EDA & QA TORNADOS

TOMAS TORTOSA MOLTO

head()

```python
tornado.head()
```

Python

	om	yr	mo	dy	date	time	tz	datetime_utc	st	stf	...	elon	len	wid	ns	sn	f1	f2	f3	f4	fc
0	192	1950	10	1	1950-10-01	21:00:00	America/Chicago	1950-10-02T03:00:00Z	OK	40	...	-102.3	15.8	10	1	1	25	0	0	0	False
1	193	1950	10	9	1950-10-09	02:15:00	America/Chicago	1950-10-09T08:15:00Z	NC	37	...	0.0	2.0	880	1	1	47	0	0	0	False
2	195	1950	11	20	1950-11-20	02:20:00	America/Chicago	1950-11-20T08:20:00Z	KY	21	...	0.0	0.1	10	1	1	177	0	0	0	False
3	196	1950	11	20	1950-11-20	04:00:00	America/Chicago	1950-11-20T10:00:00Z	KY	21	...	0.0	0.1	10	1	1	209	0	0	0	False
4	197	1950	11	20	1950-11-20	07:30:00	America/Chicago	1950-11-20T13:30:00Z	MS	28	...	0.0	2.0	37	1	1	101	0	0	0	False

5 rows × 27 columns

tail()

```python
tornado.tail()
```

Python

	om	yr	mo	dy	date	time	tz	datetime_utc	st	stf	...	elon	len	wid	ns	sn	f1	f2	f3	f4	fc
68688	621922	2022	9	28	2022-09-28	13:32:00	America/Chicago	2022-09-28T18:32:00Z	FL	12	...	-80.8841	3.00	100	1	1	9	0	0	0	False
68689	621923	2022	9	30	2022-09-30	10:25:00	America/Chicago	2022-09-30T15:25:00Z	NC	37	...	-78.3011	0.74	20	1	1	19	0	0	0	False
68690	621924	2022	9	30	2022-09-30	13:22:00	America/Chicago	2022-09-30T18:22:00Z	NC	37	...	-76.7147	0.70	12	1	1	13	0	0	0	False
68691	621900	2022	9	4	2022-09-04	15:44:00	America/Chicago	2022-09-04T20:44:00Z	OH	39	...	-80.6555	0.07	15	1	1	99	0	0	0	False
68692	621901	2022	9	9	2022-09-09	23:21:00	America/Chicago	2022-09-10T04:21:00Z	SC	45	...	-79.7537	0.68	125	1	1	19	0	0	0	False

5 rows × 27 columns

describe()

```python
tornado.describe()
```

Python

	om	yr	mo	dy	stf	mag	inj	fat	loss	slat	...	elat	68
count	68693.000000	68693.000000	68693.000000	68693.000000	68693.000000	67937.000000	68693.000000	68693.00000	4.152300e+04	68693.000000	...	68693.000000	68
mean	113201.815542	1991.854061	5.968541	15.930881	29.220255	0.778721	1.418689	0.08931	2.020898e+06	37.129386	...	22.960651	
std	226621.993899	19.565158	2.444656	8.750070	15.013273	0.895790	18.114752	1.47212	3.039588e+07	5.099005	...	18.528144	
min	1.000000	1950.000000	1.000000	1.000000	1.000000	0.000000	0.000000	0.00000	5.000000e+01	17.721200	...	0.000000	
25%	285.000000	1976.000000	4.000000	8.000000	18.000000	0.000000	0.000000	0.00000	1.000000e+04	33.180000	...	0.000000	
50%	588.000000	1995.000000	6.000000	16.000000	28.000000	1.000000	0.000000	0.00000	5.000000e+04	37.000000	...	32.550000	
75%	1118.000000	2008.000000	7.000000	24.000000	42.000000	1.000000	0.000000	0.00000	5.000000e+05	40.920000	...	38.650000	
max	622080.000000	2022.000000	12.000000	31.000000	78.000000	5.000000	1740.000000	158.00000	2.800100e+09	61.020000	...	61.020000	

8 rows × 21 columns

info()

```python
tornado.info()
```

Python

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 68693 entries, 0 to 68692
Data columns (total 27 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   om            68693 non-null  int64  
 1   yr            68693 non-null  int64  
 2   mo            68693 non-null  int64  
 3   dy            68693 non-null  int64  
 4   date          68693 non-null  object 
 5   time          68693 non-null  object 
 6   tz            68693 non-null  object 
 7   datetime_utc  68693 non-null  object 
 8   st            68693 non-null  object 
 9   stf           68693 non-null  int64  
 10  mag           67937 non-null  float64
 11  inj           68693 non-null  int64  
 12  fat           68693 non-null  int64  
 13  loss          41523 non-null  float64
 14  slat          68693 non-null  float64
 15  slon          68693 non-null  float64
 16  elat          68693 non-null  float64
 17  elon          68693 non-null  float64
 18  len           68693 non-null  float64
 19  wid           68693 non-null  int64  
...
 25  f4            68693 non-null  int64  
 26  fc            68693 non-null  bool   
dtypes: bool(1), float64(7), int64(14), object(5)
memory usage: 13.7+ MB
```

Shape()

