In [1]:
```
# modules
import numpy as np
import matplotlib.pyplot as plt
import matplotlib as mpl
import pandas as pd

%matplotlib inline

# ignore unnecessary
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
# load the data
nasa_csv = pd.read_csv('nasa.csv', index_col=0)
space_csv = pd.read_csv('space.csv', index_col=0)
```

In [3]:
```
nasa_csv.head()
```

Out[3]:

	Start_Datetime	End_Datetime	startFrequency	endFrequency	flare_Location	flare_region	in
0	1997-04-01 14:00:00	1997-04-01 14:15:00	8000	4000	S25E16	8026	
1	1997-04-07 14:30:00	1997-04-07 17:30:00	11000	1000	S28E19	8027	
2	1997-05-12 05:15:00	1997-05-14 16:00:00	12000	80	N21W08	8038	
3	1997-05-21 20:20:00	1997-05-21 22:00:00	5000	500	N05W12	8040	
4	1997-09-23 21:53:00	1997-09-23 22:16:00	6000	2000	S29E25	8088	

In [4]:
```
len(nasa_csv)
```

Out[4]: 482

In [5]:
```
space_csv.tail()
```

Out[5]:

	Rank	X_class	Region	Start_time	Max_time	End_time
45	46	X2.7	2339	2015-05-05 22:05:00	2015-05-05 22:11:00	2015-05-05 22:15:00
46	47	X2.7	488	2003-11-03 01:09:00	2003-11-03 01:30:00	2003-11-03 01:45:00
47	48	X2.7	8210	1998-05-06 07:58:00	1998-05-06 08:09:00	1998-05-06 08:20:00
48	49	X2.6	720	2005-01-15 22:25:00	2005-01-15 23:02:00	2005-01-15 23:31:00
49	50	X2.6	9632	2001-09-24 09:32:00	2001-09-24 10:38:00	2001-09-24 11:09:00

In [6]:
```
len(space_csv)
```
Out[6]: 50

Getting Data Ready for Analysis

- Removing non-numerical items from numerical columns
- Types conversion
- unifying attributes
    - NASA flare region has 5 digits. e.g. 10486
    - Space flare region has 4 digits. e.g. 0486

Seperate importance

- Seperate the importance column into 2 columns
    - importance_1: character representing the **Solar Flare** class
    - importance_2: float representing the class value

In [7]:
```
def seperateImportance(df, col_name='importance', numbers=True, lette
rs=True):
    if col_name == 'X_class':
        # remove the char in the last
        df['X_class'] = df['X_class'].apply(lambda x: x[:-1] if x[-1]
== '+' else x)

    if letters:
        df['importance_1'] = df[col_name].str.slice(start=0, stop=1)
    if numbers:
        df['importance_2'] = df[col_name].str.slice(start=1).astype(
'float')
    return df
```

In [8]:
```
# Cast attributes to datetime stamp
def to_datetime(df, nasa=False, space=False):
    if nasa:
        df.Start_Datetime = pd.to_datetime(df.Start_Datetime)
        df.End_Datetime = pd.to_datetime(df.End_Datetime)
        df.CME_Time = pd.to_datetime(df.CME_Time)
    if space:
        df.Start_time = pd.to_datetime(df.Start_time)
        df.Max_time = pd.to_datetime(df.Max_time)
        df.End_time = pd.to_datetime(df.End_time)

    return df
```

In [9]:
```
# Cast time attributes to datetime stamp
nasa_csv = to_datetime(nasa_csv, nasa=True)
space_csv = to_datetime(space_csv, space=True)
```

In [10]:
```
# replacing 'non-numerical values' with nan in the importance column
nasa_csv = nasa_csv[nasa_csv.importance != 'FILA']

# replacing 'non-numerical values' with nan in the region column
nasa_csv.flare_region = nasa_csv.flare_region.str.extract('(\d+)', ex
pand=False)
```

In [11]:
```
# cast flare region to float
nasa_csv.flare_region = nasa_csv.flare_region.astype('float')
# change NASA's flare region from 5 to 4 digits
nasa_csv.flare_region = nasa_csv.flare_region.apply(lambda x:x-10000
if x>10000 else x)

# preprocess space flare region
space_csv.Region = space_csv.Region.astype('float')
```

