Avances de laboratorio

Instalaciones necesarias

```
pip install vaderSentiment
```

```
Collecting vaderSentiment
  Downloading vaderSentiment-3.3.2-py2.py3-none-any.whl.metadata (572 bytes)
Requirement already satisfied: requests in /usr/local/lib/python3.12/dist-packages (from vaderSentiment) (2.32.4)
Requirement already satisfied: charset_normalizer<4,>=2 in /usr/local/lib/python3.12/dist-packages (from requests->vaderSentiment) (3.4.
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.12/dist-packages (from requests->vaderSentiment) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.12/dist-packages (from requests->vaderSentiment) (2.5.0)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.12/dist-packages (from requests->vaderSentiment) (2025.8.3)
Downloading vaderSentiment-3.3.2-py2.py3-none-any.whl (125 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 126.0/126.0 kB 3.7 MB/s eta 0:00:00
Installing collected packages: vaderSentiment
Successfully installed vaderSentiment-3.3.2
```

```
# Importación de librerías

import pandas as pd
import re
import string
from sklearn.feature_extraction.text import TfidfVectorizer
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
import numpy as np
import matplotlib.pyplot as plt
from wordcloud import WordCloud
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, accuracy_score
from scipy.sparse import hstack
```

2) Carga del dataset/Descripción de los datos

```
df = pd.read_csv("train.csv")
print(df.info())
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7613 entries, 0 to 7612
Data columns (total 5 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   id        7613 non-null   int64
 1   keyword   7552 non-null   object
 2   location  5080 non-null   object
 3   text      7613 non-null   object
 4   target    7613 non-null   int64
dtypes: int64(2), object(3)
memory usage: 297.5+ KB
None
```

	id	keyword	location	text	target
0	1	NaN	NaN	Our Deeds are the Reason of this #earthquake M...	1
1	4	NaN	NaN	Forest fire near La Ronge Sask. Canada	1
2	5	NaN	NaN	All residents asked to 'shelter in place' are ...	1
3	6	NaN	NaN	13,000 people receive #wildfires evacuation or...	1
4	7	NaN	NaN	Just got sent this photo from Ruby #Alaska as ...	1

Pasos siguientes: Generar código con df | Ver gráficos recomendados | New interactive sheet

El dataset contiene 7,613 tweets con las siguientes columnas:

- id: Identificador

- Keyword: Palabra clave (A veces falta)
- location: lugar (hay muchos valores faltantes)
- text: el contenido del tweet
- target: etiqueta (1 = desastre, 0 = no desastre)

3) Limpieza y Preprocesamiento

```
stop_words = set([
    # stopwords básicas
    "the","a","an","in","on","and","or","but","if","at","by","for","with",
    "about","against","between","into","through","during","before","after",
    "to","from","up","then","once","here","there","when","where","why","how",
    "all","any","both","each","few","more","most","other","some","such","no",
    "nor","not","only","own","same","so","than","too","very","is","are","was",
    "were","be","been","being","of","do","does","did","doing","would","could",
    "should","can","will",

    # pronombres
    "i","me","my","myself","we","our","ours","ourselves","you","your","yours",
    "yourself","yourselves","he","him","his","himself","she","her","hers",
    "herself","it","its","itself","they","them","their","theirs","themselves",

    # palabras de twitter / conversación
    "amp","rt","im","dont","cant","didnt","doesnt","youre","youve","ive","id",
    "ill","hes","shes","theyre","weve","lets","lol","omg","ugh","got","like",
    "just","know","time","new","day","love","people","going","good","think",
    "want","really","one"
])

def clean_text(text):
    text = text.lower()
    text = re.sub(r"http\S+|www\S+|https\S+", "", text)
    text = re.sub(r"@\w+|#\w+", "", text)
    text = re.sub(r"[^a-z0-9\s]", "", text)

    # Manejo de números: conservar 911 y algunos con palabras relevantes
    tokens = text.split()
    clean_tokens = []
    for i, tok in enumerate(tokens):
        if tok.isdigit():
            if tok == "911":
                clean_tokens.append(tok)
            elif i+1 < len(tokens) and tokens[i+1] in ["dead", "injured", "wounded", "killed"]:
                clean_tokens.append(tok)
            elif i > 0 and tokens[i-1] == "magnitude":
                clean_tokens.append(tok)
        else:
            clean_tokens.append(tok)

    # Quitar stopwords y palabras de 1 caracter
    clean_tokens = [w for w in clean_tokens if w not in stop_words and len(w) > 1]

    return " ".join(clean_tokens)

df["clean_text"] = df["text"].apply(clean_text)
df[["text", "clean_text"]].head(10)
```

