01_visualizaciones_exploratorias

November 20, 2025

1 Visualizaciones Exploratorias

Este notebook se enfoca en las seis visualizaciones requeridas para la Parte I del TP.

[14]:
```python
from pathlib import Path
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

DATA_DIR = Path('../data/nlp-getting-started')
TRAIN_PATH = DATA_DIR / 'train.csv'
sns.set_theme(style='whitegrid')
```

[15]:
```python
train_df = pd.read_csv(TRAIN_PATH)
train_df.head(30)
```

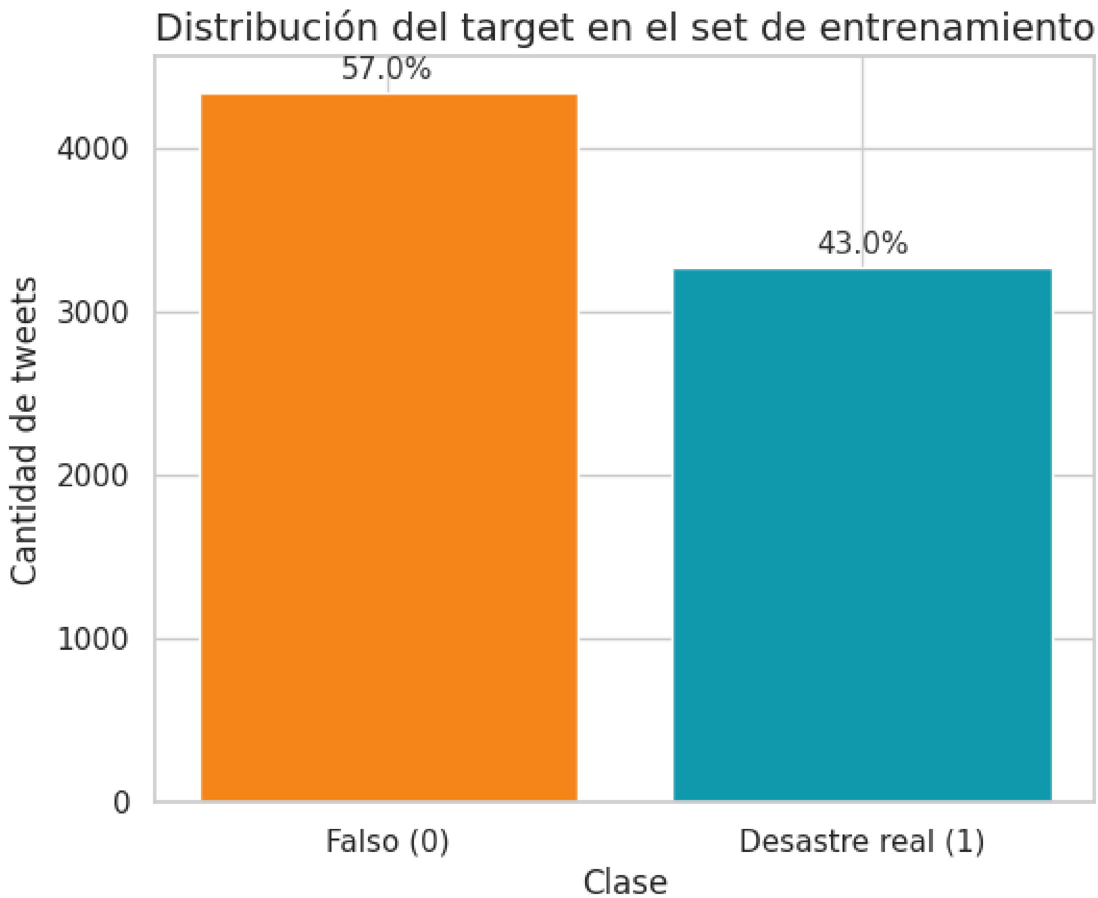
[15]:
```
    id keyword location                                               text  \
0    1     NaN      NaN  Our Deeds are the Reason of this #earthquake M…
1    4     NaN      NaN             Forest fire near La Ronge Sask. Canada
2    5     NaN      NaN  All residents asked to 'shelter in place' are …
3    6     NaN      NaN  13,000 people receive #wildfires evacuation or…
4    7     NaN      NaN  Just got sent this photo from Ruby #Alaska as …
5    8     NaN      NaN  #RockyFire Update => California Hwy. 20 closed…
6   10     NaN      NaN  #flood #disaster Heavy rain causes flash flood…
7   13     NaN      NaN  I'm on top of the hill and I can see a fire in…
8   14     NaN      NaN  There's an emergency evacuation happening now …
9   15     NaN      NaN  I'm afraid that the tornado is coming to our a…
10  16     NaN      NaN        Three people died from the heat wave so far
11  17     NaN      NaN  Haha South Tampa is getting flooded hah- WAIT …
12  18     NaN      NaN  #raining #flooding #Florida #TampaBay #Tampa 1…
13  19     NaN      NaN            #Flood in Bago Myanmar #We arrived Bago
14  20     NaN      NaN  Damage to school bus on 80 in multi car crash …
15  23     NaN      NaN                                     What's up man?
16  24     NaN      NaN                                      I love fruits
17  25     NaN      NaN                                   Summer is lovely
18  26     NaN      NaN                                  My car is so fast
19  28     NaN      NaN                       What a goooooooaaaaaal!!!!!!
```

20	31	NaN	NaN	this is ridiculous…
21	32	NaN	NaN	London is cool ;)
22	33	NaN	NaN	Love skiing
23	34	NaN	NaN	What a wonderful day!
24	36	NaN	NaN	LOOOOOOL
25	37	NaN	NaN	No way…I can't eat that shit
26	38	NaN	NaN	Was in NYC last week!
27	39	NaN	NaN	Love my girlfriend
28	40	NaN	NaN	Cooool :)
29	41	NaN	NaN	Do you like pasta?

	target
0	1
1	1
2	1
3	1
4	1
5	1
6	1
7	1
8	1
9	1
10	1
11	1
12	1
13	1
14	1
15	0
16	0
17	0
18	0
19	0
20	0
21	0
22	0
23	0
24	0
25	0
26	0
27	0
28	0
29	0

