 0.9353843632321274
```

```
model_comparison_table["LSTM"] = {
    "AUC": 0.9353843632321274, # roc_auc,
    "Description": "LSTM c/ Keras Tokenizer"
}
```

6. Clasificador con BERT

Entrenar un clasificador utilizando BERT.

- a.Utilizar BERT sin fine-tuning.
- b.Utilizar BERT con fine-tuning.

Descargar BERT.

```
!pip install transformers > /dev/null 2>&1
```

Preparación de dataset para BERT

```
from sklearn.model_selection import train_test_split
TRAIN_TEST_SPLIT = 0.2
TRAIN_VAL_SPLIT = 0.25

X = df.review.values
y = df.target.values

X_train_set, X_test, y_train_set, y_test = train_test_split(X, y, test_size=TRA
X_train, X_val, y_train, y_val = train_test_split(X_train_set,y_train_set,test_
```

```
MAX_SEQ_LENGTH = 64
```

```
from transformers import BertTokenizer

PRETRAINED_MODEL_NAME = 'bert-base-uncased'
bert_tokenizer = BertTokenizer.from_pretrained(PRETRAINED_MODEL_NAME)
```

```
def batch_encode(X, tokenizer):
    return tokenizer.batch_encode_plus(
      X,
      max_length=MAX_SEQ_LENGTH,
      add_special_tokens=True, # [CLS] y [SEP] tokens
      return_attention_mask=True,
      return_token_type_ids=False, # no es necesario para clasificador
      pad_to_max_length=True,
      return_tensors='tf'
    )
```

```
X_train_bert = batch_encode(X_train,bert_tokenizer)
X_val_bert = batch_encode(X_val,bert_tokenizer)
X_test_bert = batch_encode(X_test,bert_tokenizer)
```

```
Truncation was not explicitly activated but `max_length` is provided a speci
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.p
  FutureWarning,
```

BERT sin fine-tuning

```
import tensorflow as tf
from tensorflow.keras.metrics import AUC
from transformers import TFBertForSequenceClassification

def create_bert_model_no_ft():
```

```
def create_bert_model_no_ft():
  bert_model = TFBertForSequenceClassification.from_pretrained(
      PRETRAINED_MODEL_NAME, num_labels=2)
  # Inputs:

  # Layer de input con cadenas de token Ids
  input_ids = tf.keras.layers.Input(shape=(MAX_SEQ_LENGTH,), dtype=tf.int32, na

  # Attention Mask. Máscara binaria para saber a qué tokens prestar atención y
  attention_mask = tf.keras.layers.Input((MAX_SEQ_LENGTH,), dtype=tf.int32, nam

  # Conectar salidas anteriores con entradas de BERT:
  output = bert_model([input_ids, attention_mask])[0]

  # Clasificación binaria
  output = tf.keras.layers.Dense(1, activation='sigmoid')(output)

  model = tf.keras.models.Model(inputs=[input_ids, attention_mask], outputs=out
  model.compile(
      optimizer=tf.keras.optimizers.Adam(learning_rate=3e-5),
      loss='binary_crossentropy',
      metrics=[AUC(name="auc")]
  )
  return model

model = create_bert_model_no_ft()
model.summary()
tf.keras.utils.plot_model( model )
```

```
All model checkpoint layers were used when initializing TFBertForSequenceClas

Some layers of TFBertForSequenceClassification were not initialized from the
You should probably TRAIN this model on a down-stream task to be able to use
The parameters `output_attentions`, `output_hidden_states` and `use_cache` ca
The parameter `return_dict` cannot be set in graph mode and will always be se
Model: "model_12"
_________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
=================================================================================
```

Entrenamiento BERT sin Fine Tuning.

```
attention_mask (InputLayer)     [(None, 64)]         0
```

Como los modelos con BERT tardan mucho en entrenar en Google Colab, se agregan los siguientes callbacks para detener el entrenamiento y obtener el mejor modelo cuando empieza a ocurrir overfitting.