In [12]:
```
# show data types
space_csv.dtypes
```

Out[12]:
```
Rank                   int64
X_class               object
Region               float64
Start_time    datetime64[ns]
Max_time      datetime64[ns]
End_time      datetime64[ns]
dtype: object
```

In [13]:
```
nasa_csv.dtypes
```

Out[13]:
```
Start_Datetime    datetime64[ns]
End_Datetime      datetime64[ns]
startFrequency            object
endFrequency              object
flare_Location            object
flare_region             float64
importance                object
CME_Date                  object
CME_Time          datetime64[ns]
width                    float64
speed                    float64
CPA                       object
is_halo                     bool
lower_bound                 bool
dtype: object
```

Part 2 Q1: Replication

In [14]:
```
# seperate importance
nasa_csv = seperateImportance(nasa_csv, 'importance')
```

Sorting the dataframe according to the importance of the Solar Flare

- First, it sorts using `importance_1` values so the character `X` is put at the top of the table
- Second, it sorts using `importance_2` values so the flares with the highes value are put at the top

In [15]:
```
nasa_csv = nasa_csv.sort_values(['importance_1', 'importance_2'], asc
ending=False)
```

In [16]:
```
# drop the importance_1, importance_2 columns
nasa_csv.drop(['importance_1', 'importance_2'], axis=1, inplace=True)
```

In [17]:
```
# showing top 3
nasa_csv[:3]
```

Out[17]:

	Start_Datetime	End_Datetime	startFrequency	endFrequency	flare_Location	flare_region
242	2003-11-04 20:00:00	2003-11-05 00:00:00	10000	200	S19W83	486.0
119	2001-04-02 22:05:00	2001-04-03 02:30:00	14000	250	N19W72	9393.0
234	2003-10-28 11:10:00	2003-10-30 00:00:00	14000	40	S16E08	486.0

Replication Analysis

In [18]:
```
# get the top 50 of nasa
nasa_50 = nasa_csv[:50]
```

Replication Criteria

- in Both NASA and SPACE dataframes
  1. Get all flares that happened in the same region
  2. Get all flares that have the same starting time
  3. Check the number of rows
  4. Check the mean of the flare `X_class and importance`

In [19]:
```
dicOfMatch={}
for s_row in space_csv.itertuples(index=False):
    same_region = []
    # checking the same region
    for n_row in nasa_50.itertuples(index=False):
        if s_row.Region == n_row.flare_region:
            same_region.append(n_row)

    # chacking the same starting date[year, month, day]
    for n_row in same_region:
        if n_row.Start_Datetime.date()==s_row.Start_time.date():
            dicOfMatch[s_row]=n_row
print(f'Number of matching rows: {len(dicOfMatch)}')
```

```
Number of matching rows: 32
```

In [20]:
```
match_nasa = pd.DataFrame(dicOfMatch.values())
match_nasa[:5]
```

Out[20]:

	Start_Datetime	End_Datetime	startFrequency	endFrequency	flare_Location	flare_region	in
0	2003-11-04 20:00:00	2003-11-05 00:00:00	10000	200	S19W83	486.0	
1	2001-04-02 22:05:00	2001-04-03 02:30:00	14000	250	N19W72	9393.0	
2	2003-10-28 11:10:00	2003-10-30 00:00:00	14000	40	S16E08	486.0	
3	2001-04-15 14:05:00	2001-04-16 13:00:00	14000	40	S20W85	9415.0	
4	2003-10-29 20:55:00	2003-10-30 00:00:00	11000	500	S15W02	486.0	

In [21]:
```
match_space = pd.DataFrame(dicOfMatch.keys())
match_space[:5]
```

Out[21]:

	Rank	X_class	Region	Start_time	Max_time	End_time
0	1	X28+	486.0	2003-11-04 19:29:00	2003-11-04 19:53:00	2003-11-04 20:06:00
1	2	X20+	9393.0	2001-04-02 21:32:00	2001-04-02 21:51:00	2001-04-02 22:03:00
2	3	X17.2+	486.0	2003-10-28 09:51:00	2003-10-28 11:10:00	2003-10-28 11:24:00
3	5	X14.4	9415.0	2001-04-15 13:19:00	2001-04-15 13:50:00	2001-04-15 13:55:00
4	6	X10	486.0	2003-10-29 20:37:00	2003-10-29 20:49:00	2003-10-29 21:01:00