1.1 Visualización 1: Distribución del target

[16]:
```
labels_map = {0: 'Falso (0)', 1: 'Desastre real (1)'}
class_counts = train_df['target'].value_counts().sort_index()
class_percentages = class_counts / class_counts.sum() * 100
plot_df = pd.DataFrame(
    {
        'label': [labels_map[idx] for idx in class_counts.index],
        'count': class_counts.values,
        'percentage': class_percentages.values
    }
)

fig, ax = plt.subplots(figsize=(6, 5))
bars = ax.bar(plot_df['label'], plot_df['count'], color=['#f58518', '#1098ad'])
for bar, pct in zip(bars, plot_df['percentage']):
    ax.text(
        bar.get_x() + bar.get_width() / 2,
        bar.get_height() + 50,
        f"{pct:.1f}%",
        ha='center',
        va='bottom',
        fontsize=11,
        color='#333333'
    )
ax.set_title('Distribución del target en el set de entrenamiento', fontsize=14)
ax.set_ylabel('Cantidad de tweets')
ax.set_xlabel('Clase')
plt.tight_layout()
plt.show()
```

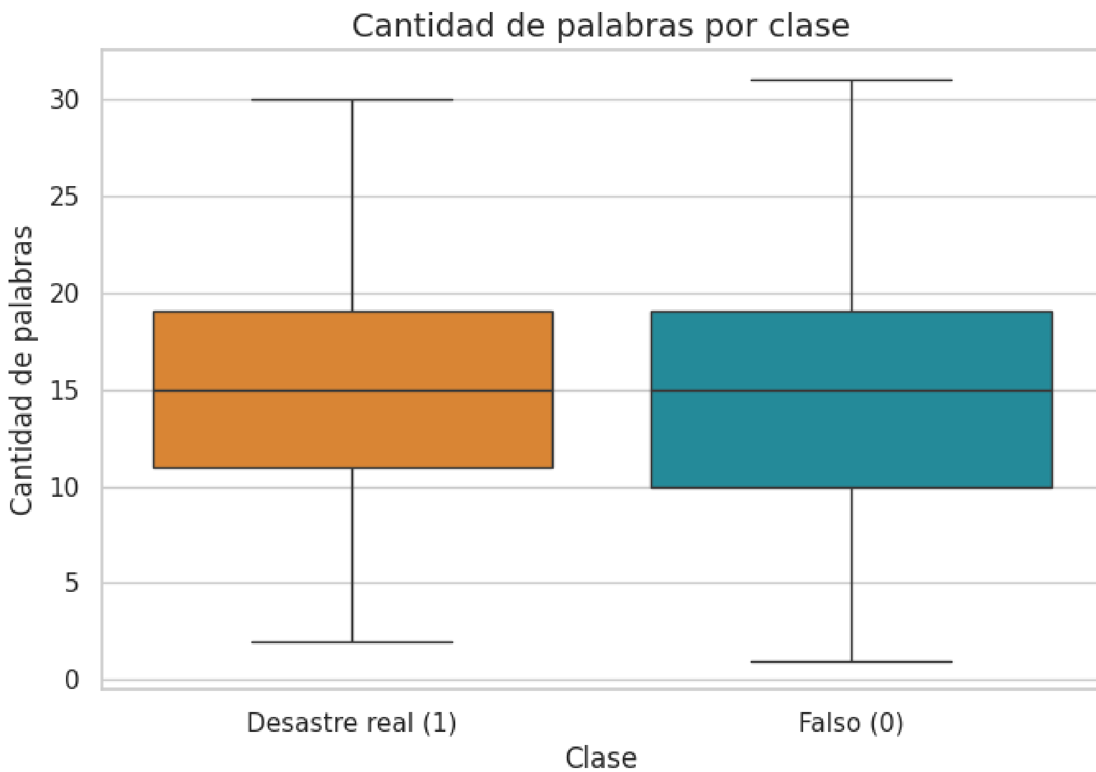


Okey más o menos igualmente distribuidos los reales de los Falsos. Algunos más falsos que reales.

1.2 Visualización 2: Impacto del conteo de palabras en la clasificación

[17]:
```python
word_counts = train_df['text'].fillna('').str.split().str.len()
plot_df = pd.DataFrame({
    'Clase': train_df['target'].map({0: 'Falso (0)', 1: 'Desastre real (1)'}),
    'Cantidad de palabras': word_counts
})

fig, ax = plt.subplots(figsize=(7, 5))
sns.boxplot(
    data=plot_df,
    x='Clase',
    y='Cantidad de palabras',
    hue='Clase',
    palette=['#f58518', '#1098ad'],
    ax=ax
```

```
)
legend = ax.legend_
if legend is not None:
    legend.remove()
ax.set_title('Cantidad de palabras por clase', fontsize=14)
ax.set_xlabel('Clase')
ax.set_ylabel('Cantidad de palabras')
plt.tight_layout()
plt.show()
```



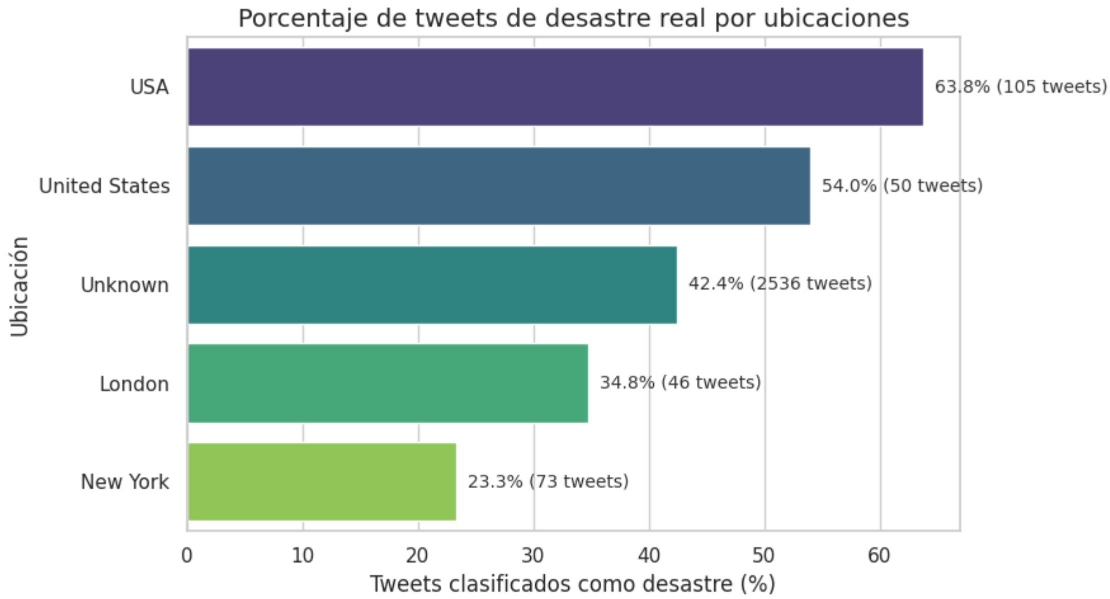
Ok, parece que no hay mucha diferencia en la cantidad de palabras entre tweets de desastre y no desastre. Podríamos intentar hacer un análisis más detallado, como cantidad de letras por tweet.