```
Total params: 109,483,781
```

```
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint,ReduceLRO
model_fit_callbacks = [
  EarlyStopping(monitor='val_loss', patience=4, verbose=0, mode='min'),
  #ModelCheckpoint('bert_nofinetuning.hdf5', save_best_only=True, monitor='val_
  ReduceLROnPlateau(monitor='val_loss', factor=0.1, patience=2, verbose=1, min_
]
```

Lamentablemente ModelCheckpoint genera un error cuando se llama a save_model. TFBertForSequenceClassification no tiene implementado get_config()?.

Para reducir los tiempos de entrenamiento y poder aumentar la cantidad de épocas se trabajará con una partición de train/val reducida.

```
REDUX_SPLIT = 0.4
TRAIN_REDUX_SIZE = int(X_train.shape[0]*REDUX_SPLIT)
VAL_REDUX_SIZE = int(X_val.shape[0]*REDUX_SPLIT)
TRAIN_REDUX_SIZE, VAL_REDUX_SIZE
```

```
(12000, 4000)
```

```
train_redux_idx = np.random.choice(np.arange(0,X_train.shape[0]),size=TRAIN_RED
X_train_redux, y_train_redux = X_train[train_redux_idx],y_train[train_redux_idx

val_redux_idx = np.random.choice(np.arange(0,X_val.shape[0]),size=VAL_REDUX_SIZ
X_val_redux,y_val_redux = X_val[val_redux_idx],y_val[val_redux_idx]

X_train_redux_bert = batch_encode(X_train_redux,bert_tokenizer)
X_val_redux_bert = batch_encode(X_val_redux,bert_tokenizer)
```

```
/usr/local/lib/python3.6/dist-packages/transformers/tokenization_utils_base.p
  FutureWarning,
```

```
BATCH_SIZE=16
NUM_EPOCHS=10

model = create_bert_model_no_ft()
history = model.fit(
    x=X_train_redux_bert.values(),
    y=y_train_redux,
    validation_data=(X_val_redux_bert.values(), y_val_redux),
    callbacks=model_fit_callbacks,
    epochs=NUM_EPOCHS,
    batch_size=BATCH_SIZE
)
```

```
The parameters `output_attentions`, `output_hidden_states` and `use_cache` ca
Epoch 1/10
The parameter `return_dict` cannot be set in graph mode and will always be se
The parameters `output_attentions`, `output_hidden_states` and `use_cache` ca
The parameter `return_dict` cannot be set in graph mode and will always be se
750/750 [==============================] - ETA: 0s - loss: 0.5682 - auc: 0.73
The parameter `return_dict` cannot be set in graph mode and will always be se
750/750 [==============================] - 193s 245ms/step - loss: 0.5681 - a
Epoch 2/10
750/750 [==============================] - 193s 258ms/step - loss: 0.2686 - a
Epoch 3/10
750/750 [==============================] - 196s 261ms/step - loss: 0.1350 - a

Epoch 00003: ReduceLROnPlateau reducing learning rate to 2.9999999242136257e-
Epoch 4/10
750/750 [==============================] - 197s 262ms/step - loss: 0.0482 - a
Epoch 5/10
750/750 [==============================] - 197s 262ms/step - loss: 0.0181 - a

Epoch 00005: ReduceLROnPlateau reducing learning rate to 2.9999998787388907e-
```