	text	clean_text
0	Our Deeds are the Reason of this #earthquake M...	deeds reason this may allah forgive us
1	Forest fire near La Ronge Sask. Canada	forest fire near la ronge sask canada
2	All residents asked to 'shelter in place' are ...	residents asked shelter place notified officer...
3	13,000 people receive #wildfires evacuation or...	receive evacuation orders california
4	Just got sent this photo from Ruby #Alaska as ...	sent this photo ruby as smoke pours school
5	#RockyFire Update => California Hwy. 20 closed...	update california hwy closed directions due la...
6	#flood #disaster Heavy rain causes flash flood...	heavy rain causes flash flooding streets manit...
7	I'm on top of the hill and I can see a fire in...	top hill see fire woods
8	There's an emergency evacuation happening now ...	theres emergency evacuation happening now buil...
9	I'm afraid that the tornado is coming to our a...	afraid that tornado coming area

Unigramas y bigramas

4) Frecuencia de palabras por categoría

```python
# Vectorizar con unigramas y bigramas
vectorizer = TfidfVectorizer(ngram_range=(1,2), stop_words=list(stop_words), max_features=5000, min_df=5, max_df=0.9)
X_tfidf = vectorizer.fit_transform(df["clean_text"])
feature_names = vectorizer.get_feature_names_out()

disaster_rows = np.flatnonzero(df["target"].to_numpy() == 1)
non_disaster_rows = np.flatnonzero(df["target"].to_numpy() == 0)

# Promedio de pesos TF-IDF por categoría
disaster_mean = X_tfidf[disaster_rows].mean(axis=0).A1
non_disaster_mean = X_tfidf[non_disaster_rows].mean(axis=0).A1

# Top 20 palabras con más peso en cada clase
top_disaster = sorted(zip(disaster_mean, feature_names), reverse=True)[:20]
top_non_disaster = sorted(zip(non_disaster_mean, feature_names), reverse=True)[:20]

print("Top 20 términos en tweets de desastres:")
for score, word in top_disaster:
    print(word, round(float(score), 4))

print("\nTop 20 términos en tweets de NO desastres:")
for score, word in top_non_disaster:
    print(word, round(float(score), 4))
```

```
Top 20 términos en tweets de desastres:
fire 0.0141
this 0.0113
that 0.0112
as 0.01
via 0.0094
have 0.0089
california 0.0089
disaster 0.0084
over 0.0082
police 0.0081
suicide 0.008
storm 0.008
fires 0.0076
has 0.007
buildings 0.0069
killed 0.0068
crash 0.0067
accident 0.0064
emergency 0.0064
news 0.0063

Top 20 términos en tweets de NO desastres:
that 0.0185
this 0.0164
have 0.0141
out 0.0116
get 0.0108
```