In [22]:
```
match_nasa = seperateImportance(match_nasa, letters=False)
match_space = seperateImportance(match_space, 'X_class', letters=Fals
e)
```

In [23]:
```
# getting the mean
print("Mean:", (abs(match_nasa.importance_2 - match_space.importance_
2)).mean())
```

```
Mean: 0.19374999999999998
```

Conclusion Analysis

- When doing the matching using the region where the flare happened and the date of the region
  - we only get 32 matching rows
  - the mean differnce between the NASA's `importance` and SPACE `X_class` is: `0.19374999999999998`
- So based on that the 2 datasets have slightly different values for the same Flare event, so we won't be able to replicate the whole data with high accuracy

Part 2 Q2: Integration

- get the common attributes
  - Start Time, End Stime, Region, CME Time, Importance
- define the matching criteria

In [24]:
```
# get smaller version of the 2 dataframes with only the common column
s
nasa_50_small = nasa_50[['importance', 'flare_region', 'Start_Datetim
e', 'End_Datetime', 'CME_Time']]
```

In [25]:
```
nasa_50_small.head()
```

Out[25]:

	importance	flare_region	Start_Datetime	End_Datetime	CME_Time
242	X28.	486.0	2003-11-04 20:00:00	2003-11-05 00:00:00	2020-03-26 19:54:00
119	X20.	9393.0	2001-04-02 22:05:00	2001-04-03 02:30:00	2020-03-26 22:06:00
234	X17.	486.0	2003-10-28 11:10:00	2003-10-30 00:00:00	2020-03-26 11:30:00
128	X14.	9415.0	2001-04-15 14:05:00	2001-04-16 13:00:00	2020-03-26 14:06:00
235	X10.	486.0	2003-10-29 20:55:00	2003-10-30 00:00:00	2020-03-26 20:54:00

Criteria

- After reading about **Solar Flares** we found that the most defining feature is the `importance` / `X_class` of the flare, so we built our criteria around it.

First

- get the difference between the current solar flare `X_class` in the **SPACE** dataframe and get the difference between it and all `importance` values in the **NASA** datafrme

Second

- get the **NASA** row with the smalles difference as the matching row

Third

- add the `Space_Rank` column to the **NASA** dataframe
- calculate the mean difference between the matched dataframe and **SPACE** dataframe

Why didn't we use the region or the starting date?

- we didn't use the region as it won't produce 50 rows, as some regions are available at **SPACE** dataframe but not in **NASA**
- we also didn't use the starting date as it's not consistent in the 2 dataframes

Why did we use NASA TOP 50 instead of NASA?

- we found that **NASA TOP 50**'s range was enough to cover the whole range of `X_class` values of **SPACE** dataframe so there will be no need to compare the whole **NASA** dataframe

In [26]:
```
def bestMatching(df1=space_csv, df2=nasa_50_small):
    # seperate the value of the X-class/Importance from space
    df1 = seperateImportance(df1, 'X_class', letters=False)
    df2 = seperateImportance(df2, letters=False)

    nasa_csv['Space_Rank'] = ""

    rows = []
    for row in df1.itertuples(index=True):
        near_x = {}
        for r in df2.itertuples(index=True):
            near_x[abs(r.importance_2 - row.importance_2)] = r
        if len(near_x) > 0:
            best_match = near_x[min(near_x.keys())]
            rows.append(best_match)
            nasa_csv.Space_Rank.loc[best_match.Index] = nasa_csv.Spac
e_Rank.loc[best_match.Index]+str(row.Rank)+' '
        # calc mean error
        mean_error = abs(pd.DataFrame(rows).importance_2 - df1.import
ance_2).mean()

    # replace "" with nan
    nasa_csv['Space_Rank'].replace("", 'nan', inplace=True)


    return pd.DataFrame(rows).drop('importance_2', axis=1), mean_erro
r
```