1.3 Visualización 3: Ubicación geográfica de los tweets

Voy a graficar la proporción de tweets de desastre por ubicación con alta cobertura para evaluar el contexto geográfico.

[18]:
```
location_clean = train_df['location'].fillna('Unknown').str.strip()
location_counts = location_clean.value_counts()
top_locations = location_counts[location_counts >= 40].head(10).index
plot_df = (
```

```python
    train_df.assign(location=location_clean)
    .loc[lambda df: df['location'].isin(top_locations)]
    .groupby('location')['target']
    .agg(tweets='size', disaster_rate='mean')
    .sort_values('disaster_rate', ascending=False)
    .reset_index()
)
plot_df['disaster_rate_pct'] = plot_df['disaster_rate'] * 100

fig, ax = plt.subplots(figsize=(9, 5))
sns.barplot(
    data=plot_df,
    x='disaster_rate_pct',
    y='location',
    hue='location',
    palette=sns.color_palette('viridis', len(plot_df)),
    dodge=False,
    ax=ax
)
legend = ax.legend_
if legend is not None:
    legend.remove()
for idx, row in plot_df.iterrows():
    ax.text(
        row['disaster_rate_pct'] + 1,
        idx,
        f"{row['disaster_rate_pct']:.1f}% ({row['tweets']} tweets)",
        va='center',
        fontsize=10,
        color='#333333'
    )
ax.set_title('Porcentaje de tweets de desastre real por ubicaciones',␣
 ↪fontsize=14)
ax.set_xlabel('Tweets clasificados como desastre (%)')
ax.set_ylabel('Ubicación')
plt.tight_layout()
plt.show()
```



[19]:
```
location_clean = train_df['location'].fillna('Unknown').str.strip()
all_locations = location_clean.value_counts()

print(f"Total unique locations: {len(all_locations)}")
print(f"\nTop 50 locations by count:")
print("="*60)
for loc, count in all_locations.head(50).items():
    print(f"{loc:40s} : {count:4d} tweets")

print(f"\n\nLocations with 'USA' or 'United States' or 'America':")
print("="*60)
usa_related = all_locations[all_locations.index.str.contains('USA|United␣
↪States|America|U.S', case=False, na=False)]
for loc, count in usa_related.items():
    print(f"{loc:40s} : {count:4d} tweets")
```

```
Total unique locations: 3279

Top 50 locations by count:
============================================================
Unknown                                  : 2536 tweets
USA                                      :  105 tweets
New York                                 :   73 tweets
United States                            :   50 tweets
London                                   :   46 tweets
Nigeria                                  :   32 tweets
Canada                                   :   30 tweets
```

```
UK                                        :   27 tweets
Los Angeles, CA                           :   26 tweets
India                                     :   24 tweets
Mumbai                                    :   22 tweets
Washington, DC                            :   21 tweets
California                                :   20 tweets
Kenya                                     :   20 tweets
Chicago, IL                               :   19 tweets
Worldwide                                 :   19 tweets
Australia                                 :   19 tweets
New York, NY                              :   16 tweets
Los Angeles                               :   15 tweets
California, USA                           :   15 tweets
Everywhere                                :   15 tweets
Indonesia                                 :   14 tweets
Florida                                   :   14 tweets
Washington, D.C.                          :   14 tweets
United Kingdom                            :   14 tweets
San Francisco                             :   14 tweets
Toronto                                   :   12 tweets
Ireland                                   :   12 tweets
NYC                                       :   12 tweets
Earth                                     :   12 tweets
Seattle                                   :   11 tweets
Chicago                                   :   11 tweets
San Francisco, CA                         :   11 tweets
Texas                                     :   11 tweets
London, UK                                :   10 tweets
London, England                           :   10 tweets
Atlanta, GA                               :   10 tweets
Dallas, TX                                :   10 tweets
ss                                        :   10 tweets
New York City                             :   10 tweets
Sacramento, CA                            :   10 tweets
Nashville, TN                             :    9 tweets
US                                        :    9 tweets
Manchester                                :    9 tweets
World                                     :    9 tweets
Denver, Colorado                          :    9 tweets
Houston, TX                               :    9 tweets
San Diego, CA                             :    9 tweets
Scotland                                  :    9 tweets
304                                       :    9 tweets


Locations with 'USA' or 'United States' or 'America':
============================================================
USA                                       :  105 tweets
```