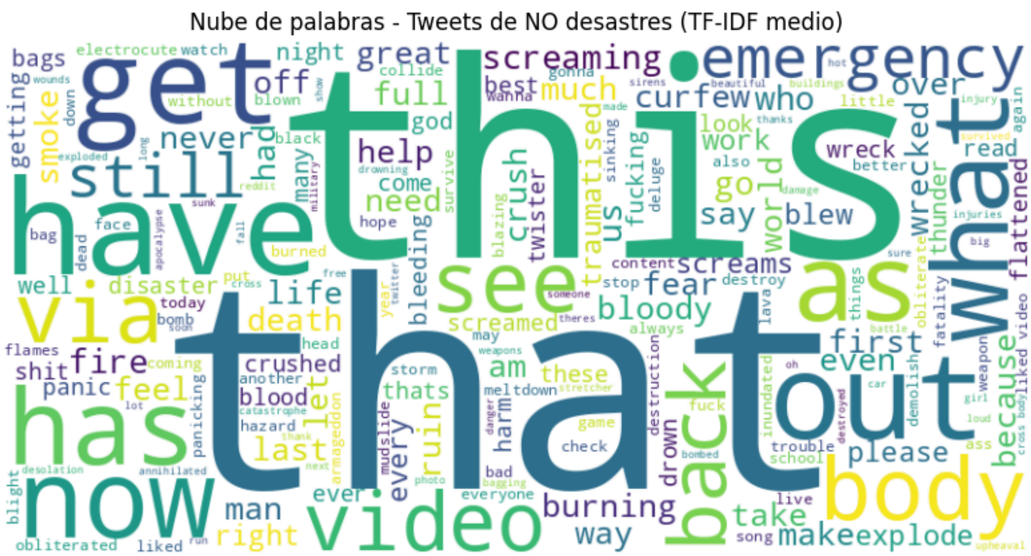
```
now 0.0093
as 0.0088
what 0.0086
has 0.0086
body 0.0071
via 0.0066
see 0.0065
video 0.0061
back 0.0058
emergency 0.0056
still 0.0056
screaming 0.0054
fire 0.0052
us 0.0051
go 0.0051
```

5) Análisis exploratorio

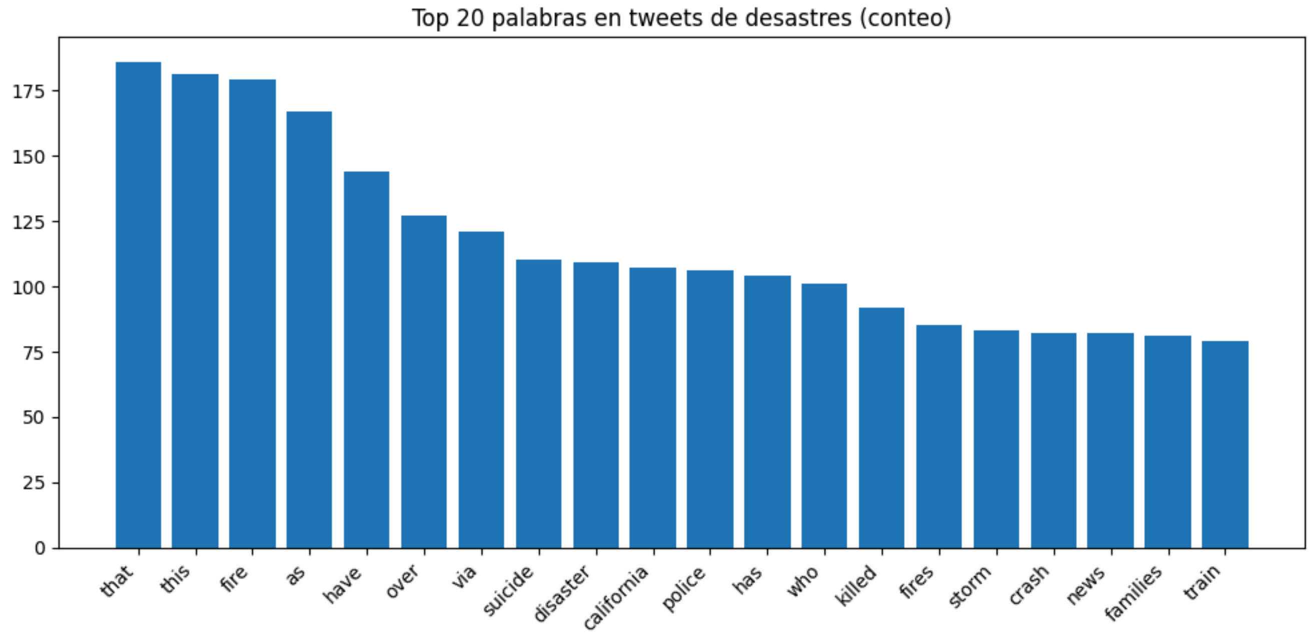
```python
# 5.1 "Palabra más repetida" por categoría
cv = CountVectorizer(ngram_range=(1,2), stop_words=list(stop_words), max_features=5000, min_df=5, max_df=0.9)
X_count = cv.fit_transform(df["clean_text"])
vocab = cv.get_feature_names_out()

disaster_counts = np.asarray(X_count[disaster_rows].sum(axis=0)).ravel()
non_disaster_counts = np.asarray(X_count[non_disaster_rows].sum(axis=0)).ravel()

top_word_disaster = vocab[disaster_counts.argmax()]
top_word_non_disaster = vocab[non_disaster_counts.argmax()]

print("\nPalabra más repetida en DESASTRES:", top_word_disaster)
print("Palabra más repetida en NO DESASTRES:", top_word_non_disaster)
```