In [27]:
```
nasa_best_matching, mean_error = bestMatching(space_csv, nasa_50)
print(f'Mean Error: {mean_error}')
nasa_best_matching.head()
```

```
Mean Error: 0.020000000000000007
```

Out[27]:

	Index	Start_Datetime	End_Datetime	startFrequency	endFrequency	flare_Location	flare_re
0	242	2003-11-04 20:00:00	2003-11-05 00:00:00	10000	200	S19W83	4
1	119	2001-04-02 22:05:00	2001-04-03 02:30:00	14000	250	N19W72	93
2	234	2003-10-28 11:10:00	2003-10-30 00:00:00	14000	40	S16E08	4
3	234	2003-10-28 11:10:00	2003-10-30 00:00:00	14000	40	S16E08	4
4	128	2001-04-15 14:05:00	2001-04-16 13:00:00	14000	40	S20W85	94

In [28]:
```
nasa_csv[:50]
```

Out[28]:

	Start_Datetime	End_Datetime	startFrequency	endFrequency	flare_Location	flare_region
242	2003-11-04 20:00:00	2003-11-05 00:00:00	10000	200	S19W83	486.0
119	2001-04-02 22:05:00	2001-04-03 02:30:00	14000	250	N19W72	9393.0
234	2003-10-28 11:10:00	2003-10-30 00:00:00	14000	40	S16E08	486.0
128	2001-04-15 14:05:00	2001-04-16 13:00:00	14000	40	S20W85	9415.0
235	2003-10-29 20:55:00	2003-10-30 00:00:00	11000	500	S15W02	486.0
8	1997-11-06 12:20:00	1997-11-07 08:30:00	14000	100	S18W63	8100.0
330	2006-12-05 10:50:00	2006-12-05 20:00:00	14000	250	S07E68	930.0
238	2003-11-02 17:30:00	2003-11-03 01:00:00	12000	250	S14W56	486.0
290	2005-01-20 07:15:00	2005-01-20 16:30:00	14000	25	N14W61	720.0
360	2011-08-09 08:20:00	2011-08-09 08:35:00	16000	4000	N17W69	1263.0
333	2006-12-06 19:00:00	2006-12-09 00:00:00	16000	30	S05E64	930.0
319	2005-09-09 19:45:00	2005-09-09 22:00:00	10000	50	S12E67	808.0
83	2000-07-14 10:30:00	2000-07-15 14:30:00	14000	80	N22W07	9077.0
123	2001-04-06 19:35:00	2001-04-07 01:50:00	14000	230	S21E31	9415.0
376	2012-03-07 01:00:00	2012-03-08 19:00:00	16000	30	N17E27	1429.0
137	2001-08-25 16:50:00	2001-08-25 23:00:00	8000	170	S17E34	9591.0
444	2014-02-25 00:56:00	2014-02-25 11:28:00	14000	100	S13E82	1990.0
195	2002-07-23 00:50:00	2002-07-23 04:00:00	11000	400	S13E72	39.0
106	2000-11-26 17:00:00	2000-11-26 17:15:00	14000	7000	N18W38	9236.0
240	2003-11-03 10:00:00	2003-11-03 12:30:00	6000	400	N08W77	488.0
289	2005-01-17 10:00:00	2005-01-17 10:35:00	6100	1500	N15W25	720.0
223	2003-05-28 01:00:00	2003-05-29 00:30:00	1000	200	S06W21	365.0
162	2001-12-28 20:35:00	2001-12-29 03:00:00	14000	350	S26E90	9756.0