United States	:	50 tweets
California, USA	:	15 tweets
Pennsylvania, USA	:	7 tweets
California, United States	:	6 tweets
Texas, USA	:	5 tweets
Florida, USA	:	5 tweets
New York, USA	:	5 tweets
U.S.A	:	4 tweets
North Carolina, USA	:	4 tweets
Massachusetts, USA	:	4 tweets
Tulsa, Oklahoma	:	3 tweets
Oregon, USA	:	3 tweets
Upstairs.	:	3 tweets
New Orleans ,Louisiana	:	3 tweets
St. Louis, MO	:	3 tweets
America of Founding Fathers	:	3 tweets
Hawaii, USA	:	3 tweets
Illinois, USA	:	3 tweets
America	:	3 tweets
Virginia, USA	:	3 tweets
South, USA	:	3 tweets
Ohio, USA	:	2 tweets
Washington, USA	:	2 tweets
somewhere USA	:	2 tweets
Moncton, New Brunswick	:	2 tweets
Georgia, USA	:	2 tweets
USA (Formerly @usNOAAgov)	:	2 tweets
Louisville, KY	:	2 tweets
Michigan, USA	:	2 tweets
West Virginia, USA	:	2 tweets
Redding, California, USA	:	2 tweets
Jerusalem	:	2 tweets
Louisiana	:	2 tweets
United States of America	:	2 tweets
vancouver usa	:	2 tweets
The American Wasteland (MV)	:	2 tweets
Tucson, AZ	:	1 tweets
Americas Newsroom	:	1 tweets
New Mexico, USA	:	1 tweets
Outside The Matrix, I Think.	:	1 tweets
Missouri, USA	:	1 tweets
somewhere outside	:	1 tweets
Tucson, Arizona	:	1 tweets
Las Vegas, NV USA	:	1 tweets
3?3?7?SLOPelousas??2?2?5?	:	1 tweets
Afghanistan, USA	:	1 tweets
Littleton, CO, USA	:	1 tweets
Virginia, United States	:	1 tweets

```
Northern Kentucky, USA                  :    1 tweets
America | New Zealand                   :    1 tweets
New Brunswick, NJ                       :    1 tweets
Moscow, Russia                          :    1 tweets
In the clouds…                         :    1 tweets
SEATTLE, WA USA                         :    1 tweets
USA , AZ                                :    1 tweets
Lancaster, Pennsylvania, USA            :    1 tweets
Lindenhurst                             :    1 tweets
Cape Cod, Massachusetts USA             :    1 tweets
Purgatory, USA                          :    1 tweets
Sunshine Coast, Queensland              :    1 tweets
USA, WA                                 :    1 tweets
USAoV                                   :    1 tweets
U.S                                     :    1 tweets
Made in America                         :    1 tweets
Los Angeles,CA, USA                     :    1 tweets
the void, U.S.A                         :    1 tweets
Detroit, MI, United States              :    1 tweets
Maryland, USA                           :    1 tweets
Texas-USA ã¢ ?                          :    1 tweets
Washington, Krasnodar (Russia)          :    1 tweets
Basketball City, USA                    :    1 tweets
Iowa, USA                               :    1 tweets
USA/SO FLORIDA via BROOKLYN NY          :    1 tweets
St. Louis Mo.                           :    1 tweets
Hickville, USA                          :    1 tweets
U.S.                                    :    1 tweets
USA, Haiti, Nepal                       :    1 tweets
Philadelphia, PA USA                    :    1 tweets
U.S.A. - Global Members Site            :    1 tweets
 Û¢5 Û¢12 Û¢14 Û¢ | åÈ#SaviourSquadåÇ    :    1 tweets
Saint Louis, Missouri                   :    1 tweets
Jonesboro, Arkansas USA                 :    1 tweets
Hudson Valley, NY                       :    1 tweets
Alaska, USA                             :    1 tweets
Nevada, USA                             :    1 tweets
Alexandria, VA, USA                     :    1 tweets
U.S. Northern Virginia                  :    1 tweets
Jerusalem!                              :    1 tweets
USA, Alabama                            :    1 tweets
New Orleans, Louisiana                  :    1 tweets
Northern California U.S.A.              :    1 tweets
Eureka, California, USA                 :    1 tweets
Los Angeles… CA… USA                  :    1 tweets
AKRON OHIO USA                          :    1 tweets
Livingston, IL  U.S.A.                  :    1 tweets
The Hammock, FL, USA                    :    1 tweets
```

Jerusalem, Israel	1 tweets
United States where it's warm	1 tweets
Midwestern USA	1 tweets
louisville, kentucky	1 tweets
St. Louis, Missouri	1 tweets
Tucson, Az	1 tweets
Freeport IL. USA	1 tweets
Hawaii USA	1 tweets
I ACCEPT SONG REQUESTS	1 tweets
North America	1 tweets
Elk Grove, CA, USA	1 tweets
Books Published, USA	1 tweets
Orlando,FL USA	1 tweets
Georgia, U.S.A.	1 tweets
Madison, WI & St. Louis MO	1 tweets
Russia	1 tweets
San Jose, CA, USA	1 tweets
st.louis county missouri	1 tweets
Oklahoma, USA	1 tweets
St. Louis, Mo	1 tweets
Tennessee, USA	1 tweets
Wausau, Wisconsin	1 tweets
Jonesboro, AR MO, IOWA USA	1 tweets
sÌ£o luis	1 tweets
Colorado, USA	1 tweets
Phoenix, Arizona, USA	1 tweets
Malibu/SantaFe/Winning!	1 tweets
USA, North Dakota	1 tweets
San Luis Obispo, CA	1 tweets
828/704(Soufside)/while looking goofy in NJ	1 tweets
Pro-American and Anti-#Occupy	1 tweets
Not a U.S resident	1 tweets
MI,USA	1 tweets
missouri USA	1 tweets
New York, United States	1 tweets
russia	1 tweets
LP, MN USA	1 tweets
USA - Canada - Europe - Asia	1 tweets
Tulsa, OK	1 tweets
Upstate New York	1 tweets
U.S.A. FEMA Region 5	1 tweets
Spain - China - Latin America.	1 tweets
Philadelphia, Pennsylvania USA	1 tweets
trapped in America	1 tweets
Montana, USA	1 tweets
Utah, USA	1 tweets
PA.USA	1 tweets
Madison, Wisconsin, USA	1 tweets

```
Nomad, USA                                  :     1 tweets
North East Unsigned Radio                   :     1 tweets
Duval, WV 25573, USA ?                      :     1 tweets
Soufside                                    :     1 tweets
PSA Nursing                                 :     1 tweets
Louisiana, USA                              :     1 tweets
Bon Temps Louisiana                         :     1 tweets
West Coast, USA                             :     1 tweets
U.S.A and Canada                            :     1 tweets
Minority Privilege, USA                     :     1 tweets
New Jersey, USA                             :     1 tweets
Reston, VA, USA                             :     1 tweets
Tornado Alley, USA                          :     1 tweets
PA, USA                                     :     1 tweets
LITTLETON, CO, USA, TERRAN                  :     1 tweets
South Carolina, USA                         :     1 tweets
Atlanta, Georgia USA                        :     1 tweets
Kentucky, USA                               :     1 tweets
Gotham City,USA                             :     1 tweets
Cambridge, Massachusetts, U.S.              :     1 tweets
St Louis, MO                                :     1 tweets
Wisconsin, USA                              :     1 tweets
eBooks, North America                       :     1 tweets
Indiana, USA                                :     1 tweets
Very SW CA, USA…Draenor                  :     1 tweets
New Hampshire, USA                          :     1 tweets
West Coast, Cali USA                        :     1 tweets
Savage States of America                    :     1 tweets
GrC Founder, 8,000 Subscribers              :     1 tweets
CT, USA                                     :     1 tweets
Proud @BuckMasonUSA supporter!              :     1 tweets
N. California USA                           :     1 tweets
Vermont, USA                                :     1 tweets
pettyville, usa                             :     1 tweets
Florida USA                                 :     1 tweets
St. Louis                                   :     1 tweets
North East USA                              :     1 tweets
Alabama, USA                                :     1 tweets
```

claro, el campo location está totalmente destruido. Necesito armarme una feature "country". Usé la API Pública de geocoders para sacar el país de la ubicación dada. Dejo el codigo abajo!