```
NUM_EPOCHS_TRAINED = len(history.history["auc"])
fig,axes = plt.subplots(1,2,figsize=(24,4))
plt.suptitle("BERT con Fine Tuning")
axes[0].set_title("AUC")
axes[0].plot(np.arange(NUM_EPOCHS_TRAINED),history.history['auc'])
axes[0].plot(np.arange(NUM_EPOCHS_TRAINED),history.history['val_auc'])
axes[0].legend(["Training","Validation"])
axes[0].grid(which="Both")
axes[0].set_xlabel("Época")
axes[1].set_title("Loss")
axes[1].plot(np.arange(NUM_EPOCHS_TRAINED),history.history['loss'])
axes[1].plot(np.arange(NUM_EPOCHS_TRAINED),history.history['val_loss'])
axes[1].legend(["Training","Validation"])
axes[1].grid(which="Both")
axes[1].set_xlabel("Época")
plt.show()
```

Se reentrena con una época porque se vé que no hay una mejora luego. Esta vez se usa el

```
NUM_EPOCHS = 1
BATCH_SIZE=16
model = create_bert_model_no_ft()
history = model.fit(
    #x=X_train_redux_bert.values(),
    #y=y_train_redux,
    x=X_train_bert.values(),
    y=y_train,
    validation_data=(X_val_bert.values(), y_val),
    #validation_data=(X_val_redux_bert.values(), y_val_redux),
    #callbacks=model_fit_callbacks,
    epochs=NUM_EPOCHS,
    batch_size=BATCH_SIZE
)
```

```
All model checkpoint layers were used when initializing TFBertForSequenceClas

Some layers of TFBertForSequenceClassification were not initialized from the
You should probably TRAIN this model on a down-stream task to be able to use
The parameters `output_attentions`, `output_hidden_states` and `use_cache` ca
The parameter `return_dict` cannot be set in graph mode and will always be se
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The parameters `output_attentions`, `output_hidden_states` and `use_cache` ca
The parameter `return_dict` cannot be set in graph mode and will always be se
1875/1875 [==============================] - ETA: 0s - loss: 0.4464 - auc: 0.
The parameter `return_dict` cannot be set in graph mode and will always be se
1875/1875 [==============================] - 469s 245ms/step - loss: 0.4464 -
```
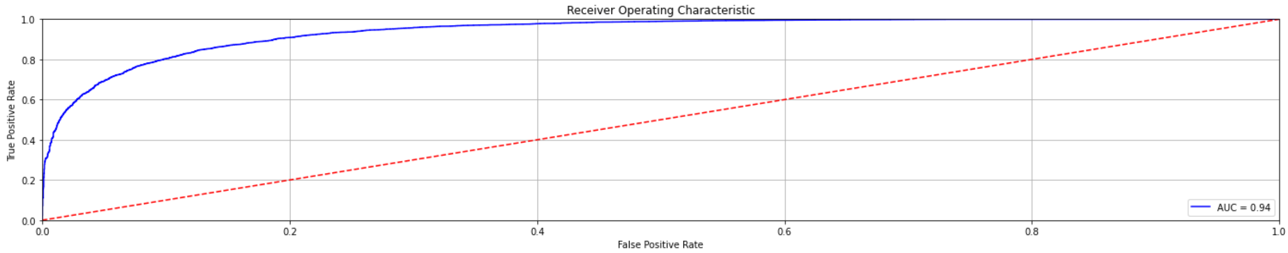

```
y_test_pred = model.predict([X_test_bert.input_ids,X_test_bert.attention_mask])
```

```
The parameters `output_attentions`, `output_hidden_states` and `use_cache` ca
The parameter `return_dict` cannot be set in graph mode and will always be se
```

```
import sklearn
from sklearn.metrics import auc

fpr, tpr, thresholds = sklearn.metrics.roc_curve(y_test, y_test_pred)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(24,4))
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.grid(which="Both")
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

```
print("AUC:",roc_auc)
```



AUC: 0.93906602808635

```
model_comparison_table["BERT-NoFT"] = {
    "AUC": 0.93906602808635, #roc_auc, #0.9257985149861581, # roc_auc,
    "Description": "BERT sin Fine Tuning"
}
```