	Start_Datetime	End_Datetime	startFrequency	endFrequency	flare_Location	flare_region
334	2006-12-13 02:45:00	2006-12-13 10:40:00	12000	150	S06W23	930.0
194	2002-07-20 21:30:00	2002-07-20 22:20:00	10000	2000	SE90b	39.0
405	2013-05-14 01:16:00	2013-05-14 02:35:00	16000	700	N08E77	1748.0
202	2002-08-24 01:45:00	2002-08-24 03:25:00	5000	400	S02W81	69.0
404	2013-05-13 16:15:00	2013-05-13 19:10:00	16000	300	N11E85	1748.0
19	1998-05-06 08:25:00	1998-05-06 08:35:00	14000	5000	S11W65	8210.0
239	2003-11-03 01:15:00	2003-11-03 01:25:00	3000	1500	N10W83	488.0
9	1997-11-27 13:30:00	1997-11-27 14:00:00	14000	7000	N17E63	8113.0
144	2001-09-24 10:45:00	2001-09-25 20:00:00	7000	30	S16E23	9632.0
286	2005-01-15 23:00:00	2005-01-15 00:00:00	3000	40	N15W05	720.0
278	2004-11-10 02:25:00	2004-11-10 03:40:00	14000	1000	N09W49	696.0
73	2000-06-06 15:20:00	2000-06-08 09:00:00	14000	40	N20E18	9026.0
101	2000-11-24 15:25:00	2000-11-24 22:00:00	14000	200	N22W07	9236.0
125	2001-04-10 05:24:00	2001-04-11 00:00:00	14000	100	S23W09	9415.0
347	2011-02-15 02:10:00	2011-02-15 07:00:00	16000	400	S20W12	1158.0
7	1997-11-04 06:00:00	1997-11-05 04:30:00	14000	100	S14W33	8100.0
320	2005-09-10 21:45:00	2005-09-10 01:00:00	14000	300	S13E47	808.0
362	2011-09-06 22:30:00	2011-09-07 15:40:00	16000	150	N14W18	1283.0
421	2013-10-25 15:08:00	2013-10-25 22:32:00	16000	200	S06E69	1882.0
100	2000-11-24 05:10:00	2000-11-24 15:00:00	14000	100	N20W05	9236.0
127	2001-04-12 10:20:00	2001-04-12 10:40:00	14000	7000	S19W43	9415.0
276	2004-11-07 16:25:00	2004-11-08 20:00:00	14000	60	N09W17	696.0
287	2005-01-17 09:25:00	2005-01-17 16:00:00	14000	30	N15W25	720.0

	Start_Datetime	End_Datetime	startFrequency	endFrequency	flare_Location	flare_region
104	2000-11-25 19:00:00	2000-11-25 19:35:00	6000	2000	N20W23	9236.0
49	1999-10-14 09:10:00	1999-10-14 10:00:00	14000	4000	N11E32	8731.0
102	2000-11-24 22:24:00	2000-11-24 22:36:00	4000	3000	N21W14	9236.0
191	2002-07-18 07:55:00	2002-07-18 08:45:00	14000	1500	N19W30	30.0

Part 2 Q3: Analysis

In [29]:
```
# our colors
colors_list = ['#5cb85c','#d9534f']

# autolabel
def autolabel(rects):
    """Attach a text label above each bar in *rects*, displaying its
 height."""
    for rect in rects:
        height = rect.get_height()
        ax.annotate(f'{height*100:.2f}%',
                    xy=(rect.get_x() + rect.get_width() / 2, height),
                    xytext=(0, 3),  # 3 points vertical offset
                    textcoords="offset points",
                    ha='center', va='bottom')
```

Halo Proportion: Nasa vs Nasa Top 50

First

- we get the *proportion* of **Halos** in the **NASA** and **NASA TOP 50** dataframes