[20]:
```python
import json

'''

Usé este script para generar location_to_country.json que me mapea las␣
↪ubicaciones de los usuarios a países.
```

```
from geopy.geocoders import Nominatim
from time import sleep

geolocator = Nominatim(user_agent="tweet-checker")

unique_locations = train_df['location'].dropna().unique()
location_to_country = {}

print(f"Processing {len(unique_locations)} unique locations...")

for i, location in enumerate(unique_locations):
    if pd.isna(location) or location.strip() == '' or location == 'Unknown':
        location_to_country[location] = None
        continue

    try:
        result = geolocator.geocode(location, addressdetails=True, timeout=10)
        if result and 'address' in result.raw:
            country = result.raw['address'].get('country')
            location_to_country[location] = country
        else:
            location_to_country[location] = None
    except Exception as e:
        location_to_country[location] = None

    if (i + 1) % 50 == 0:
        print(f"Processed {i + 1}/{len(unique_locations)}")

    sleep(1)

print(f"Done. Detected {sum(1 for v in location_to_country.values() if v is not␣
 ↪None)} countries")

for loc, country in list(location_to_country.items())[:20]:
    print(f"{loc:40s} -> {country}")


with open('../data/location_to_country.json', 'w', encoding='utf-8') as f:
    json.dump(location_to_country, f, ensure_ascii=False, indent=2)

'''

with open('../data/location_to_country.json', 'r', encoding='utf-8') as f:
  location_to_country = json.load(f)
```

[21]:
```python
train_df['country'] = train_df['location'].map(location_to_country)

print(f"Rows with country: {train_df['country'].notna().sum()}")
print(f"Rows without country: {train_df['country'].isna().sum()}")

print("\nTop countries:")
print(train_df['country'].value_counts().head(15))

train_df[train_df['country'].notna()][['location', 'country', 'text']].head(10)
```

```
Rows with country: 4060
Rows without country: 3553

Top countries:
country
United States of America    2153
United Kingdom               438
Canada                       222
Australia                    150
India                        138
Nigeria                       76
Philippines                   45
Kenya                         40
South Africa                  37
France                        37
Indonesia                     33
Brasil                        30
                           26
Deutschland                   26
Éire / Ireland                26
Name: count, dtype: int64
```

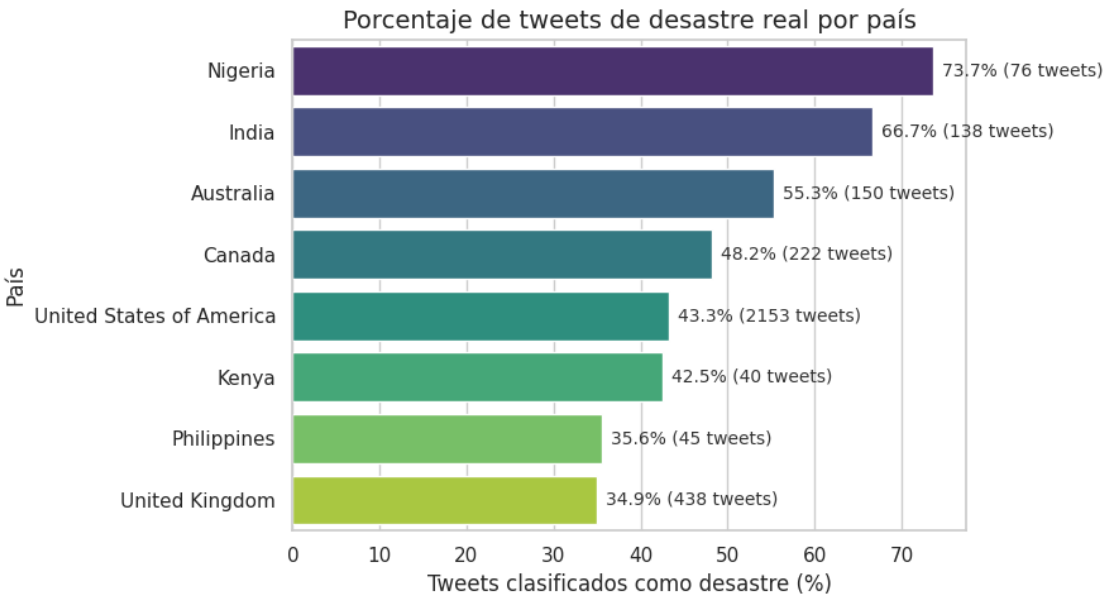
[21]:
```
                       location                   country  \
31                   Birmingham            United Kingdom
34             Philadelphia, PA  United States of America
35                   London, UK            United Kingdom
36                     Pretoria              South Africa
37                 World Wide!!  United States of America
39               Paranaque City               Philippines
42                    milky way                     Sesel
46   GREENSBORO,NORTH CAROLINA  United States of America
49                     England.            United Kingdom
50   Sheffield Township, Ohio  United States of America

                                                 text
31  @bbcmtd Wholesale Markets ablaze http://t.co/l…
34                 Crying out for more! Set me ablaze
35  On plus side LOOK AT THE SKY LAST NIGHT IT WAS…
```

```
36  @PhDSquares #mufc they've built so much hype a…
37  INEC Office in Abia Set Ablaze - http://t.co/3…
39                             Ablaze for you Lord :D
42  Had an awesome time visiting the CFC head offi…
46  How the West was burned: Thousands of wildfire…
49  First night with retainers in. It's quite weir…
50  Deputies: Man shot before Brighton home set ab…
```

Me cierra. El que ni idea es milky way pero no había mucha esperanza para esa.

