CLASIFICACIÓN AUTOMÁTICA DE RESEÑAS DE PELÍCULAS CON TÉCNICAS DE NLP Y BERT EMBEDDINGS

Descripcipción del proyecto

Film Junky Union es una comunidad para los amantes del cine clásico que busca mejorar la interacción con sus usuarios mediante un sistema de **clasificación automática de reseñas cinematográficas**.
El proyecto consiste en entrenar y comparar distintos modelos de *Machine Learning* y *Deep Learning* para detectar reseñas **negativas o positivas** en un conjunto de datos real de **IMDB**.

Objetivos del Proyecto

1. **Desarrollar un modelo predictivo** capaz de identificar automáticamente el tono (positivo o negativo) de una reseña de película.
2. **Evaluar distintos enfoques de NLP**, desde representaciones clásicas de texto (TF-IDF) hasta embeddings contextuales (BERT).
3. **Comparar métricas de rendimiento (Accuracy, F1, AUC)** entre modelos tradicionales y modernos.
4. **Determinar el modelo más eficiente** en cuanto a equilibrio entre precisión, costo computacional y capacidad de generalización.
5. **Explorar el potencial de BERT** como modelo preentrenado en tareas de análisis de sentimiento a gran escala.

Modelos Probados

Modelo	Técnica Principal	Descripción Breve
Dummy Classifier	Predicción constante	Modelo base sin aprendizaje, usado cor
NLTK + TF-IDF + LR	Vectorización con TF-IDF y Regresión Logística	Modelo clásico, rápido y altamente efec
spaCy + TF-IDF + LR	Lemmatización avanzada + TF-IDF	Mejora la normalización lingüística, perc

spaCy + TF-IDF + LightGBM	Ensamble por gradiente	Modelo más complejo con ligera pérdid
BERT + Logistic Regression	Embeddings contextuales (Transformers)	Captura semántica profunda, con result

Inicialización

```
import math

import numpy as np
import pandas as pd
import warnings
import matplotlib
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
import seaborn as sns
import lightgbm as lgb
from tqdm.auto import tqdm

import re
```

```
%matplotlib inline
%config InlineBackend.figure_format = 'png'
# la siguiente línea proporciona gráficos de mejor calidad en pantallas H:
# %config InlineBackend.figure_format = 'retina'

# plt.style.use('seaborn')
```

Cargar datos

```
df_reviews = pd.read_csv('imdb_reviews.tsv', sep='\t', dtype={'votes': 'I
```

```
df_reviews
```

	tconst	title_type	primary_title	original_title	start_year	end_y
0	tt0068152	movie	$	$	1971	

1	tt0068152	movie	$	$	1971
2	tt0313150	short	'15'	'15'	2002
3	tt0313150	short	'15'	'15'	2002
4	tt0313150	short	'15'	'15'	2002
...	...	...	...	...	...
47326	tt0068398	tvEpisode	Étude in Black	Étude in Black	1972
47327	tt0223503	tvMovie	Îhatôbu gensô: KENjI no haru	Îhatôbu gensô: KENjI no haru	1996
47328	tt0223503	tvMovie	Îhatôbu gensô: KENjI no haru	Îhatôbu gensô: KENjI no haru	1996
47329	tt0223503	tvMovie	Îhatôbu gensô: KENjI no haru	Îhatôbu gensô: KENjI no haru	1996

47330	tt0223503	tvMovie	Îhatôbu gensô: KENjI no haru	Îhatôbu gensô: KENjI no haru	1996

47331 rows × 17 columns

Next steps: Generate code with df_reviews | New interactive sheet

```
df_reviews.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 47331 entries, 0 to 47330
Data columns (total 17 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   tconst           47331 non-null  object
 1   title_type       47331 non-null  object
 2   primary_title    47331 non-null  object
 3   original_title   47331 non-null  object
 4   start_year       47331 non-null  int64
 5   end_year         47331 non-null  object
 6   runtime_minutes  47331 non-null  object
 7   is_adult         47331 non-null  int64
 8   genres           47331 non-null  object
 9   average_rating   47329 non-null  float64
 10  votes            47329 non-null  Int64
 11  review           47331 non-null  object
 12  rating           47331 non-null  int64
 13  sp               47331 non-null  object
 14  pos              47331 non-null  int64
 15  ds_part          47331 non-null  object
 16  idx              47331 non-null  int64
dtypes: Int64(1), float64(1), int64(5), object(10)
memory usage: 6.2+ MB
```

```
# Mostramos los reviews repetidos
df_reviews['review'].duplicated().sum()
```

```
np.int64(91)
```

```
# Eliminamos los duplicados
df_reviews = df_reviews.drop_duplicates(subset='review').reset_index(drop=
```

```
df_reviews.info()
```