```
tornado.shape
```

Python

```
(68693, 27)
```

Eliminamos columnas que no son necesarias (ID del tornado, zona horaria y DateTime)

```python
tornado = tornado.drop('om', axis=1)
tornado = tornado.drop('tz', axis=1)
tornado = tornado.drop('datetime_utc', axis=1)
tornado
```

Python

	yr	mo	dy	date	time	st	stf	mag	inj	fat	...	elon	len	wid	ns	sn	f1	f2	f3	f4	fc
0	1950	10	1	1950-10-01	21:00:00	OK	40	1.0	0	0	...	-102.3000	15.80	10	1	1	25	0	0	0	False
1	1950	10	9	1950-10-09	02:15:00	NC	37	3.0	3	0	...	0.0000	2.00	880	1	1	47	0	0	0	False
2	1950	11	20	1950-11-20	02:20:00	KY	21	2.0	0	0	...	0.0000	0.10	10	1	1	177	0	0	0	False
3	1950	11	20	1950-11-20	04:00:00	KY	21	1.0	0	0	...	0.0000	0.10	10	1	1	209	0	0	0	False
4	1950	11	20	1950-11-20	07:30:00	MS	28	1.0	3	0	...	0.0000	2.00	37	1	1	101	0	0	0	False
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
68688	2022	9	28	2022-09-28	13:32:00	FL	12	0.0	0	0	...	-80.8841	3.00	100	1	1	9	0	0	0	False
68689	2022	9	30	2022-09-30	10:25:00	NC	37	0.0	0	0	...	-78.3011	0.74	20	1	1	19	0	0	0	False
68690	2022	9	30	2022-09-30	13:22:00	NC	37	NaN	0	0	...	-76.7147	0.70	12	1	1	13	0	0	0	False
68691	2022	9	4	2022-09-04	15:44:00	OH	39	0.0	0	0	...	-80.6555	0.07	15	1	1	99	0	0	0	False
68692	2022	9	9	2022-09-09	23:21:00	SC	45	0.0	0	0	...	-79.7537	0.68	125	1	1	19	0	0	0	False

68693 rows × 24 columns

Aplicamos LabelEncoder a las columnas ST y FC

```python
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
tornado.st = le.fit_transform(tornado.st)
tornado.fc = le.fit_transform(tornado.fc)
tornado
```

Python

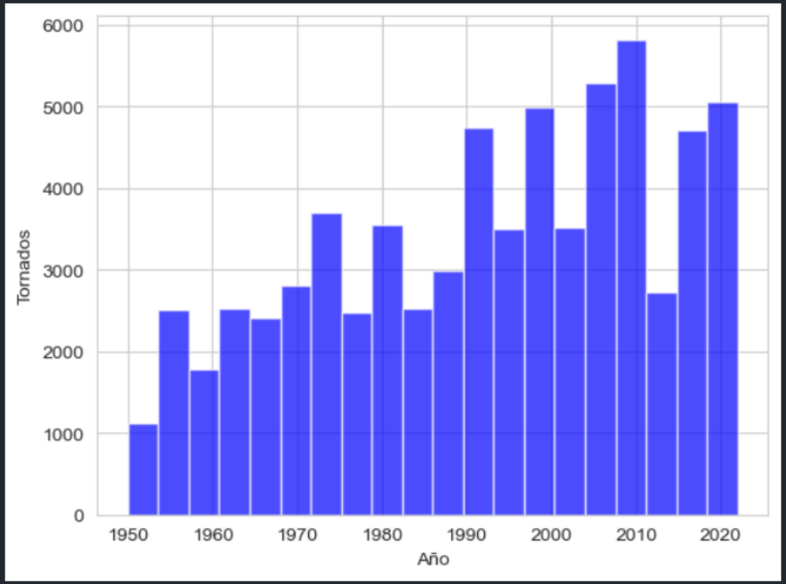
	yr	mo	dy	date	time	st	stf	mag	inj	fat	...	elon	len	wid	ns	sn	f1	f2	f3	f4	fc
0	1950	10	1	1950-10-01	1900-01-01 21:00:00	36	40	1.0	0	0	...	-102.3000	15.80	10	1	1	25	0	0	0	0
1	1950	10	9	1950-10-09	1900-01-01 02:15:00	27	37	3.0	3	0	...	0.0000	2.00	880	1	1	47	0	0	0	0
2	1950	11	20	1950-11-20	1900-01-01 02:20:00	17	21	2.0	0	0	...	0.0000	0.10	10	1	1	177	0	0	0	0
3	1950	11	20	1950-11-20	1900-01-01 04:00:00	17	21	1.0	0	0	...	0.0000	0.10	10	1	1	209	0	0	0	0
4	1950	11	20	1950-11-20	1900-01-01 07:30:00	25	28	1.0	3	0	...	0.0000	2.00	37	1	1	101	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
68688	2022	9	28	2022-09-28	1900-01-01 13:32:00	9	12	0.0	0	0	...	-80.8841	3.00	100	1	1	9	0	0	0	0
68689	2022	9	30	2022-09-30	1900-01-01 10:25:00	27	37	0.0	0	0	...	-78.3011	0.74	20	1	1	19	0	0	0	0
68690	2022	9	30	2022-09-30	1900-01-01 13:22:00	27	37	NaN	0	0	...	-76.7147	0.70	12	1	1	13	0	0	0	0
68691	2022	9	4	2022-09-04	1900-01-01 15:44:00	35	39	0.0	0	0	...	-80.6555	0.07	15	1	1	99	0	0	0	0
68692	2022	9	9	2022-09-09	1900-01-01 23:21:00	41	45	0.0	0	0	...	-79.7537	0.68	125	1	1	19	0	0	0	0

68693 rows × 24 columns

Muestro los tornados de cada año para pensar si hay que hacer binarización