[22]:
```python
country_counts = train_df['country'].value_counts()
top_countries = country_counts[country_counts >= 40].head(10).index

plot_df = (
    train_df[train_df['country'].isin(top_countries)]
    .groupby('country')['target']
    .agg(tweets='size', disaster_rate='mean')
    .sort_values('disaster_rate', ascending=False)
    .reset_index()
)
plot_df['disaster_rate_pct'] = plot_df['disaster_rate'] * 100

fig, ax = plt.subplots(figsize=(9, 5))
sns.barplot(
    data=plot_df,
    x='disaster_rate_pct',
    y='country',
    hue='country',
    palette=sns.color_palette('viridis', len(plot_df)),
    dodge=False,
    ax=ax
)
legend = ax.legend_
if legend is not None:
    legend.remove()
for idx, row in plot_df.iterrows():
    ax.text(
        row['disaster_rate_pct'] + 1,
        idx,
        f"{row['disaster_rate_pct']:.1f}% ({row['tweets']} tweets)",
        va='center',
        fontsize=10,
        color='#333333'
    )
ax.set_title('Porcentaje de tweets de desastre real por país', fontsize=14)
ax.set_xlabel('Tweets clasificados como desastre (%)')
ax.set_ylabel('País')
```

```
plt.tight_layout()
plt.show()
```

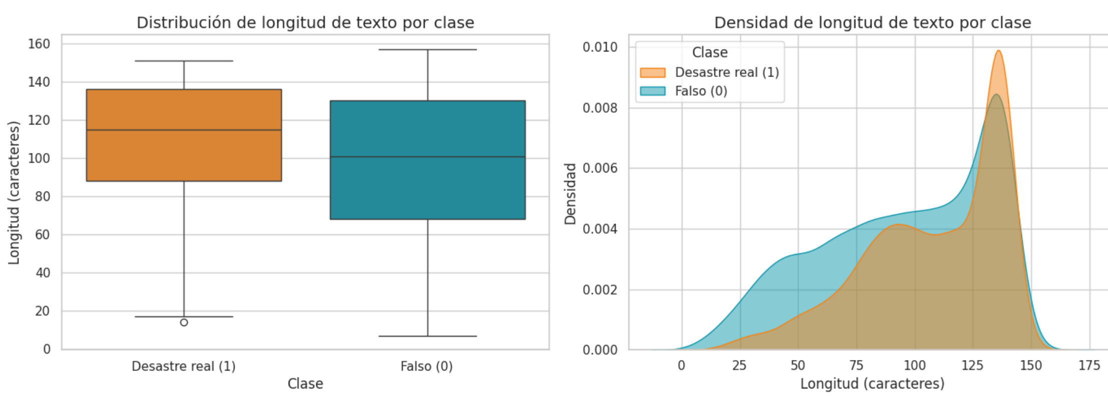


Okey!! Vemos data bastante más util ahora, la normalización por país diferenció bastante más! Aunque claro, se mencionó bastante en una clase de la materia, que ante menos población, la variabilidad es mucho mayor. Aun así, me encantaron los resultados, me quedo fuerte con esta feature.

1.4 Visualización 4: Longitud de texto vs target

[23]:
```
text_lengths = train_df['text'].fillna('').str.len()
plot_df = pd.DataFrame({
    'Clase': train_df['target'].map({0: 'Falso (0)', 1: 'Desastre real (1)'}),
    'Longitud de texto (caracteres)': text_lengths
})

fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(14, 5))

sns.boxplot(
    data=plot_df,
    x='Clase',
    y='Longitud de texto (caracteres)',
    hue='Clase',
    palette=['#f58518', '#1098ad'],
    ax=ax1
)
legend = ax1.legend_
```

```
if legend is not None:
    legend.remove()
ax1.set_title('Distribución de longitud de texto por clase', fontsize=14)
ax1.set_xlabel('Clase')
ax1.set_ylabel('Longitud (caracteres)')

sns.kdeplot(
    data=plot_df,
    x='Longitud de texto (caracteres)',
    hue='Clase',
    fill=True,
    palette=['#f58518', '#1098ad'],
    alpha=0.5,
    ax=ax2
)
ax2.set_title('Densidad de longitud de texto por clase', fontsize=14)
ax2.set_xlabel('Longitud (caracteres)')
ax2.set_ylabel('Densidad')

plt.tight_layout()
plt.show()
```



okey! Sorprendentemente los tweets falsos tienen menos texto que los otros. inesperado pero bueno.

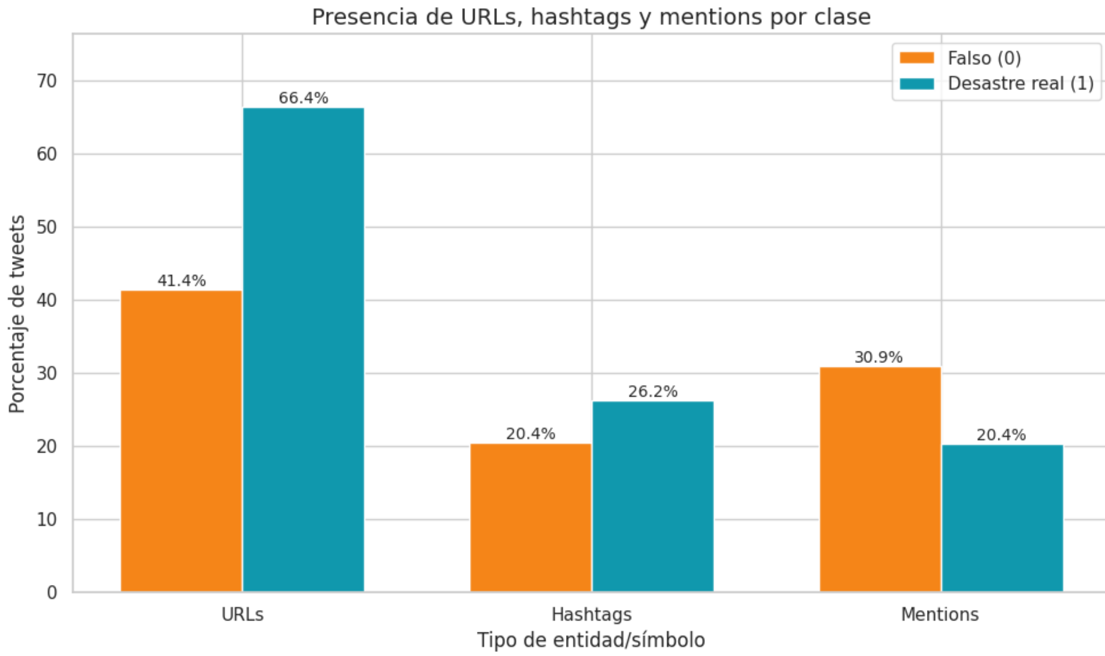
1.5 Visualización 5: Entidades y símbolos

Resaltar cómo la presencia de URLs, hashtags o mentions se relaciona con el target.