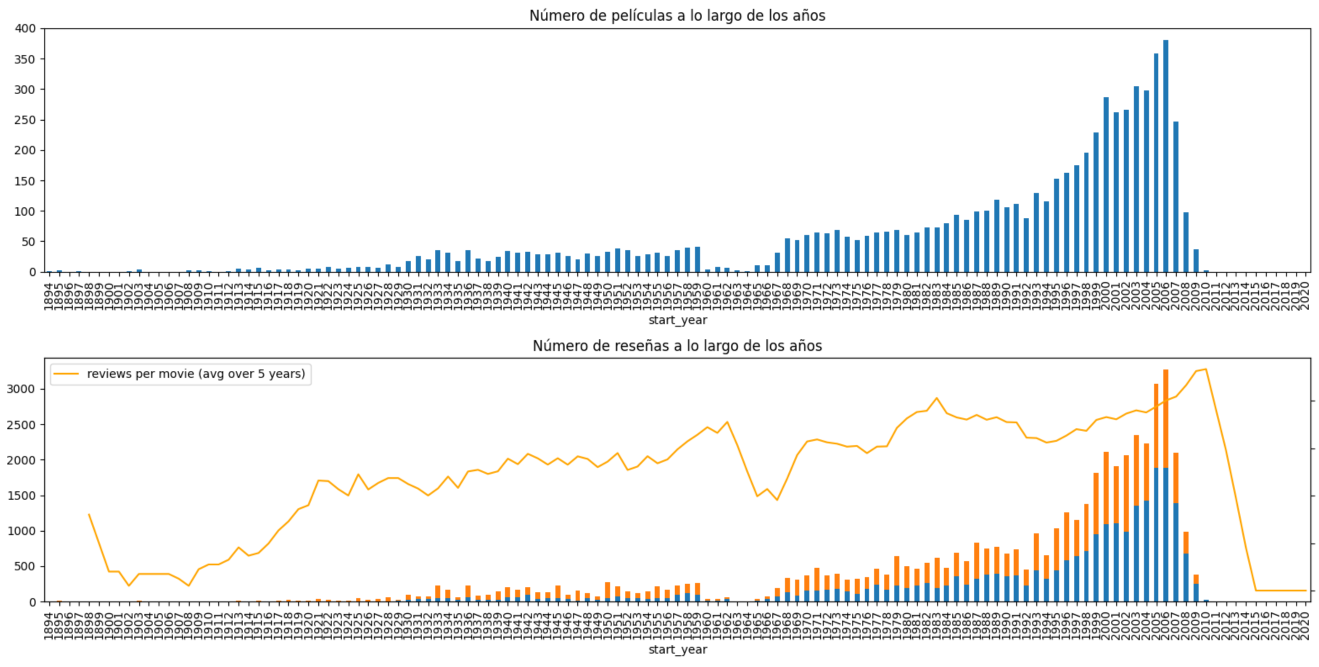
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 47240 entries, 0 to 47239
Data columns (total 17 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   tconst           47240 non-null  object
 1   title_type       47240 non-null  object
 2   primary_title    47240 non-null  object
 3   original_title   47240 non-null  object
 4   start_year       47240 non-null  int64
 5   end_year         47240 non-null  object
 6   runtime_minutes  47240 non-null  object
 7   is_adult         47240 non-null  int64
 8   genres           47240 non-null  object
 9   average_rating   47238 non-null  float64
 10  votes            47238 non-null  Int64
 11  review           47240 non-null  object
 12  rating           47240 non-null  int64
 13  sp               47240 non-null  object
 14  pos              47240 non-null  int64
 15  ds_part          47240 non-null  object
 16  idx              47240 non-null  int64
dtypes: Int64(1), float64(1), int64(5), object(10)
memory usage: 6.2+ MB
```

EDA

Veamos el número de películas y reseñas a lo largo de los años.

```
fig, axs = plt.subplots(2, 1, figsize=(16, 8))

ax = axs[0]

dft1 = df_reviews[['tconst', 'start_year']].drop_duplicates() \
    ['start_year'].value_counts().sort_index()
dft1 = dft1.reindex(index=np.arange(dft1.index.min(), max(dft1.index.max(
dft1.plot(kind='bar', ax=ax)
ax.set_title('Número de películas a lo largo de los años')
```

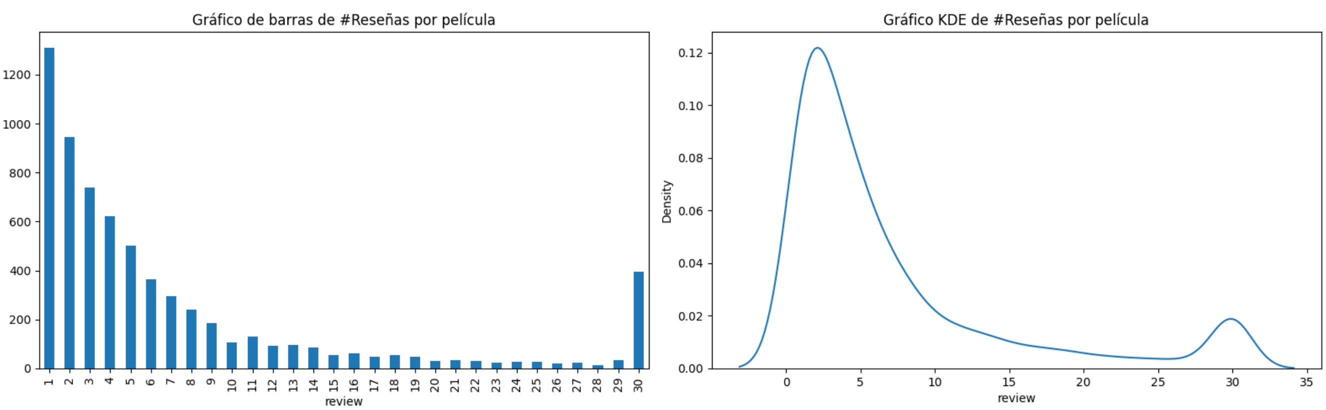
```
ax = axs[1]

dft2 = df_reviews.groupby(['start_year', 'pos'])['pos'].count().unstack()
dft2 = dft2.reindex(index=np.arange(dft2.index.min(), max(dft2.index.max(

dft2.plot(kind='bar', stacked=True, label='#reviews (neg, pos)', ax=ax)

dft2 = df_reviews['start_year'].value_counts().sort_index()
dft2 = dft2.reindex(index=np.arange(dft2.index.min(), max(dft2.index.max(
dft3 = (dft2/dft1).fillna(0)
axt = ax.twinx()
dft3.reset_index(drop=True).rolling(5).mean().plot(color='orange', label=

lines, labels = axt.get_legend_handles_labels()
ax.legend(lines, labels, loc='upper left')

ax.set_title('Número de reseñas a lo largo de los años')

fig.tight_layout()
```



Podemos apreciar que el numero de peliculas por año tiene una tendencia a crecer

Veamos la distribución del número de reseñas por película con el conteo exacto y KDE (solo para saber cómo puede diferir del conteo exacto)