Second

- we use a barplot to show the 2 proportions side by side

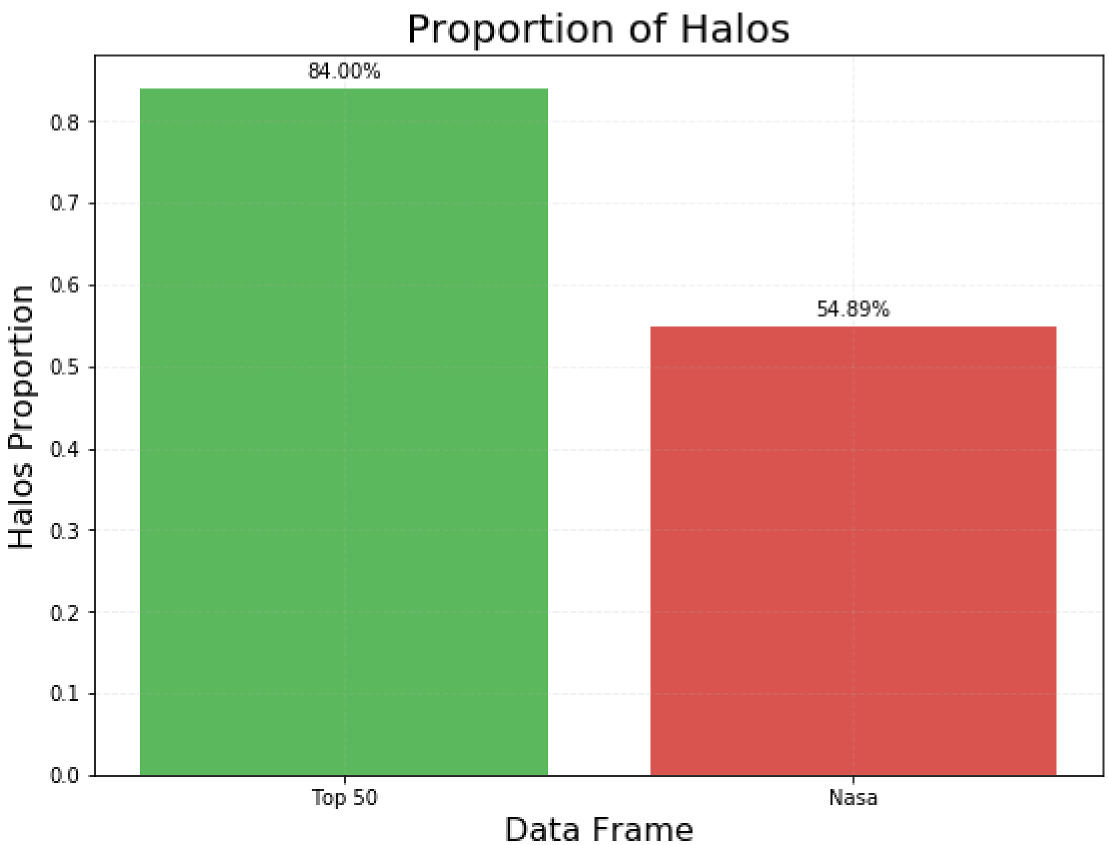
Analysis

- it's clear that **NASA TOP 50** dataframe has a higher percentage `84.00%` of **HALOS** vs `54.89%` in **NASA**
- Flares which have higher `X_class` / `importance` values tend to have more **HALOS**
  - the more powerful the **Solar Flare** is the more likely for it to have a **HALO**

Coronal Mass Ejection

In [30]:
```
# get the props of halos in both dataframes
nasa_halo_perc = nasa_csv.is_halo.sum()/len(nasa_csv)
nasa_50_halo_perc = nasa_50.is_halo.sum()/len(nasa_50)
props = [nasa_50_halo_perc, nasa_halo_perc]
fig = plt.figure(figsize=(7, 5))
ax = fig.add_axes([0, 0, 1, 1])
ax.bar(['Top 50', 'Nasa'], props, color=colors_list)
ax.set_title('Proportion of Halos', fontsize=20)
ax.set_ylabel('Halos Proportion', fontsize=16)
ax.set_xlabel('Data Frame', fontsize=16)
ax.grid(True, alpha=0.2, ls='--')
autolabel(ax.patches)

plt.show()
```



Do Strong Flares Cluster in Time?

In [31]:
```
# get the number of flares per month for the given dataset
def flares_per_month(df):
    flares_num = {}
    for t in df.Start_Datetime:
        if t.month in flares_num:
            flares_num[t.month] += 1
        else:
            flares_num[t.month] = 1

    return flares_num
```

In [32]:
```
# the number of flares per month in the nasa top 50
flares_num_50 = flares_per_month(nasa_50)
```