```python
plt.hist(tornado.yr, bins=20, color='blue', alpha=0.7)
plt.xlabel('Año')
plt.ylabel('Tornados')
plt.show()
```

Python



Aplico binarización de 4 bins

```python
bins = panda.qcut(tornado.yr, q=4, labels=False)
bins
```

Python

```
0        0
1        0
2        0
3        0
4        0
        ..
68688    3
68689    3
68690    3
68691    3
68692    3
Name: yr, Length: 68693, dtype: int64
```

```python
bins = panda.qcut(tornado.yr, q=4)
bins
```

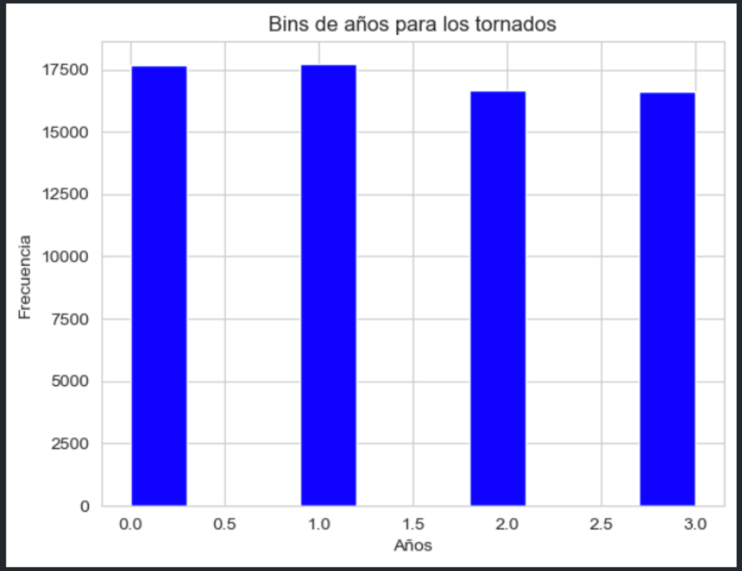
Python

```
0        (1949.999, 1976.0]
1        (1949.999, 1976.0]
2        (1949.999, 1976.0]
3        (1949.999, 1976.0]
4        (1949.999, 1976.0]
                ...
68688      (2008.0, 2022.0]
68689      (2008.0, 2022.0]
68690      (2008.0, 2022.0]
68691      (2008.0, 2022.0]
68692      (2008.0, 2022.0]
Name: yr, Length: 68693, dtype: category
Categories (4, interval[float64, right]): [(1949.999, 1976.0] < (1976.0, 1995.0] < (1995.0, 2008.0] < (2008.0, 2022.0]]
```

Muestro bins, los años no aparecen bien