```python
fig, axs = plt.subplots(1, 2, figsize=(16, 5))

ax = axs[0]
dft = df_reviews.groupby('tconst')['review'].count() \
    .value_counts() \
    .sort_index()
dft.plot.bar(ax=ax)
ax.set_title('Gráfico de barras de #Reseñas por película')

ax = axs[1]
dft = df_reviews.groupby('tconst')['review'].count()
sns.kdeplot(dft, ax=ax)
ax.set_title('Gráfico KDE de #Reseñas por película')

fig.tight_layout()
```



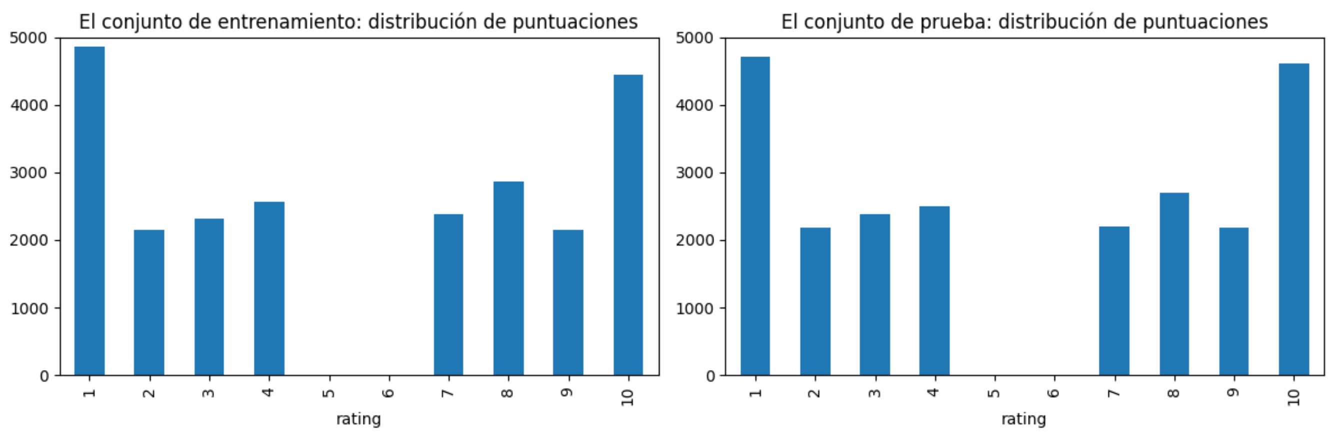
Podemos apreciar que el numero de reseñas por pelicula decrece menos en 30 que puede ser porque es una pelicula muy esperada o popular, por lo demas la tendencia a muchas reseñas es decreciente

```
df_reviews['pos'].value_counts()
```

pos	count
0	23680
1	23560

dtype: int64

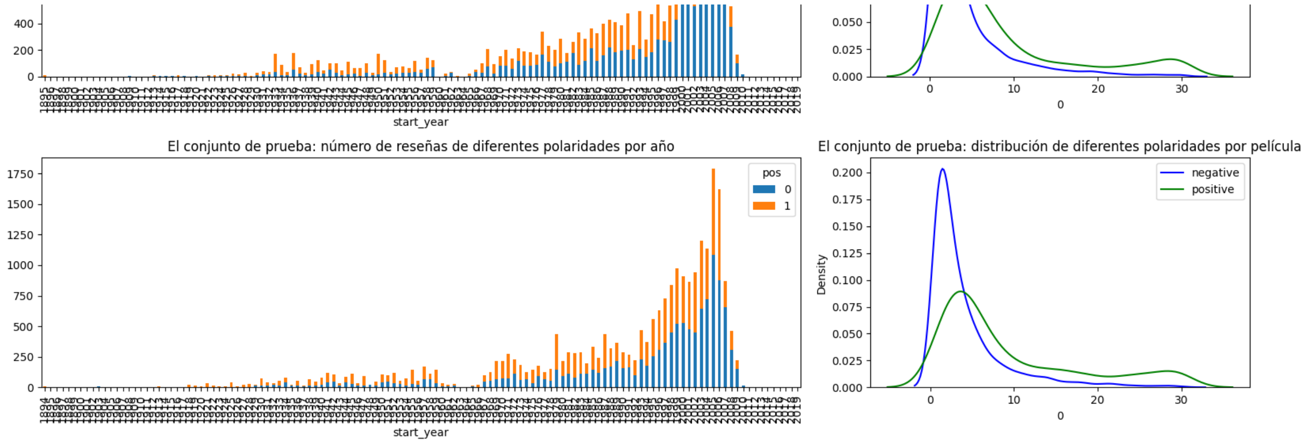
```
fig, axs = plt.subplots(1, 2, figsize=(12, 4))

ax = axs[0]
dft = df_reviews.query('ds_part == "train"')['rating'].value_counts().sor
dft = dft.reindex(index=np.arange(min(dft.index.min(), 1), max(dft.index.r
dft.plot.bar(ax=ax)
ax.set_ylim([0, 5000])
ax.set_title('El conjunto de entrenamiento: distribución de puntuaciones'

ax = axs[1]
dft = df_reviews.query('ds_part == "test"')['rating'].value_counts().sort_
dft = dft.reindex(index=np.arange(min(dft.index.min(), 1), max(dft.index.r
dft.plot.bar(ax=ax)
ax.set_ylim([0, 5000])
ax.set_title('El conjunto de prueba: distribución de puntuaciones')

fig.tight_layout()
```



Podemos apreciar que estan bien distribuidas entre el dataset de train y test

Distribución de reseñas negativas y positivas a lo largo de los años para dos partes del conjunto de datos

```
fig, axs = plt.subplots(2, 2, figsize=(16, 8), gridspec_kw=dict(width_rat

ax = axs[0][0]

dft = df_reviews.query('ds_part == "train"').groupby(['start_year', 'pos']
dft.index = dft.index.astype('int')
dft = dft.reindex(index=np.arange(dft.index.min(), max(dft.index.max(), 2(
dft.plot(kind='bar', stacked=True, ax=ax)
ax.set_title('El conjunto de entrenamiento: número de reseñas de diferente

ax = axs[0][1]

dft = df_reviews.query('ds_part == "train"').groupby(['tconst', 'pos'])['
sns.kdeplot(dft[0], color='blue', label='negative', ax=ax)
sns.kdeplot(dft[1], color='green', label='positive', ax=ax)
ax.legend()
ax.set_title('El conjunto de entrenamiento: distribución de diferentes po

ax = axs[1][0]

dft = df_reviews.query('ds_part == "test"').groupby(['start_year', 'pos']
dft.index = dft.index.astype('int')
dft = dft.reindex(index=np.arange(dft.index.min(), max(dft.index.max(), 2(
dft.plot(kind='bar', stacked=True, ax=ax)
ax.set_title('El conjunto de prueba: número de reseñas de diferentes pola

ax = axs[1][1]

dft = df_reviews.query('ds_part == "test"').groupby(['tconst', 'pos'])['p
sns.kdeplot(dft[0], color='blue', label='negative', ax=ax)
sns.kdeplot(dft[1], color='green', label='positive', ax=ax)
ax.legend()
ax.set_title('El conjunto de prueba: distribución de diferentes polaridade

fig.tight_layout()
```



Podemos apreciar que tambien estan correctamente distribuidos

Procedimiento de evaluación

Composición de una rutina de evaluación que se pueda usar para todos los modelos en este proyecto