BERT con fine-tuning

Ahora se entrenará la misma arquitectura del caso anterior pero con una capa agrega de Dropout y una capa densa.

```
def create_bert_model_ft():
  bert_model = TFBertForSequenceClassification.from_pretrained(PRETRAINED_MODEL
                                                           num_labels=2)
  # Inputs:

  # Layer de input con cadenas de token Ids
  input_ids = tf.keras.layers.Input(shape=(MAX_SEQ_LENGTH,), dtype=tf.int32, na

  # Attention Mask. Máscara binaria para saber a qué tokens prestar atención y
  attention_mask = tf.keras.layers.Input((MAX_SEQ_LENGTH,), dtype=tf.int32, nam

  # Conectar salidas anteriores con entradas de BERT:
  output = bert_model([input_ids, attention_mask])[0]

  # Capas custom
  output = tf.keras.layers.Dropout(rate=0.15)(output)
  output = tf.keras.layers.Dense(64)(output)

  # Clasificación binaria
  output = tf.keras.layers.Dense(1, activation='sigmoid')(output)

  model = tf.keras.models.Model(inputs=[input_ids, attention_mask], outputs=out

  model.compile(
      optimizer=tf.keras.optimizers.Adam(learning_rate=3e-5),
      loss='binary crossentropy',
```