```python
plt.hist(panda.qcut(tornado.yr, q=4, labels=False), color='blue')
plt.title('Bins de años para los tornados')
plt.xlabel('Años')
plt.ylabel('Frecuencia')
plt.show()
```

Python



Obtengo el valor de los bins y me quedo con el index

```python
years = bins.value_counts().index
years
```

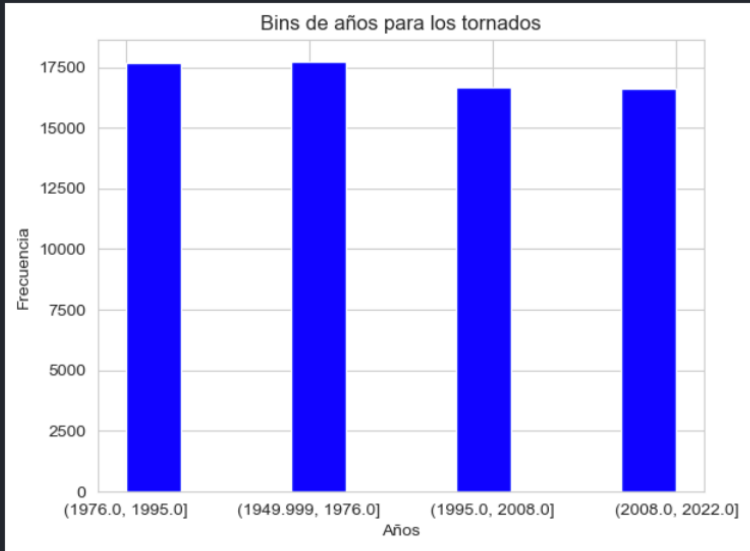
Python

```
CategoricalIndex([(1976.0, 1995.0], (1949.999, 1976.0], (1995.0, 2008.0],
                  (2008.0, 2022.0]],
                 categories=[(1949.999, 1976.0], (1976.0, 1995.0], (1995.0, 2008.0], (2008.0, 2022.0]], ordered=True, dtype='category', name='yr')
```

Muestro gráfico de bins cargando los años anteriores

```python
plt.hist(panda.qcut(tornado.yr, q=4, labels=False), color='blue')
plt.title('Bins de años para los tornados')
plt.xlabel('Años')
plt.ylabel('Frecuencia')
plt.xticks(range(4), years)
plt.show()
```

Python



Compruebo columnas nulas

```python
tornado.isnull().sum()
```

Python

```
yr                  0
mo                  0
dy                  0
date                0
time                0
datetime_utc        0
st                  0
stf                 0
mag               756
inj                 0
fat                 0
loss            27170
slat                0
slon                0
elat                0
elon                0
len                 0
wid                 0
ns                  0
sn                  0
f1                  0
f2                  0
f3                  0
f4                  0
fc                  0
dtype: int64
```

Calculo media de la columna mag

```python
mag = tornado.mag.mean()
print("Esto es media de mag", mag)
magNotNulls = tornado.mag.mean(skipna=True)
print("Esto es media de mag sin nulls", magNotNulls)
```

Python

```
Esto es media de mag 0.778721462531463
Esto es media de mag sin nulls 0.778721462531463
```

Como la media no afecta, elimino filas que no tienen magnitud

```python
tornado = tornado.dropna(subset=['mag'])
tornado
```

Python

	yr	mo	dy	date	time	st	stf	mag	inj	fat	...	elon	len	wid	ns	sn	f1	f2	f3	f4	fc
0	1950	10	1	1950-10-01	1900-01-01 21:00:00	36	40	1.0	0	0	...	-102.3000	15.80	10	1	1	25	0	0	0	0
1	1950	10	9	1950-10-09	1900-01-01 02:15:00	27	37	3.0	3	0	...	0.0000	2.00	880	1	1	47	0	0	0	0
2	1950	11	20	1950-11-20	1900-01-01 02:20:00	17	21	2.0	0	0	...	0.0000	0.10	10	1	1	177	0	0	0	0
3	1950	11	20	1950-11-20	1900-01-01 04:00:00	17	21	1.0	0	0	...	0.0000	0.10	10	1	1	209	0	0	0	0
4	1950	11	20	1950-11-20	1900-01-01 07:30:00	25	28	1.0	3	0	...	0.0000	2.00	37	1	1	101	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
68687	2022	9	28	2022-09-28	1900-01-01 03:56:00	9	12	0.0	0	0	...	-80.0680	0.20	50	1	1	99	0	0	0	0
68688	2022	9	28	2022-09-28	1900-01-01 13:32:00	9	12	0.0	0	0	...	-80.8841	3.00	100	1	1	9	0	0	0	0
68689	2022	9	30	2022-09-30	1900-01-01 10:25:00	27	37	0.0	0	0	...	-78.3011	0.74	20	1	1	19	0	0	0	0
68691	2022	9	4	2022-09-04	1900-01-01 15:44:00	35	39	0.0	0	0	...	-80.6555	0.07	15	1	1	99	0	0	0	0
68692	2022	9	9	2022-09-09	1900-01-01 23:21:00	41	45	0.0	0	0	...	-79.7537	0.68	125	1	1	19	0	0	0	0

67937 rows × 24 columns

Compruebo información para columna loss