[24]:
```
train_df['has_url'] = train_df['text'].fillna('').str.contains(r'http[s]?://',␣
 ↪regex=True)
train_df['has_hashtag'] = train_df['text'].fillna('').str.contains(r'#\w+',␣
 ↪regex=True)
```

```python
train_df['has_mention'] = train_df['text'].fillna('').str.contains(r'@\w+',␣
↪regex=True)

features = ['has_url', 'has_hashtag', 'has_mention']
feature_names = ['URLs', 'Hashtags', 'Mentions']

stats = []
for target_val in [0, 1]:
    for feature, name in zip(features, feature_names):
        pct = train_df[train_df['target'] == target_val][feature].mean() * 100
        stats.append({
            'Clase': 'Falso (0)' if target_val == 0 else 'Desastre real (1)',
            'Feature': name,
            'Porcentaje': pct
        })

plot_df = pd.DataFrame(stats)

fig, ax = plt.subplots(figsize=(10, 6))
x = np.arange(len(feature_names))
width = 0.35

false_data = plot_df[plot_df['Clase'] == 'Falso (0)']['Porcentaje'].values
disaster_data = plot_df[plot_df['Clase'] == 'Desastre real (1)']['Porcentaje'].
↪values

bars1 = ax.bar(x - width/2, false_data, width, label='Falso (0)',␣
↪color='#f58518')
bars2 = ax.bar(x + width/2, disaster_data, width, label='Desastre real (1)',␣
↪color='#1098ad')

for bars in [bars1, bars2]:
    for bar in bars:
        height = bar.get_height()
        ax.text(bar.get_x() + bar.get_width()/2., height,
                f'{height:.1f}%',
                ha='center', va='bottom', fontsize=10)

ax.set_xlabel('Tipo de entidad/símbolo')
ax.set_ylabel('Porcentaje de tweets')
ax.set_title('Presencia de URLs, hashtags y mentions por clase', fontsize=14)
ax.set_xticks(x)
ax.set_xticklabels(feature_names)
ax.legend()
ax.set_ylim(0, max(plot_df['Porcentaje']) * 1.15)

plt.tight_layout()
```

```
plt.show()
```



Bueno, por lo menos hay una correspondencia entre simbolos y tweets de desastre. Nuevamente pensé que sería al revés la relación, pero lo tomo. Parece que el más determinante es si tiene o no URL.

1.6 Visualización 6: Nube de palabras - Palabras asociadas con desastres

Nube de palabras mostrando las palabras más frecuentes (mín 5 tweets). Tamaño = frecuencia, Color = tasa de desastre.

[25]:
```
from wordcloud import WordCloud
import re
from collections import Counter

# Filtro un par de palabras que no me interesa ver distribuciones: (igual me␣
↪quedé cortísimo)
stop_words = set(['the', 'a', 'an', 'and', 'or', 'but', 'in', 'on', 'at', 'to',␣
↪'for',
                  'of', 'with', 'by', 'from', 'as', 'is', 'was', 'are', 'been',␣
↪'be',
                  'have', 'has', 'had', 'do', 'does', 'did', 'will', 'would',␣
↪'should',
                  'could', 'may', 'might', 'must', 'can', 'this', 'that',␣
↪'these', 'those',
```

```
                  'i', 'you', 'he', 'she', 'it', 'we', 'they', 'what', 'which',␣
↪'who',
                  'when', 'where', 'why', 'how', 'all', 'each', 'every',␣
↪'both', 'few',
                  'more', 'most', 'other', 'some', 'such', 'no', 'nor', 'not',␣
↪'only',
                  'own', 'same', 'so', 'than', 'too', 'very', 'just', 'https',␣
↪'http',
                  'co', 't', 's', 'm', 're', 've', 'll', 'd'])

word_stats = {}
for idx, row in train_df.iterrows():
    text = str(row['text']).lower()
    text = re.sub(r'http\S+', '', text)
    text = re.sub(r'[^a-z\s]', ' ', text)
    words = text.split()
    words = [w for w in words if w not in stop_words and len(w) > 2]

    for word in set(words):
        if word not in word_stats:
            word_stats[word] = {'count': 0, 'disaster_count': 0}
        word_stats[word]['count'] += 1
        word_stats[word]['disaster_count'] += row['target']

word_data = []
for word, stats in word_stats.items():
    if stats['count'] >= 5:
        disaster_rate = stats['disaster_count'] / stats['count']
        word_data.append({
            'word': word,
            'count': stats['count'],
            'disaster_rate': disaster_rate
        })

word_df = pd.DataFrame(word_data).sort_values('count', ascending=False)

frequencies = {row['word']: row['count'] for _, row in word_df.iterrows()}
disaster_rates = {row['word']: row['disaster_rate'] for _, row in word_df.
↪iterrows()}

def color_func(word, **kwargs):
    rate = disaster_rates.get(word, 0.5)
    if rate > 0.7:
        return 'rgb(200, 50, 50)'
    elif rate > 0.5:
        return 'rgb(255, 150, 50)'
    elif rate > 0.3:
```

```python
        return 'rgb(100, 150, 200)'
    else:
        return 'rgb(50, 100, 200)'

wc = WordCloud(
    width=1200,
    height=600,
    background_color='white',
    max_words=100,
    relative_scaling=0.5,
    min_font_size=10
).generate_from_frequencies(frequencies)

fig, ax = plt.subplots(figsize=(16, 8))
ax.imshow(wc.recolor(color_func=color_func), interpolation='bilinear')
ax.axis('off')
ax.set_title('Word Cloud - Palabras asociadas con desastres\n(Tamaño = frecuencia, Color = disaster rate: Rojo >70%, Naranja >50%, Celeste >30%, Azul <30%)',
             fontsize=14, pad=20)
plt.tight_layout()
plt.show()

print(f"\nTop 20 palabras por disaster rate (min 5 tweets):")
print(word_df.nlargest(20, 'disaster_rate')[['word', 'count', 'disaster_rate']])
```