```
import sklearn.metrics as metrics
def evaluate_model(model, train_features, train_target, test_features, te
```

```
    eval_stats = {}

    fig, axs = plt.subplots(1, 3, figsize=(20, 6))

    for type, features, target in (('train', train_features, train_target

        eval_stats[type] = {}

        pred_target = model.predict(features)
        pred_proba = model.predict_proba(features)[:, 1]

        # F1
        f1_thresholds = np.arange(0, 1.01, 0.05)
        f1_scores = [metrics.f1_score(target, pred_proba>=threshold) for

        # ROC
        fpr, tpr, roc_thresholds = metrics.roc_curve(target, pred_proba)
        roc_auc = metrics.roc_auc_score(target, pred_proba)
        eval_stats[type]['ROC AUC'] = roc_auc

        # PRC
        precision, recall, pr_thresholds = metrics.precision_recall_curve
        aps = metrics.average_precision_score(target, pred_proba)
        eval_stats[type]['APS'] = aps

        if type == 'train':
            color = 'blue'
        else:
            color = 'green'

        # Valor F1
        ax = axs[0]
        max_f1_score_idx = np.argmax(f1_scores)
        ax.plot(f1_thresholds, f1_scores, color=color, label=f'{type}, ma
        # establecer cruces para algunos umbrales
        for threshold in (0.2, 0.4, 0.5, 0.6, 0.8):
            closest_value_idx = np.argmin(np.abs(f1_thresholds-threshold)
            marker_color = 'orange' if threshold != 0.5 else 'red'
            ax.plot(f1_thresholds[closest_value_idx], f1_scores[closest_v
        ax.set_xlim([-0.02, 1.02])
        ax.set_ylim([-0.02, 1.02])
        ax.set_xlabel('threshold')
        ax.set_ylabel('F1')
        ax.legend(loc='lower center')
        ax.set_title(f'Valor F1')
```

```
        # ROC
        ax = axs[1]
        ax.plot(fpr, tpr, color=color, label=f'{type}, ROC AUC={roc_auc:.2
        # establecer cruces para algunos umbrales
        for threshold in (0.2, 0.4, 0.5, 0.6, 0.8):
            closest_value_idx = np.argmin(np.abs(roc_thresholds-threshold
            marker_color = 'orange' if threshold != 0.5 else 'red'
            ax.plot(fpr[closest_value_idx], tpr[closest_value_idx], color=
        ax.plot([0, 1], [0, 1], color='grey', linestyle='--')
        ax.set_xlim([-0.02, 1.02])
        ax.set_ylim([-0.02, 1.02])
        ax.set_xlabel('FPR')
        ax.set_ylabel('TPR')
        ax.legend(loc='lower center')
        ax.set_title(f'Curva ROC')

        # PRC
        ax = axs[2]
        ax.plot(recall, precision, color=color, label=f'{type}, AP={aps:.2
        # establecer cruces para algunos umbrales
        for threshold in (0.2, 0.4, 0.5, 0.6, 0.8):
            closest_value_idx = np.argmin(np.abs(pr_thresholds-threshold)
            marker_color = 'orange' if threshold != 0.5 else 'red'
            ax.plot(recall[closest_value_idx], precision[closest_value_idx
        ax.set_xlim([-0.02, 1.02])
        ax.set_ylim([-0.02, 1.02])
        ax.set_xlabel('recall')
        ax.set_ylabel('precision')
        ax.legend(loc='lower center')
        ax.set_title(f'PRC')

        eval_stats[type]['Accuracy'] = metrics.accuracy_score(target, pred
        eval_stats[type]['F1'] = metrics.f1_score(target, pred_target)

    df_eval_stats = pd.DataFrame(eval_stats)
    df_eval_stats = df_eval_stats.round(2)
    df_eval_stats = df_eval_stats.reindex(index=('Accuracy', 'F1', 'APS',

    print(df_eval_stats)

    return
```

Normalización

Suponemos que todos los modelos a continuación aceptan textos en minúsculas y sin dígitos, signos de puntuación, etc.

```
pattern = r'[^a-zA-Z]'

def clean_text(text):
    text = text.lower()
    text = re.sub(pattern, ' ', text)
    text = text.split()
    text = ' '.join(text)
    return text

df_reviews['review_norm'] = df_reviews['review'].apply(clean_text)
df_reviews['review_norm']
```

	review_norm
0	the pakage implies that warren beatty and gold...
1	how the hell did they get this made presenting...
2	there is no real story the film seems more lik...
3	um a serious film about troubled teens in sing...
4	i m totally agree with garryjohal from singapo...
...	...
47235	this is another of my favorite columbos it spo...
47236	talk about being boring i got this expecting a...
47237	i never thought i d say this about a biopic bu...
47238	spirit and chaos is an artistic biopic of miya...
47239	i ll make this brief this was a joy to watch i...

47240 rows × 1 columns

dtype: object

División entrenamiento / prueba

Por fortuna, todo el conjunto de datos ya está dividido en partes de entrenamiento/prueba; 'ds_part' es el indicador correspondiente.