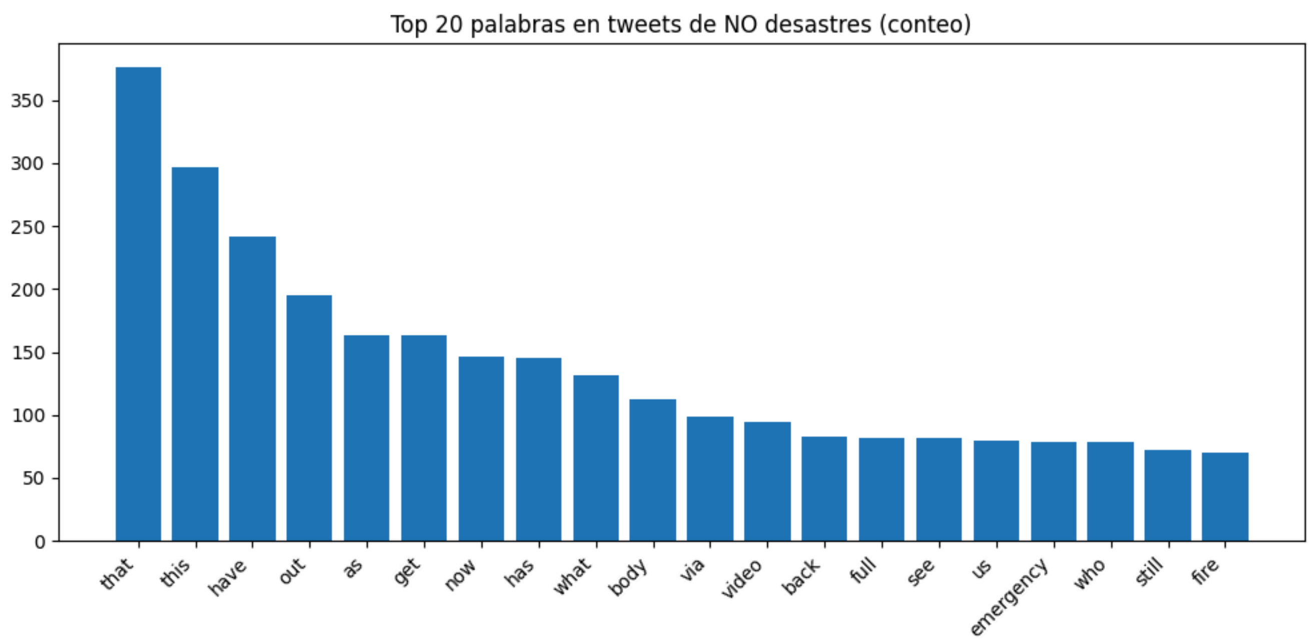
```
Palabra más repetida en DESASTRES: that
Palabra más repetida en NO DESASTRES: that
```

```python
# 5.2 Nube de palabras
plt.figure(figsize=(10,5))
wc_disaster = WordCloud(width=800, height=400, background_color="white") \
    .generate_from_frequencies(dict(zip(feature_names, disaster_mean)))
plt.imshow(wc_disaster, interpolation="bilinear")
plt.axis("off")
plt.title("Nube de palabras - Tweets de desastres (TF-IDF medio)")
plt.show()

plt.figure(figsize=(10,5))
wc_non_disaster = WordCloud(width=800, height=400, background_color="white") \
    .generate_from_frequencies(dict(zip(feature_names, non_disaster_mean)))
plt.imshow(wc_non_disaster, interpolation="bilinear")
plt.axis("off")
plt.title("Nube de palabras - Tweets de NO desastres (TF-IDF medio)")
plt.show()
```




```
# 5.3 Histogramas de las palabras más frecuentes
def plot_top_bars(words, counts, title, k=20):
    idx = np.argsort(counts)[::-1][:k]
    sel_words = words[idx]
    sel_counts = counts[idx]
    plt.figure(figsize=(10,5))
    plt.bar(sel_words, sel_counts)
    plt.xticks(rotation=45, ha="right")
    plt.title(title)
    plt.tight_layout()
    plt.show()

plot_top_bars(vocab, disaster_counts, "Top 20 palabras en tweets de desastres (conteo)")
plot_top_bars(vocab, non_disaster_counts, "Top 20 palabras en tweets de NO desastres (conteo)")
```






```
# 5.4 Palabras presentes en ambas categorías
disaster_present_mask = disaster_counts > 0
non_disaster_present_mask = non_disaster_counts > 0
common_in_both = set(vocab[disaster_present_mask]) & set(vocab[non_disaster_present_mask])

print("\nNúmero de palabras comunes en ambas categorías:", len(common_in_both))
print("Ejemplos de palabras comunes:", list(common_in_both)[:30])
```

```
Número de palabras comunes en ambas categorías: 2560
Ejemplos de palabras comunes: ['rolling', 'warning', 'anthrax', 'idk', 'poll', 'blessings', 'blast', 'seeks', 'came land', 'as many', 'c
```