Word Cloud - Palabras asociadas con desastres
(Tamaño = frecuencia, Color = disaster rate: Rojo >70%, Naranja >50%, Celeste >30%, Azul <30%)

```
Top 20 palabras por disaster rate (min 5 tweets):
                word  count  disaster_rate
843         northern     64            1.0
407           debris     49            1.0
1987          severe     44            1.0
1763      derailment     40            1.0
2044    legionnaires     39            1.0
2093        migrants     37            1.0
2348   investigators     37            1.0
926           mosque     33            1.0
2542       detonated     31            1.0
1577             pkk     31            1.0
1556          turkey     27            1.0
949          israeli     27            1.0
483       helicopter     25            1.0
2565    conclusively     25            1.0
2196          saipan     25            1.0
2356       projected     24            1.0
2051           signs     23            1.0
2384          trench     23            1.0
2484         refugio     22            1.0
2486        costlier     22            1.0
```

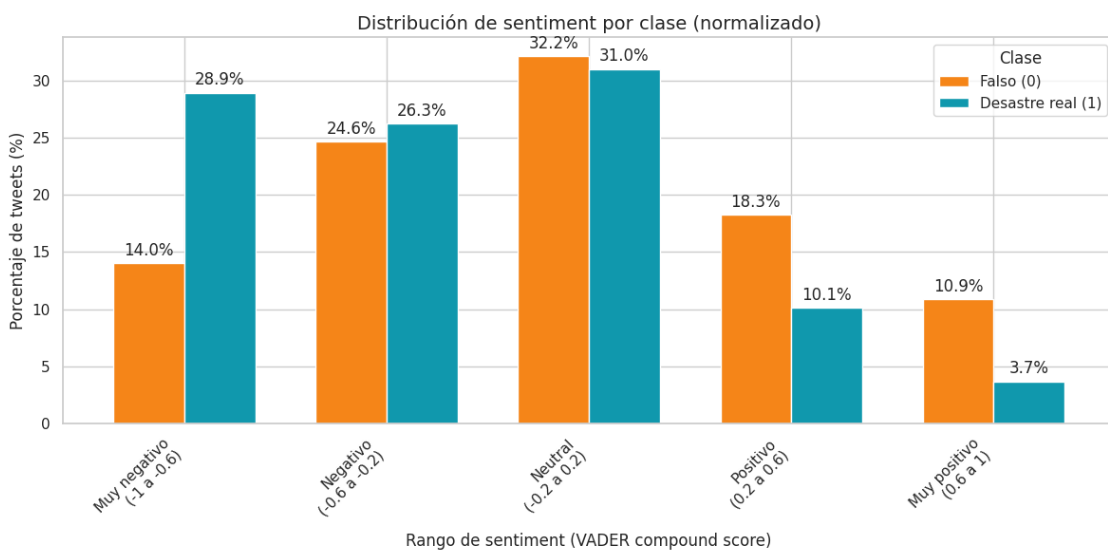
Okey hay palabras que claramente se asocian más a desastres, como "news", "fire", "accident", etc. Mientras que otras como "like", "get", "your" se asocian más a tweets no relacionados con desastres. Igual son palabras bastante generales. filtré algunas con stop words pero en general no hay nada muy específico a los no desastres, pero bueno, si estás tweeteando un desastre probablemente no digas "like" o "your". Debido a la seriedad del tema.

1.7 Visualización 7: Análisis de sentimiento del texto del tweet

[26]:
```python
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer

analyzer = SentimentIntensityAnalyzer()

def get_sentiment_compound(text):
    if pd.isna(text) or text.strip() == '':
        return 0.0
    return analyzer.polarity_scores(text)['compound']

train_df['sentiment'] = train_df['text'].apply(get_sentiment_compound)

bins = [-1, -0.6, -0.2, 0.2, 0.6, 1]
labels = ['Muy negativo\n(-1 a -0.6)', 'Negativo\n(-0.6 a -0.2)', 'Neutral\n(-0.
 ↪2 a 0.2)',
          'Positivo\n(0.2 a 0.6)', 'Muy positivo\n(0.6 a 1)']
train_df['sentiment_bin'] = pd.cut(train_df['sentiment'], bins=bins,␣
 ↪labels=labels, include_lowest=True)
```

```python
plot_df = train_df.groupby(['sentiment_bin', 'target']).size().
    ↪unstack(fill_value=0)

plot_df_pct = plot_df.div(plot_df.sum(axis=0), axis=1) * 100
plot_df_pct.columns = ['Falso (0)', 'Desastre real (1)']

fig, ax = plt.subplots(figsize=(12, 6))
plot_df_pct.plot(kind='bar', ax=ax, color=['#f58518', '#1098ad'], width=0.7)

for container in ax.containers:
    ax.bar_label(container, fmt='%.1f%%', padding=3)

ax.set_title('Distribución de sentiment por clase (normalizado)', fontsize=14)
ax.set_xlabel('Rango de sentiment (VADER compound score)')
ax.set_ylabel('Porcentaje de tweets (%)')
ax.legend(title='Clase', loc='upper right')
ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right')
plt.tight_layout()
plt.show()

print("\nEstadísticas de sentiment por clase:")
print(train_df.groupby('target')['sentiment'].describe())
```

```
/tmp/ipykernel_76021/4106497693.py:17: FutureWarning: The default of
observed=False is deprecated and will be changed to True in a future version of
pandas. Pass observed=False to retain current behavior or observed=True to adopt
the future default and silence this warning.
  plot_df = train_df.groupby(['sentiment_bin',
'target']).size().unstack(fill_value=0)
```



```
Estadísticas de sentiment por clase:
         count      mean       std     min     25%     50%     75%     max
target
0       4342.0 -0.052444  0.465568 -0.9883 -0.4588  0.0000  0.3182  0.9730
1       3271.0 -0.267240  0.434629 -0.9686 -0.6390 -0.3182  0.0000  0.9471
```

Okey!!! Me gustó este, realmente parece haber correlación entre el sentimiento del tweet y si es desastre o no. Sobretodo se ve muy fuerte en las puntas. Los tweets de desastre tienden a tener sentimientos más negativos, mientras que los no desastres son más neutrales o positivos. Tiene mucho sentido así que voy a re usar la feature de sentimiento en el modelo.