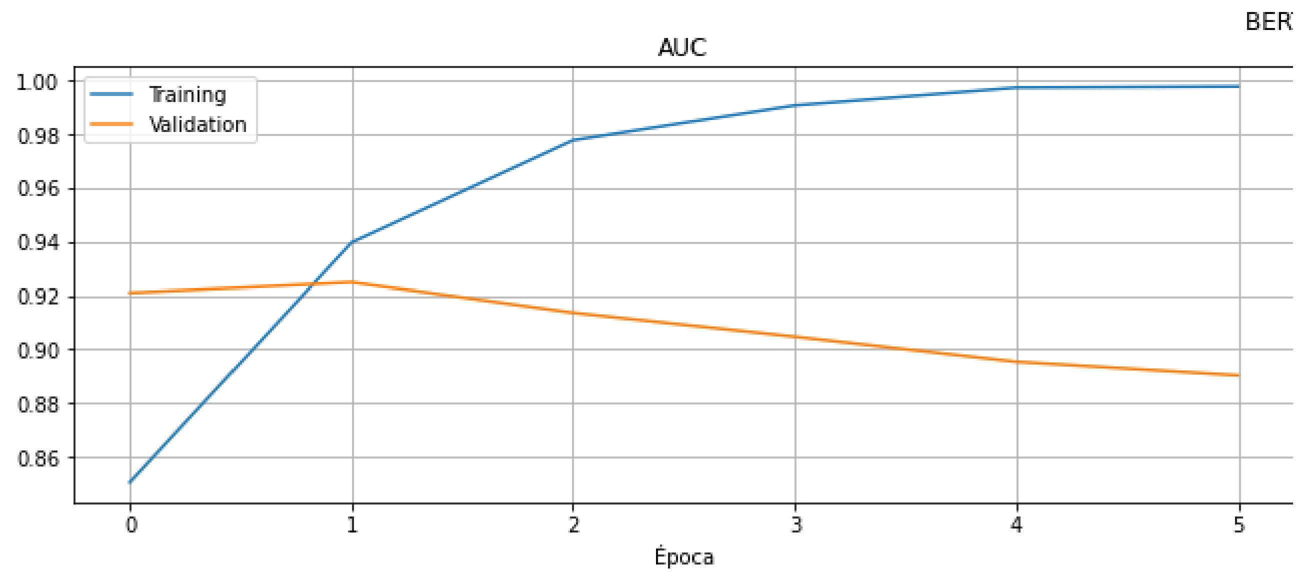
```
      metrics=[AUC(name="auc")]
  )
  return model
```

```
model = create_bert_model_ft()
model.summary()
tf.keras.utils.plot_model( model )

BATCH_SIZE=16
NUM_EPOCHS=10

history = model.fit(
    x=X_train_redux_bert.values(),
    y=y_train_redux,
    validation_data=(X_val_redux_bert.values(), y_val_redux),
    callbacks=model_fit_callbacks,
    epochs=NUM_EPOCHS,
    batch_size=BATCH_SIZE
)
```

```
All model checkpoint layers were used when initializing TFBertForSequenceClas

Some layers of TFBertForSequenceClassification were not initialized from the
You should probably TRAIN this model on a down-stream task to be able to use
The parameters `output_attentions`, `output_hidden_states` and `use_cache` ca
The parameter `return_dict` cannot be set in graph mode and will always be se
Model: "model_2"
________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
================================================================================
input_ids (InputLayer)          [(None, 64)]         0
________________________________________________________________________________
attention_mask (InputLayer)     [(None, 64)]         0
________________________________________________________________________________
tf_bert_for_sequence_classifica TFSequenceClassifier 109483778   input_ids[0]
                                                                 attention_ma
________________________________________________________________________________
dropout_115 (Dropout)           (None, 2)            0           tf_bert_for_
________________________________________________________________________________
dense_3 (Dense)                 (None, 64)           192         dropout_115[
________________________________________________________________________________
dense_4 (Dense)                 (None, 1)            65          dense_3[0][0
================================================================================
Total params: 109,484,035
Trainable params: 109,484,035
Non-trainable params: 0
________________________________________________________________________________
The parameters `output_attentions`, `output_hidden_states` and `use_cache` ca
The parameter `return_dict` cannot be set in graph mode and will always be se
Epoch 1/10
The parameters `output_attentions`, `output_hidden_states` and `use_cache` ca
The parameter `return_dict` cannot be set in graph mode and will always be se
750/750 [==============================] - ETA: 0s - loss: 0.5619 - auc: 0.75
The parameter `return_dict` cannot be set in graph mode and will always be se
750/750 [==============================] - 185s 235ms/step - loss: 0.5618 - a
Epoch 2/10
750/750 [==============================] - 180s 240ms/step - loss: 0.3153 - a
Epoch 3/10
```

```
750/750 [==============================] - 181s 241ms/step - loss: 0.1737 - a
Epoch 4/10
750/750 [==============================] - 182s 243ms/step - loss: 0.1116 - a

Epoch 00004: ReduceLROnPlateau reducing learning rate to 2.9999999242136257e-
Epoch 5/10
750/750 [==============================] - 183s 244ms/step - loss: 0.0595 - a
Epoch 6/10
750/750 [==============================] - 183s 243ms/step - loss: 0.0443 - a

Epoch 00006: ReduceLROnPlateau reducing learning rate to 2.9999998787388907e-
```

```
NUM_EPOCHS_TRAINED = len(history.history["auc"])
fig,axes = plt.subplots(1,2,figsize=(24,4))
plt.suptitle("BERT con Fine Tuning")
axes[0].set_title("AUC")
axes[0].plot(np.arange(NUM_EPOCHS_TRAINED),history.history['auc'])
axes[0].plot(np.arange(NUM_EPOCHS_TRAINED),history.history['val_auc'])
axes[0].legend(["Training","Validation"])
axes[0].grid(which="Both")
axes[0].set_xlabel("Época")
axes[1].set_title("Loss")
axes[1].plot(np.arange(NUM_EPOCHS_TRAINED),history.history['loss'])
axes[1].plot(np.arange(NUM_EPOCHS_TRAINED),history.history['val_loss'])
axes[1].legend(["Training","Validation"])
axes[1].grid(which="Both")
axes[1].set_xlabel("Época")
plt.show()
```




```
model = create_bert_model_ft()
BATCH_SIZE=16
NUM_EPOCHS=1
history = model.fit(
    #x=X_train_redux_bert.values(),
    #y=y_train_redux,
    x=X_train_bert.values(),
```