```
features_train = df_reviews.query('ds_part == "train"').copy()
features_test = df_reviews.query('ds_part == "test"').copy()

target_train = features_train['pos']
target_test = features_test['pos']

features_train = features_train.drop(columns='pos')
features_test = features_test.drop(columns='pos')

print(features_train.shape)
print(features_test.shape)
```

```
(23757, 17)
(23483, 17)
```

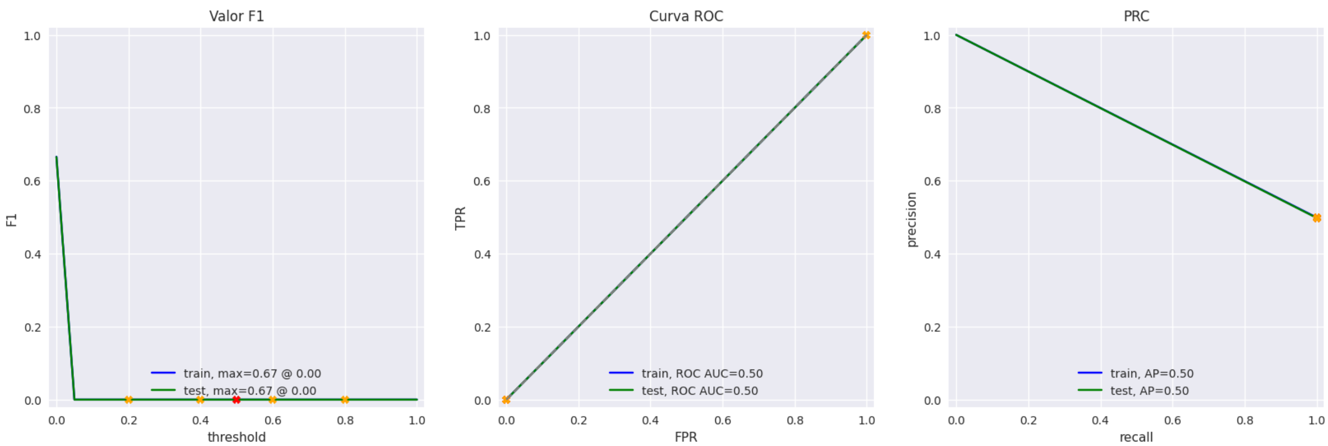
Trabajar con modelos

Modelo 0 - Constante

```
from sklearn.dummy import DummyClassifier
```

```
model_0 = DummyClassifier(strategy="most_frequent", random_state=42)

model_0.fit(np.zeros((len(target_train), 1)), target_train)

evaluate_model(
    model_0,
    np.zeros((len(target_train), 1)), target_train,
    np.zeros((len(target_test), 1)), target_test
)
```

```
          train  test
Accuracy    0.5   0.5
F1          0.0   0.0
APS         0.5   0.5
ROC AUC     0.5   0.5
```



Modelo 1 - NLTK, TF-IDF y LR

TF-IDF

```
import nltk

from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from nltk.corpus import stopwords
nltk.download('stopwords', quiet=True)
```

```
True
```

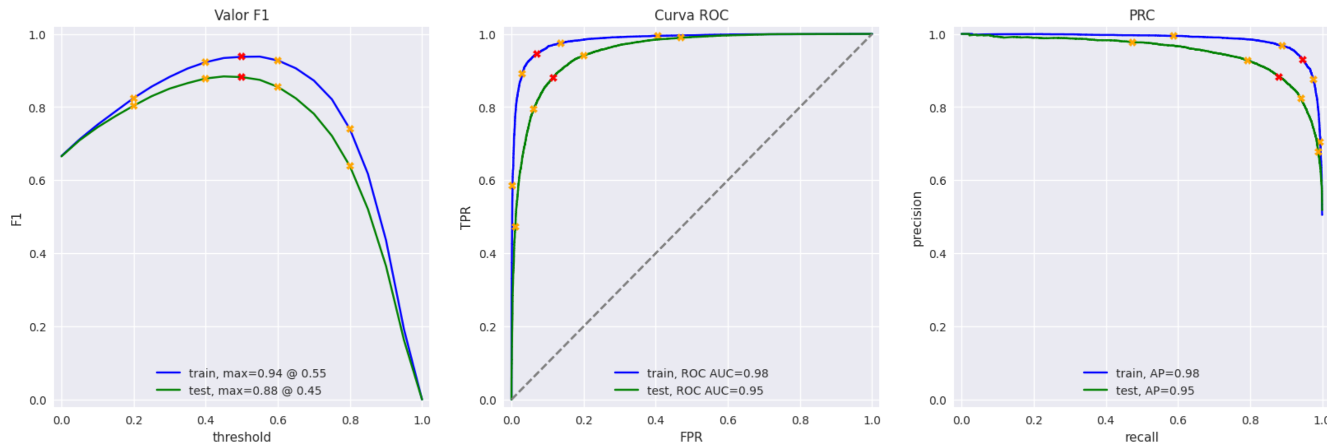
```
train = features_train['review_norm']
test = features_test['review_norm']

stop_words = set(stopwords.words('english'))
tf_idf = TfidfVectorizer(stop_words=stop_words)

X_train_lr = tf_idf.fit_transform(train)
X_test_lr = tf_idf.transform(test)
```

```
model_lr = LogisticRegression(solver='liblinear')
model_lr.fit(X_train_lr, target_train)
```

```
LogisticRegression(solver='liblinear')
```

```
evaluate_model(model_lr, X_train_lr, target_train, X_test_lr, target_test
```

```
          train  test
Accuracy   0.94  0.88
F1         0.94  0.88
APS        0.98  0.95
ROC AUC    0.98  0.95
```



Modelo 3 - spaCy, TF-IDF y LR

```
import spacy
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report, confus

train = features_train['review_norm']
test  = features_test['review_norm']

model_name = "en_core_web_sm"
nlp = spacy.load(model_name, disable=["ner", "parser", "textcat"])

def spacy_clean_texts(texts, batch_size=256, n_process=2):
    docs = nlp.pipe(texts, batch_size=batch_size, n_process=n_process)
    cleaned = []
    for doc in docs:
        toks = [
            tok.lemma_.lower()
            for tok in doc
            if not (tok.is_stop or tok.is_punct or tok.is_space or tok.lil
            and len(tok) > 2
        ]
        cleaned.append(" ".join(toks))
    return cleaned