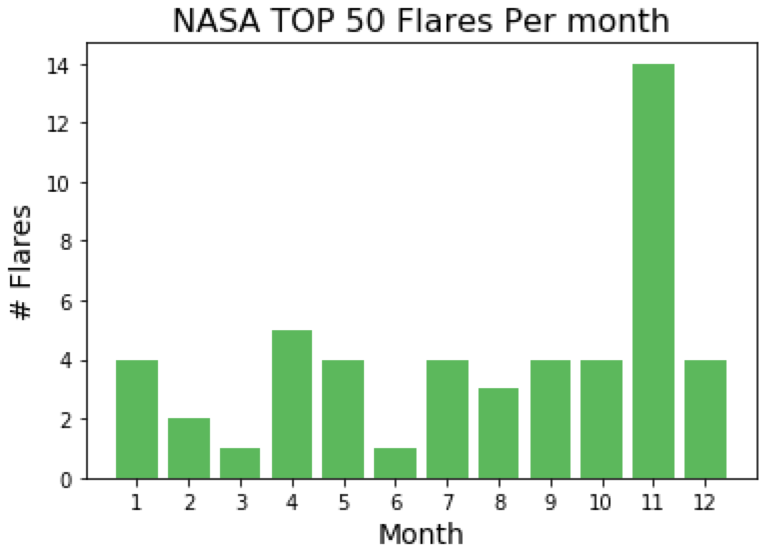
In [33]:
```
len(flares_num_50)
```

Out[33]:
```
12
```

In [34]:
```
flares_num_50
```

Out[34]:
```
{11: 14, 4: 5, 10: 4, 12: 4, 1: 4, 8: 3, 9: 4, 7: 4, 3: 1, 2: 2, 5:
4, 6: 1}
```

In [35]:
```
plt.bar(flares_num_50.keys(), flares_num_50.values(), color=colors_li
st[0])
plt.xticks(range(1,13))
plt.title('NASA TOP 50 Flares Per month', fontsize=16)
plt.xlabel('Month', fontsize=14)
plt.ylabel('# Flares', fontsize=14)
plt.show()
```



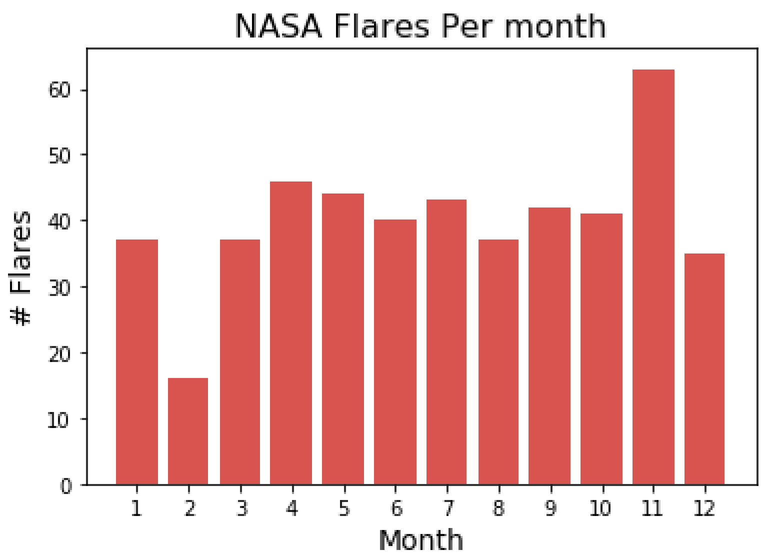
In [36]:
```
flares_num_all = flares_per_month(nasa_csv)
len(flares_num_all)
```

Out[36]:
```
12
```

In [37]:
```
flares_num_all
```

Out[37]:
```
{11: 63,
 4: 46,
 10: 41,
 12: 35,
 1: 37,
 8: 37,
 9: 42,
 7: 43,
 3: 37,
 2: 16,
 5: 44,
 6: 40}
```

In [38]:
```
plt.bar(flares_num_all.keys(), flares_num_all.values() ,color=colors_list[1])
plt.xticks(range(1,13))
plt.title('NASA Flares Per month', fontsize=16)
plt.xlabel('Month', fontsize=14)
plt.ylabel('# Flares', fontsize=14)
plt.show()
```