```python
print("Media de loss:", tornado.loss.median())
print("Minimo de loss:", tornado.loss.min())
print("Maximo de loss:", tornado.loss.max())
print("La desviación típica es:", tornado.loss.std())
```

✓ 0.0s Python

```
Media de loss: 50000.0
Minimo de loss: 50.0
Maximo de loss: 2800100000.0
La desviación típica es: 23651659.21147494
```

Guardo en la columna loss números randoms a partir de la desviación típica

```python
import math

medianValue = tornado.loss.median()
stdValue = math.sqrt(49950)
new_data = np.random.normal(medianValue, stdValue, len(tornado[tornado['loss'].isnull()]))
tornado.loc[tornado['loss'].isnull(), 'loss'] = new_data
```

✓ 0.0s Python

Muestro cantidad de tornados para cada una de las magnitudes

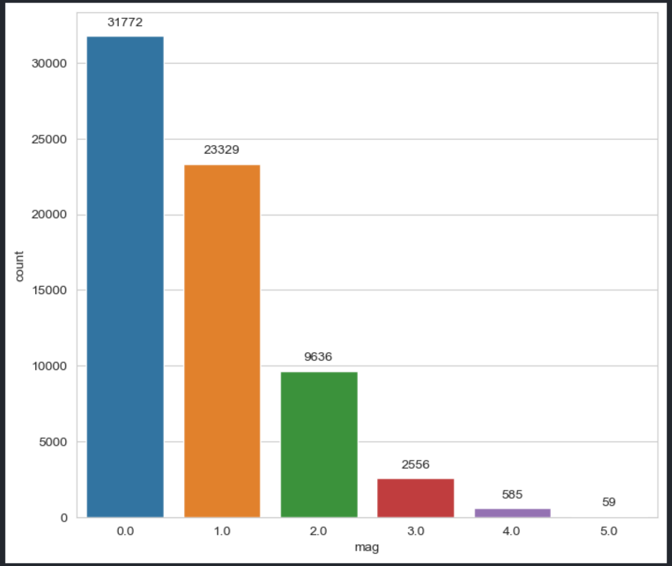
```python
plt.figure(figsize=(8, 7))
ax = sns.countplot(x='mag', data=tornado)

for p in ax.patches:
    ax.annotate(f'{int(p.get_height())}', (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='center', xytext=(0, 10), textcoords='offset points')

plt.show()
```

✓ 0.0s

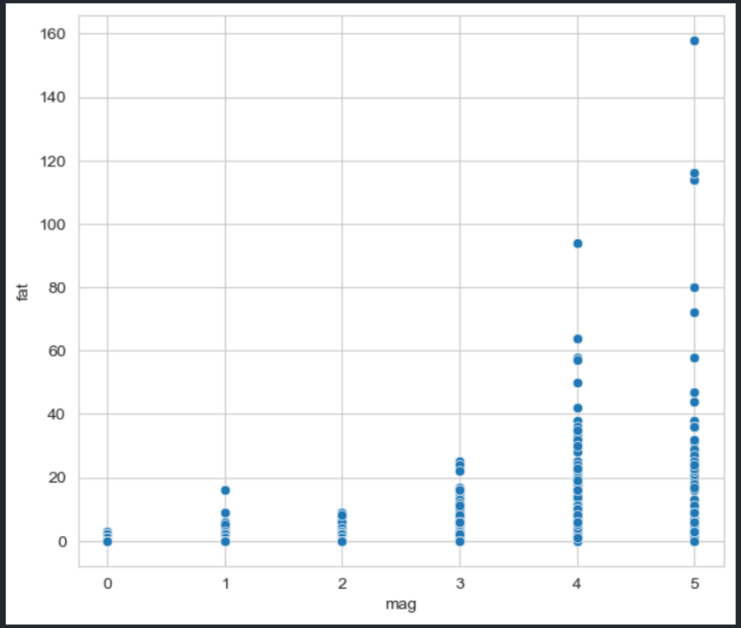
Python



Muestro relación entre magnitud y fallecimientos