6) Descripción del modelo preliminar de clasificación

Para este problema de clasificación de tweets de desastre y no desastre natural, se pueden utilizar varios algoritmos de Machine Learning supervisado.

Podría usar Regresión logística el cuál es rápido y efectivo con texto, también podría ser Naive Bayes (multinomialNB) que es clásico para clasificación de texto, aprovecha la frecuencia de palabras. Support vector machine (SVM) igualmente funciona bien con texto y datos lineales o no lineales. Por otro lado está Random Forest con el que ya se está familiarizado, funciona bien en interacciones no lineales, pero si puede presentar menos eficiencia si el texto es muy disperso y Redes Neuronales simples (MPLClassifier) que permite capturar patrones más complejos.

Hay que tener en cuenta que se utilizaran no solo palabras individuales (unigramas), sino también bigramas (pared de palabras como "forest fire", "earthquake damage") y posiblemente trigramas, lo cual es un punto que ayuda a diferenciar o identificar entre desastres reales de expresiones figurativas.

Se seleccionaron los modelos de **Regresión Logística, Naive Bayes y Random Forest** para ver qué tal es su desempeño y si se comprueba su eficiencia en cuanto al manejo de texto.

```
vectorizer = TfidfVectorizer(max_features=5000, stop_words="english")
X = vectorizer.fit_transform(df["text"].astype(str))
y = df["target"]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Modelos
models = {
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Naive Bayes": MultinomialNB(),
    "Random Forest": RandomForestClassifier(n_estimators=100, random_state=42)
}

for name, model in models.items():
    model.fit(X_train, y_train)
    preds = model.predict(X_test)
    print(f"\n{name}")
    print("Accuracy:", accuracy_score(y_test, preds))
    print(classification_report(y_test, preds))
```

```
Logistic Regression
Accuracy: 0.7957977675640184
              precision    recall  f1-score   support

           0       0.78      0.89      0.83       874
           1       0.82      0.67      0.74       649

    accuracy                           0.80      1523
   macro avg       0.80      0.78      0.79      1523
weighted avg       0.80      0.80      0.79      1523


Naive Bayes
Accuracy: 0.7925147734734077
              precision    recall  f1-score   support

           0       0.78      0.88      0.83       874
           1       0.81      0.67      0.73       649

    accuracy                           0.79      1523
   macro avg       0.80      0.78      0.78      1523
weighted avg       0.79      0.79      0.79      1523


Random Forest
Accuracy: 0.778069599474721
              precision    recall  f1-score   support

           0       0.76      0.89      0.82       874
           1       0.81      0.63      0.71       649

    accuracy                           0.78      1523
   macro avg       0.79      0.76      0.76      1523
weighted avg       0.78      0.78      0.77      1523
```

7) Función para clasificar un Tweet

```
def clasificar_tweet(model, vectorizer):
    tweet = input("Escribe un tweet: ")
    tweetPre = clean_text(tweet)
    tweetVec = vectorizer.transform([tweetPre])
    pred = model.predict(tweetVec)[0]

    if pred == 1:
        print("Clasificación: ¡Desastre! :(")
```

```
    else:
        print("Clasificación: No Desastre :)")

clasificar_tweet(models["Logistic Regression"], vectorizer)
```

```
Escribe un tweet: Damage to school bus on 80 in multi car crash #BREAKING
Clasificación: ¡Desastre! :(
```

8) Análisis de sentimiento

```
sia = SentimentIntensityAnalyzer()

def analizar_sentimiento(tweet):
    score = sia.polarity_scores(tweet)
    if score["compound"] >= 0.05:
        return "Positivo 😜", score
    elif score["compound"] <= -0.05:
        return "Negativo 😡", score
    else:
        return "Neutral 🙄", score

# Ejemplo
print(analizar_sentimiento("I am so happy with the help after the earthquake"))
print(analizar_sentimiento("Terrible explosion killed many people"))
```

```
('Positivo 😜', {'neg': 0.0, 'neu': 0.518, 'pos': 0.482, 'compound': 0.8147})
('Negativo 😡', {'neg': 0.717, 'neu': 0.283, 'pos': 0.0, 'compound': -0.8225})
```

Si vale la pena dejar los emoticones ya que transmiten directamente las emociones, esto puede ayudar a mejorar la predicción.