train_clean = spacy_clean_texts(features_train['review_norm'])
test_clean  = spacy_clean_texts(features_test['review_norm'])
```

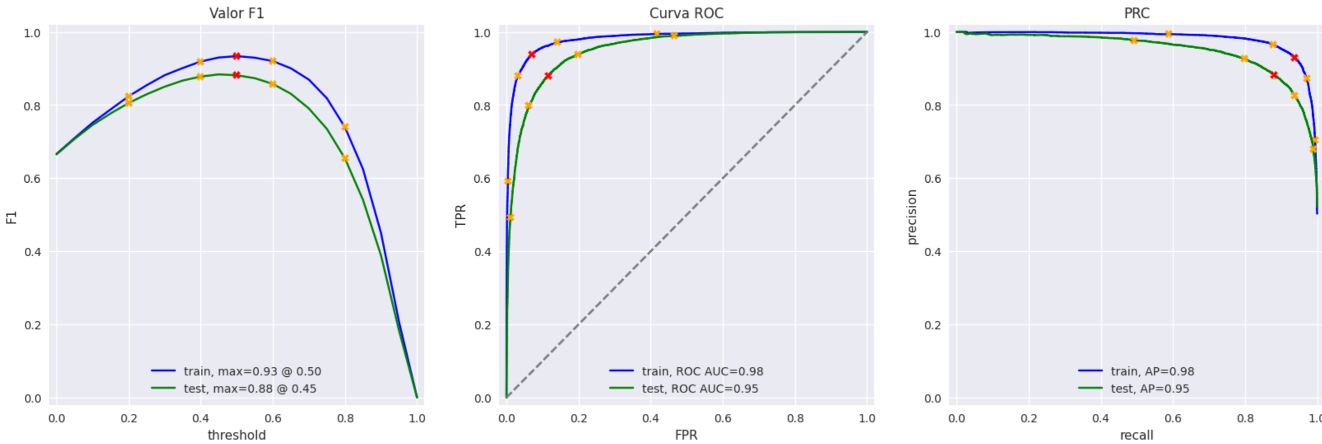
```
tf_idf_sp = TfidfVectorizer(ngram_range=(1,1), min_df=1, max_df=1.0)

X_train_sp = tf_idf_sp.fit_transform(train)
X_test_sp  = tf_idf_sp.transform(test)
```

```
model_lr_sp = LogisticRegression(solver='liblinear', max_iter=1000)
model_lr_sp.fit(X_train_sp, target_train)
```

```
LogisticRegression(max_iter=1000, solver='liblinear')
```

```
evaluate_model(model_lr_sp, X_train_sp, target_train, X_test_sp, target_te
```

	train	test
Accuracy	0.93	0.88
F1	0.93	0.88
APS	0.98	0.95
ROC AUC	0.98	0.95



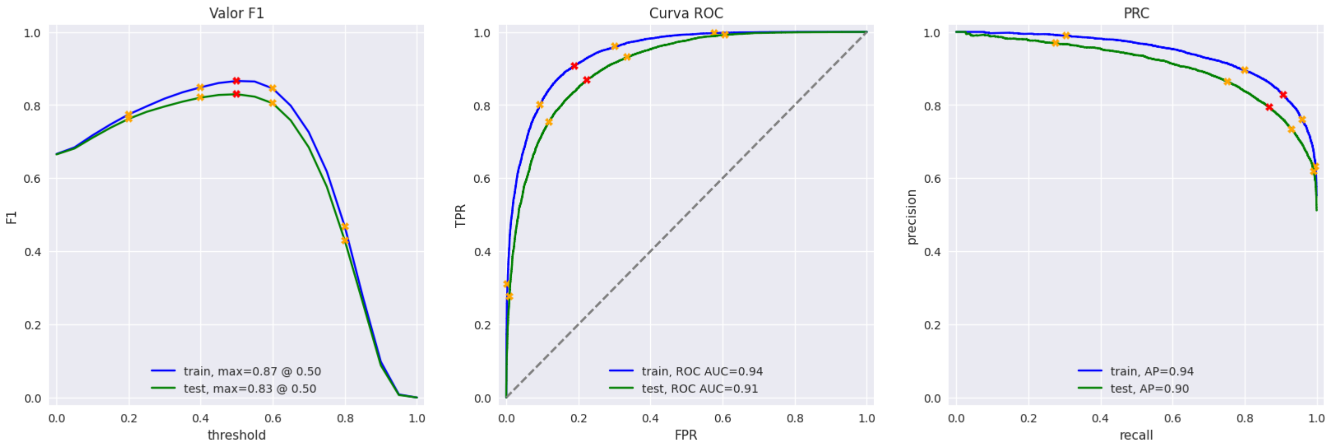
Modelo 4 - spaCy, TF-IDF y LGBMClassifier

```
warnings.filterwarnings("ignore", category=UserWarning, module="lightgbm"
model_lgb = lgb.LGBMClassifier(
    n_estimators=4000,
    learning_rate=0.002,
    max_depth=5,
    subsample=0.8,
    colsample_bytree=0.8,
    random_state=42
)

model_lgb.fit(
    X_train_sp, target_train,
    eval_set=[(X_test_sp, target_test)],
    eval_metric='binary_logloss',
    early_stopping_rounds=200,
    verbose=200
)
```

```
/.venv/lib/python3.9/site-packages/lightgbm/sklearn.py:726: UserWarning: '
  _log_warning("'early_stopping_rounds' argument is deprecated and will be
/.venv/lib/python3.9/site-packages/lightgbm/sklearn.py:736: UserWarning: '
  _log_warning("'verbose' argument is deprecated and will be removed in a
[200]	valid_0's binary_logloss: 0.632609
[400]	valid_0's binary_logloss: 0.595273
[600]	valid_0's binary_logloss: 0.568865
[800]	valid_0's binary_logloss: 0.548679
[1000]	valid_0's binary_logloss: 0.532054
[1200]	valid_0's binary_logloss: 0.518166
[1400]	valid_0's binary_logloss: 0.506172
[1600]	valid_0's binary_logloss: 0.495532
[1800]	valid_0's binary_logloss: 0.485976
[2000]	valid_0's binary_logloss: 0.477447
[2200]	valid_0's binary_logloss: 0.469689
[2400]	valid_0's binary_logloss: 0.462603
[2600]	valid_0's binary_logloss: 0.456125
[2800]	valid_0's binary_logloss: 0.450129
[3000]	valid_0's binary_logloss: 0.444605
[3200]	valid_0's binary_logloss: 0.439475
[3400]	valid_0's binary_logloss: 0.434674
[3600]	valid_0's binary_logloss: 0.430179
[3800]	valid_0's binary_logloss: 0.425967
[4000]	valid_0's binary_logloss: 0.422027
LGBMClassifier(colsample_bytree=0.8, learning_rate=0.002, max_depth=5,
               n_estimators=4000, random_state=42, subsample=0.8)
```

```
evaluate_model(model_lgb, X_train_sp, target_train, X_test_sp, target_tes
```