```python
plt.figure(figsize=(7, 6))
sns.scatterplot(x='mag', y='fat', data=tornado)
plt.show()
```

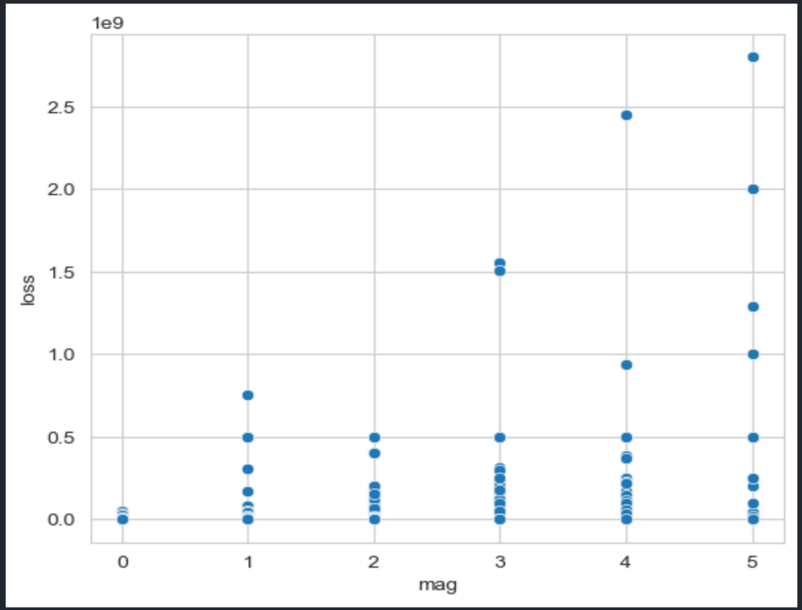
✓ 0.1s   Python



Muestro relación entre pérdidas materiales y magnitud

```
plt.figure(figsize=(6, 5))
sns.scatterplot(x='mag', y='loss', data=tornado)
plt.show()
```

✓ 0.1s Python



Compruebo cuántos tornados hay con un loss mayor a 1 billón

```python
tornado[tornado.loss>1000000000]
```

✓ 0.0s

Python

	yr	mo	dy	date	time	st	stf	mag	inj	fat	...	elon	len	wid	ns	sn	f1	f2	f3	f4	fc
55272	2011	4	27	2011-04-27	14:05:00	1	1	5.0	145	72	...	-86.1511	132.00	2200	2	0	0	0	0	0	0
55288	2011	4	27	2011-04-27	15:43:00	1	1	4.0	1500	64	...	-86.7436	80.68	2600	1	1	63	125	73	0	0
55592	2011	5	22	2011-05-22	16:34:00	24	29	5.0	1150	158	...	-94.2213	21.62	1600	1	1	145	97	145	0	0
57584	2013	5	20	2013-05-20	13:56:00	36	40	5.0	212	24	...	-97.3999	13.85	1900	1	1	87	27	0	0	0
63647	2019	10	20	2019-10-20	19:58:00	44	48	3.0	0	0	...	-96.6833	15.76	1300	1	1	113	0	0	0	0
65427	2020	3	3	2020-03-03	00:32:00	43	47	3.0	220	5	...	-85.8904	60.13	1600	1	1	37	189	159	0	0

6 rows × 24 columns

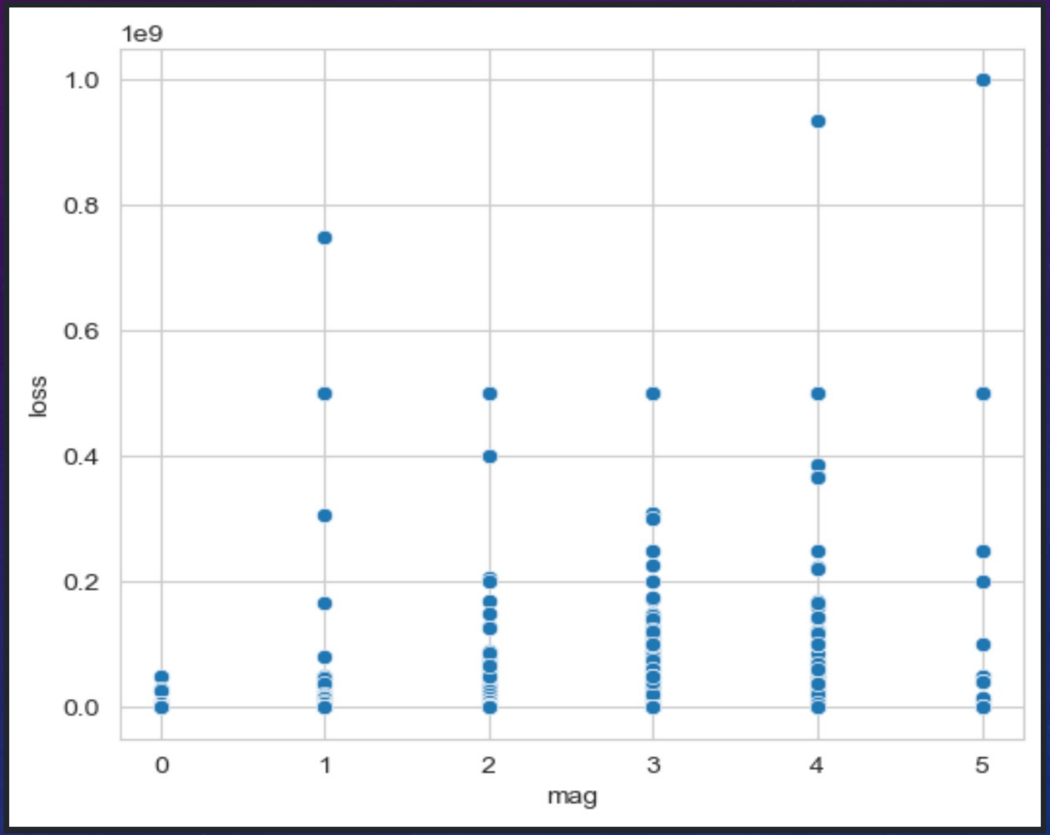
Elimino estos 6 datos para que no causen errores en el modelo