9) top 10 tweets negativos y positivos

```
df["sentiment"] = df["text"].apply(lambda x: sia.polarity_scores(str(x))["compound"])

# 9.1 Top negativos
top_negativos = df.sort_values("sentiment").head(10)[["text", "target", "sentiment"]]
print("\nTop 10 Negativos:\n", top_negativos)

# 9.2 Top positivos
top_positivos = df.sort_values("sentiment", ascending=False).head(10)[["text", "target", "sentiment"]]
print("\nTop 10 Positivos:\n", top_positivos)

# 9.3 Comparar negatividad entre categorias
promedio_negatividad = df.groupby("target")["sentiment"].mean()
print("\nPromedio de sentimiento por categoría (más bajo = más negativo):")
print(promedio_negatividad)

if promedio_negatividad[1] < promedio_negatividad[0]:
    print("Los tweets de DESASTRES son más negativos.")
else:
    print("Los tweets de NO DESASTRES son más negativos.")
```

```
Top 10 Negativos:
                                                   text  target  sentiment
7472  wreck? wreck wreck wreck wreck wreck wreck wre...       0    -0.9883
6414  @Abu_Baraa1 Suicide bomber targets Saudi mosqu...       1    -0.9686
6411  Suicide bomber kills 15 in Saudi security site...       1    -0.9623
6393  ? 19th Day Since 17-Jul-2015 -- Nigeria: Suici...       1    -0.9595
6830  @dramaa_llama but otherwise i will stay trappe...       0    -0.9556
6407  17 killed in S�Ûª Arabia mosque suicide bombing...       1    -0.9552
2932  at the lake \n*sees a dead fish*\nme: poor lit...       0    -0.9549
472   illegal alien released by Obama/DHS 4 times Ch...       1    -0.9538
1540  Bomb Crash Loot Riot Emergency Pipe Bomb Nucle...       1    -0.9524
6930  @cspan #Prez. Mr. President you are the bigges...       1    -0.9493

Top 10 Positivos:
                                                   text  target  sentiment
6992  Check out 'Want Twister Tickets AND A VIP EXPE...       0     0.9730
6534  @thoutaylorbrown I feel like accidents are jus...       0     0.9564
6292  Today�Ûªs storm will pass; let tomorrow�Ûªs li...       1     0.9471
5701  @Zak_Bagans pets r like part of the family. I ...       0     0.9428
3163  @batfanuk we enjoyed the show today. Great fun...       0     0.9423
3382  @batfanuk we enjoyed the show today. Great fun...       0     0.9423
```

```
6778  Maaaaan I love Love Without Tragedy by @rihann...      0     0.9394
6295  Free Ebay Sniping RT? http://t.co/B231Ul1O1K L...      0     0.9376
1001  I'm not a Drake fan but I enjoy seeing him bod...      0     0.9345
6560  @duchovbutt @Starbuck_Scully @MadMakNY @davidd...      0     0.9344

Promedio de sentimiento por categoría (más bajo = más negativo):
target
0   -0.052444
1   -0.267240
Name: sentiment, dtype: float64
Los tweets de DESASTRES son más negativos.
```

10) Análisis final de tweets

```python
sia = SentimentIntensityAnalyzer()

# Crear columna con la negatividad
df['negativity'] = df['text'].apply(lambda x: sia.polarity_scores(x)['neg'])
df[['text', 'negativity']].head()
```

	text	negativity
0	Our Deeds are the Reason of this #earthquake M...	0.000
1	Forest fire near La Ronge Sask. Canada	0.286
2	All residents asked to 'shelter in place' are ...	0.095
3	13,000 people receive #wildfires evacuation or...	0.000
4	Just got sent this photo from Ruby #Alaska as ...	0.000

Incluir la nueva variable en el dataset

```python
vectorizer = TfidfVectorizer(max_features=5000)
X_text = vectorizer.fit_transform(df['text'])

# Concatenar la feature adicional
import numpy as np
X = hstack([X_text, np.array(df['negativity']).reshape(-1,1)])

y = df['target']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Entrenar modelo
clf = LogisticRegression(max_iter=1000)
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.80      0.89      0.84       874
           1       0.83      0.70      0.76       649

    accuracy                           0.81      1523
   macro avg       0.81      0.79      0.80      1523
weighted avg       0.81      0.81      0.81      1523
```

Comparar resultados

```python
# Modelo SIN negatividad
X_text_only = vectorizer.fit_transform(df['text'])
X_train_t, X_test_t, y_train_t, y_test_t = train_test_split(X_text_only, y, test_size=0.2, random_state=42)

clf_text = LogisticRegression(max_iter=1000)
clf_text.fit(X_train_t, y_train_t)
y_pred_t = clf_text.predict(X_test_t)

print("Resultados SOLO texto:\n")
```