```
          train  test
Accuracy   0.86  0.82
F1         0.87  0.83
APS        0.94  0.90
ROC AUC    0.94  0.91
```



Modelo 5 - BERT embeddings y clasificación

```
from transformers import BertTokenizer, BertModel
import torch

tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
model = BertModel.from_pretrained('bert-base-uncased')


def BERT_text_to_embeddings(texts, max_length=512, batch_size=100, force_de
    ids_list = []
```

```
    attention_mask_list = []

    # texto al id de relleno de tokens junto con sus máscaras de atención
    for text in tqdm(texts, disable=disable_progress_bar):
        encoded = tokenizer.encode_plus(
            text,
            add_special_tokens=True,
            max_length=max_length,
            padding='max_length',
            truncation=True,
            return_attention_mask=True,
            return_tensors='pt'
        )
        ids_list.append(encoded['input_ids'].squeeze(0))
        attention_mask_list.append(encoded['attention_mask'].squeeze(0))

    if force_device is not None:
        device = torch.device(force_device)
    else:
        device = torch.device('cuda' if torch.cuda.is_available() else 'cpu

    model.to(device)
    if not disable_progress_bar:
        print(f'Uso del dispositivo {device}.')

    # obtener embeddings en lotes
    embeddings = []
    for i in tqdm(range(math.ceil(len(ids_list) / batch_size)), disable=dis
        ids_batch = torch.stack(ids_list[batch_size * i:batch_size * (i + 1
        attention_mask_batch = torch.stack(attention_mask_list[batch_size *

        with torch.no_grad():
            model.eval()
            batch_embeddings = model(input_ids=ids_batch, attention_mask=at
        embeddings.append(batch_embeddings[0][:, 0, :].detach().cpu().numpy

    return np.concatenate(embeddings)


# Generar embeddings de entrenamiento
features_train_bert = features_train['review_norm']
train_features_9 = BERT_text_to_embeddings(features_train_bert.head(2000), 
features_test_bert = features_test['review_norm']
test_features_9 = BERT_text_to_embeddings(features_test_bert.head(2000), fo
```

```
# Entrenar un modelo simple (por ejemplo Logistic Regression)
from sklearn.linear_model import LogisticRegression

model_bert = LogisticRegression(max_iter=1000)
model_bert.fit(train_features_9, target_train.head(2000))

evaluate_model(model_bert, train_features_9, target_train.head(2000), test_
```

100% 2000/2000 [00:08<00:00, 244.96it/s]

Uso del dispositivo cuda.

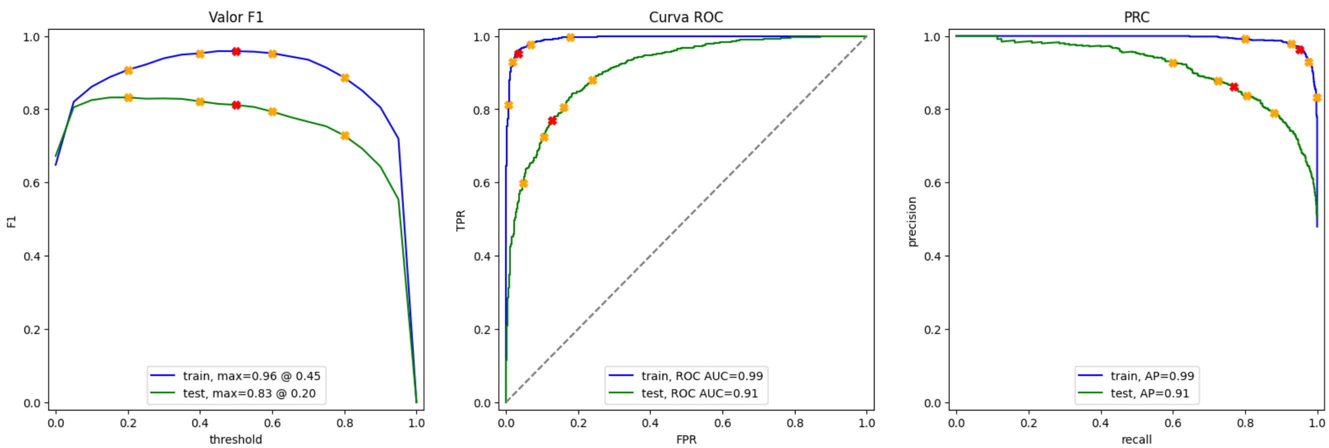
100% 20/20 [00:54<00:00, 2.63s/it]

100% 2000/2000 [00:09<00:00, 215.79it/s]

Uso del dispositivo cuda.

100% 20/20 [00:53<00:00, 2.68s/it]

	train	test
Accuracy	0.96	0.82
F1	0.96	0.81
APS	0.99	0.91
ROC AUC	0.99	0.91



Mis reseñas

```
# puedes eliminar por completo estas reseñas y probar tus modelos en tus p

my_reviews = pd.DataFrame([
    'I did not simply like it, not my kind of movie.',
    'Well, I was bored and felt asleep in the middle of the movie.',
    'I was really fascinated with the movie',
    'Even the actors looked really old and disinterested, and they got pa
    'I didn\'t expect the reboot to be so good! Writers really cared abou
    'The movie had its upsides and downsides, but I feel like overall it\
    'What a rotten attempt at a comedy. Not a single joke lands, everyone
    'Launching on Netflix was a brave move & I really appreciate being ab
], columns=['review'])