```python
tornado = tornado[tornado['loss'] <= 1000000000]
```

✓ 0.0s

Python

Muestro de nuevo el gráfico para comprobar correcto resultado



Cambio tipo de los datos en las fechas

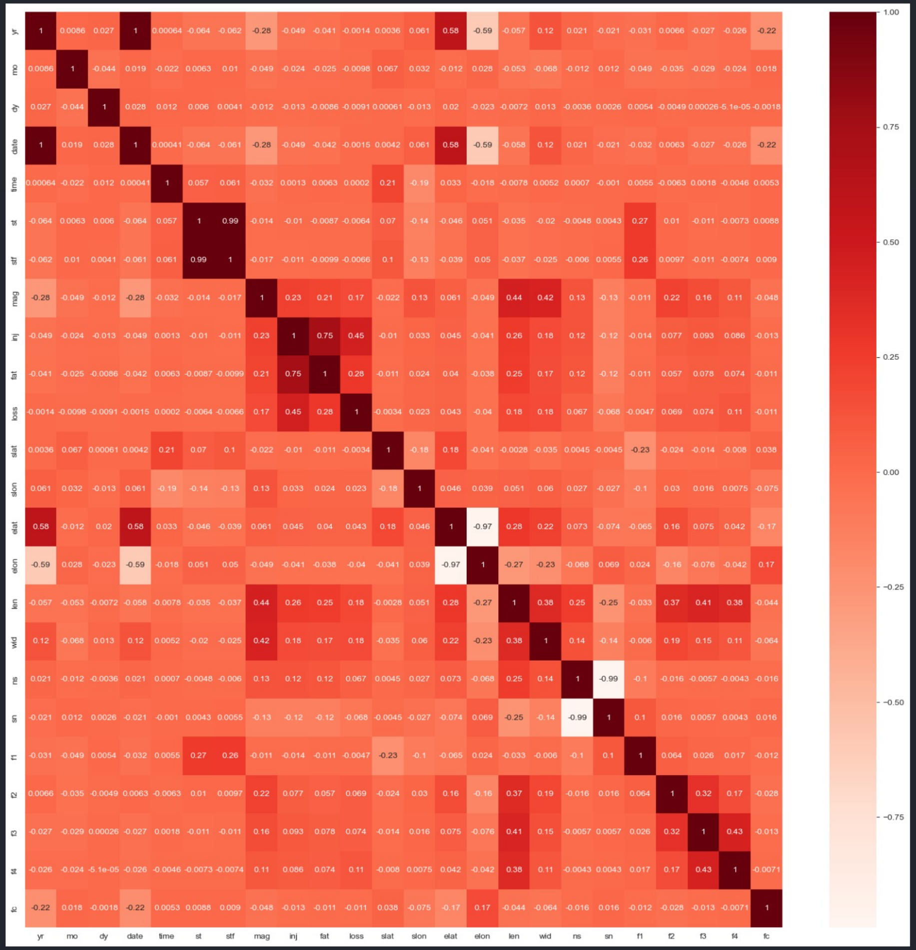
```python
tornado['date'] = panda.to_datetime(tornado['date'])
tornado['time'] = panda.to_datetime(tornado['time'], format='%H:%M:%S')
```

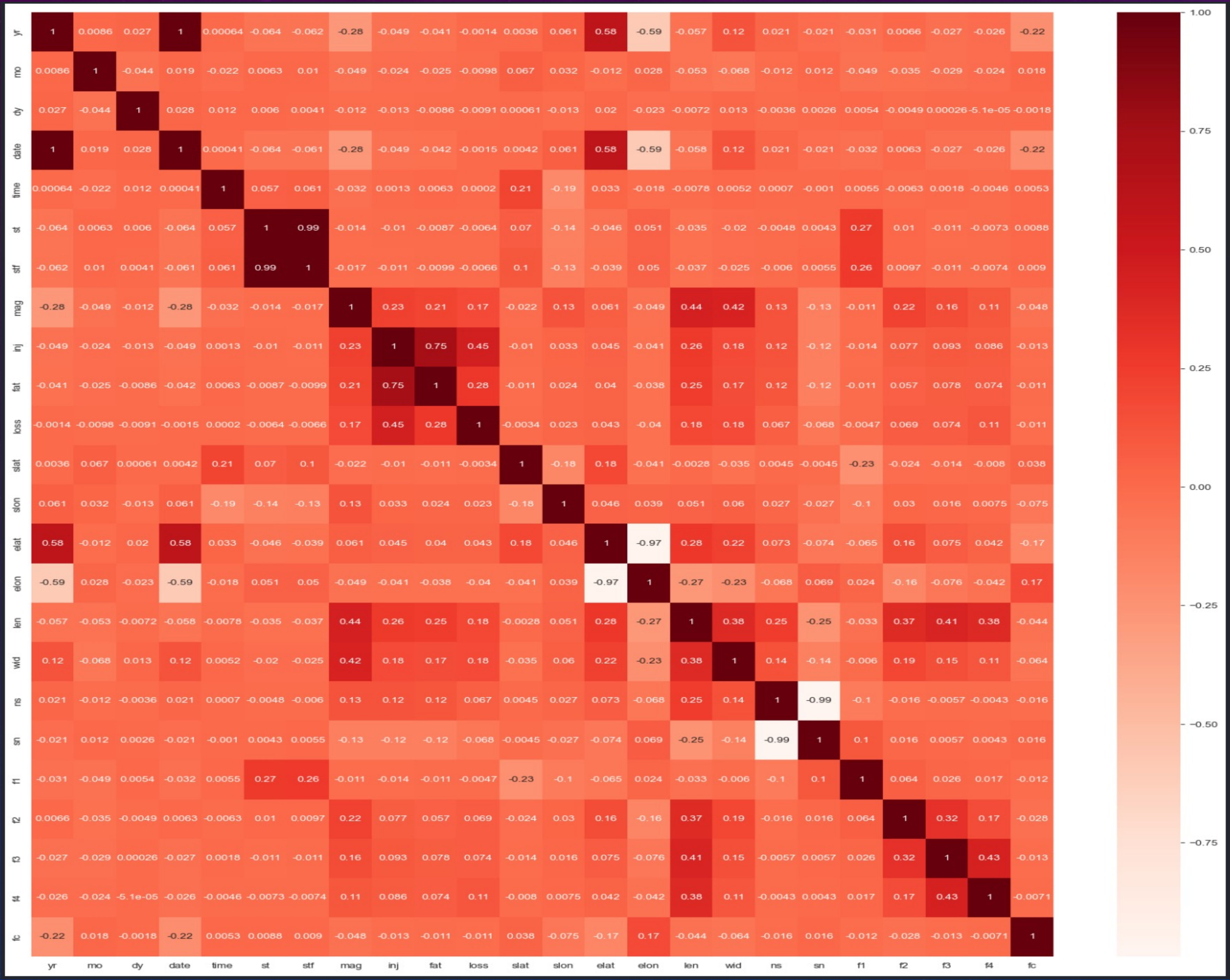
✓ 0.0s Python

Genero escalado

```python
plt.figure(figsize=(20,20))
cor = tornado.corr() #Por defecto calculamos el de Pearson, para calcular Spearman -> df.corr(method='spearman')
sns.heatmap(cor, annot=True, cmap=plt.cm.Reds)
plt.show()
```

0.7s




yr
mo
dy
date
time
st
stf
mag
inj
fat
loss
slat
slon
elat
elon
len
wid
ns
sn
f1
f2
f3
f4
fc
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75