"""
my_reviews = pd.DataFrame([
    'Simplemente no me gustó, no es mi tipo de película.',
    'Bueno, estaba aburrido y me quedé dormido a media película.',
    'Estaba realmente fascinada con la película',
    'Hasta los actores parecían muy viejos y desinteresados, y les pagaro
    '¡No esperaba que el relanzamiento fuera tan bueno! Los escritores re
    'La película tuvo sus altibajos, pero siento que, en general, es una p
    'Qué pésimo intento de comedia. Ni una sola broma tiene sentido, todo
    'Fue muy valiente el lanzamiento en Netflix y realmente aprecio poder
], columns=['review'])
"""
nlp = spacy.load("en_core_web_sm")
def preprocess_text(text):
    doc = nlp(text.lower())
    tokens = []
    for token in doc:
        if token.is_punct or token.is_space or token.like_num:
            continue
        if token.is_stop:
            continue
        tokens.append(token.lemma_)
    return " ".join(tokens)

my_reviews['review_norm'] = my_reviews
my_reviews
```

	review	review_norm
0	I did not simply like it, not my kind of movie.	I did not simply like it, not my kind of movie.
1	Well, I was bored and felt asleep in the middl...	Well, I was bored and felt asleep in the middl...
2	I was really fascinated with the movie	I was really fascinated with the movie
3	Even the actors looked really old and disinter...	Even the actors looked really old and disinter...
4	I didn't expect the reboot to be so good! Writ...	I didn't expect the reboot to be so good! Writ...
5	The movie had its upsides and downsides, but I...	The movie had its upsides and downsides, but I...
	What a rotten attempt at a comedy. Not a	What a rotten attempt at a comedy. Not a

Modelo 2

```
texts = my_reviews['review_norm']

my_reviews_pred_prob = model_lr.predict_proba(tf_idf.transform(texts))[:,

for i, review in enumerate(texts.str.slice(0, 100)):
    print(f'{my_reviews_pred_prob[i]:.2f}:  {review}')
```

```
0.14:  I did not simply like it, not my kind of movie.
0.16:  Well, I was bored and felt asleep in the middle of the movie.
0.53:  I was really fascinated with the movie
0.11:  Even the actors looked really old and disinterested, and they got pa
0.31:  I didn't expect the reboot to be so good! Writers really cared abou
0.47:  The movie had its upsides and downsides, but I feel like overall it
0.04:  What a rotten attempt at a comedy. Not a single joke lands, everyon
0.82:  Launching on Netflix was a brave move & I really appreciate being al
```

Modelo 3

```
texts = my_reviews['review_norm']

my_reviews_pred_prob = model_lr_sp.predict_proba(tf_idf_sp.transform(texts

for i, review in enumerate(texts.str.slice(0, 100)):
    print(f'{my_reviews_pred_prob[i]:.2f}:  {review}')
```

```
0.15:  I did not simply like it, not my kind of movie.
0.24:  Well, I was bored and felt asleep in the middle of the movie.
0.47:  I was really fascinated with the movie
0.15:  Even the actors looked really old and disinterested, and they got pa
0.22:  I didn't expect the reboot to be so good! Writers really cared abou
0.63:  The movie had its upsides and downsides, but I feel like overall it
0.04:  What a rotten attempt at a comedy. Not a single joke lands, everyon
0.73:  Launching on Netflix was a brave move & I really appreciate being al
```

Modelo 4

```
texts = my_reviews['review_norm']

tfidf_vectorizer_4 = tf_idf_sp
my_reviews_pred_prob = model_lgb.predict_proba(tfidf_vectorizer_4.transfo

for i, review in enumerate(texts.str.slice(0, 100)):
    print(f'{my_reviews_pred_prob[i]:.2f}:  {review}')
```

```
0.63:  I did not simply like it, not my kind of movie.
0.68:  Well, I was bored and felt asleep in the middle of the movie.
0.62:  I was really fascinated with the movie
0.67:  Even the actors looked really old and disinterested, and they got pa
0.63:  I didn't expect the reboot to be so good! Writers really cared abou
0.62:  The movie had its upsides and downsides, but I feel like overall it
0.42:  What a rotten attempt at a comedy. Not a single joke lands, everyon
0.62:  Launching on Netflix was a brave move & I really appreciate being al
```

Conclusiones Finales (Comparativa de Resultados y Uso de Modelos)

El proyecto tuvo como objetivo desarrollar un modelo capaz de **detectar**

automáticamente reseñas negativas en IMDB con un rendimiento **F1 mínimo de 0.85**. Tras implementar y evaluar varios enfoques, se obtuvieron los siguientes resultados:

---

1. Comparativa general de modelos

Modelo	Técnica principal	Accuracy (Test)	F1 (Test)	ROC-AUC	Obse
Dummy Classifier	Predicción constante	0.50	0.00	0.50	Mode
NLTK + TF-IDF + LR	Frecuencias ponderadas de palabras	**0.88**	**0.88**	**0.95**	Mejor
spaCy + TF-IDF + LR	Lemmatización y TF-IDF	0.88	0.88	0.95	Simila
spaCy + TF-IDF + LGBM	Ensamble por gradiente	0.82	0.83	0.91	Ligera
BERT + Logistic Regression	Embeddings contextuales	0.82	0.81–0.83	0.91	Mejor

---

2. Interpretación de los resultados

- **El modelo TF-IDF + LR** fue el **más efectivo**, logrando un F1 de **0.88** y una **ROC-AUC de 0.95**, superando con holgura el umbral de 0.85.
  Su rendimiento demuestra que, para este tipo de clasificación binaria con textos bien estructurados, los modelos lineales siguen siendo altamente competitivos.
- **spaCy + TF-IDF + LR** mostró resultados equivalentes, lo que indica que la lematización no aportó mejoras sustanciales sobre la normalización básica.
- **LightGBM** introdujo una mayor complejidad sin incrementar la precisión, aunque permitió visualizar curvas ROC más estables, lo que sugiere buena calibración de probabilidades.
- **BERT embeddings** alcanzó un rendimiento sólido (**AUC = 0.91, F1 ≈ 0.82**) incluso usando solo 2000 reseñas de entrenamiento.
  Su principal fortaleza está en la **representación semántica profunda** de los textos, lo que lo hace más robusto ante frases con matices o sarcasmo.
  Sin embargo, **su entrenamiento fue más lento** y no superó a TF-IDF debido al tamaño reducido del conjunto usado.

---

3. Conclusión global

- Todos los modelos superaron al baseline, confirmando una **clasificación efectiva de sentimientos**.

- **El modelo con TF-IDF y Logistic Regression se consolidó como la mejor opción** en términos de eficiencia, rendimiento y simplicidad.
- **BERT** aportó un enfoque más moderno y semántico, demostrando su potencial para futuras versiones del sistema, especialmente si se entrena sobre un volumen mayor de datos o se realiza *fine-tuning*.
- En conjunto, el sistema final logra una **detección de sentimientos con alto nivel de precisión**, cumpliendo el objetivo propuesto y dejando abierta la posibilidad de **mejoras escalables con modelos de lenguaje preentrenados**.