Number of Flares per Months

- Plotting the two plots next to each other to better understand the difference

Analysis

First

- The solares flares events are spread and occur during all months of the year

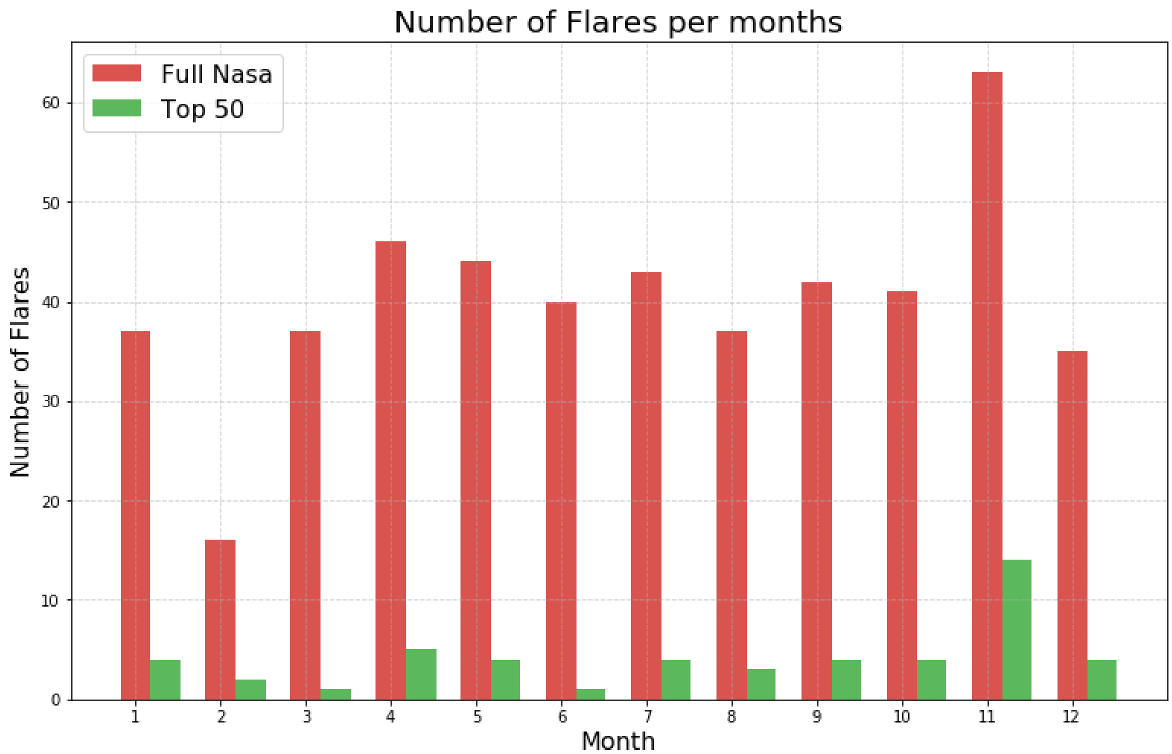
Second

- All types of **Solar Flares** are minimum during **February**
- Strong **Solar flares** are minimum during **March** and **june**

Third

- The highest number of **Solar Flares** events occurs in **November**
- And **November** has also the highest number of Strong **Solar Flares**

In [39]:
```
fig = plt.figure(figsize=(10, 6))
ax = fig.add_axes([0, 0, 1, 1])
ax.bar(flares_num_all.keys(), flares_num_all.values(), color=colors_l
ist[1], width=0.35)
ax.bar(np.array(list(flares_num_50.keys())) + .35, flares_num_50.valu
es(), color=colors_list[0], width=0.35)
ax.set_ylabel('Number of Flares', fontsize=16)
ax.set_xlabel('Month', fontsize=16)
ax.set_title('Number of Flares per months', fontsize=20)
ax.set_xticks(range(1, 13))
ax.legend(labels=['Full Nasa', 'Top 50'], fontsize=16)
ax.grid(True, alpha=0.5, ls='--')
plt.show()
```



In [40]:
```
# sort nasa according to the starting time
nasa_50_sorted = nasa_50.sort_values(['Start_Datetime'])
nasa_50_sorted = seperateImportance(nasa_50_sorted, letters=False)
```

The Top 50 Solar Flares over time

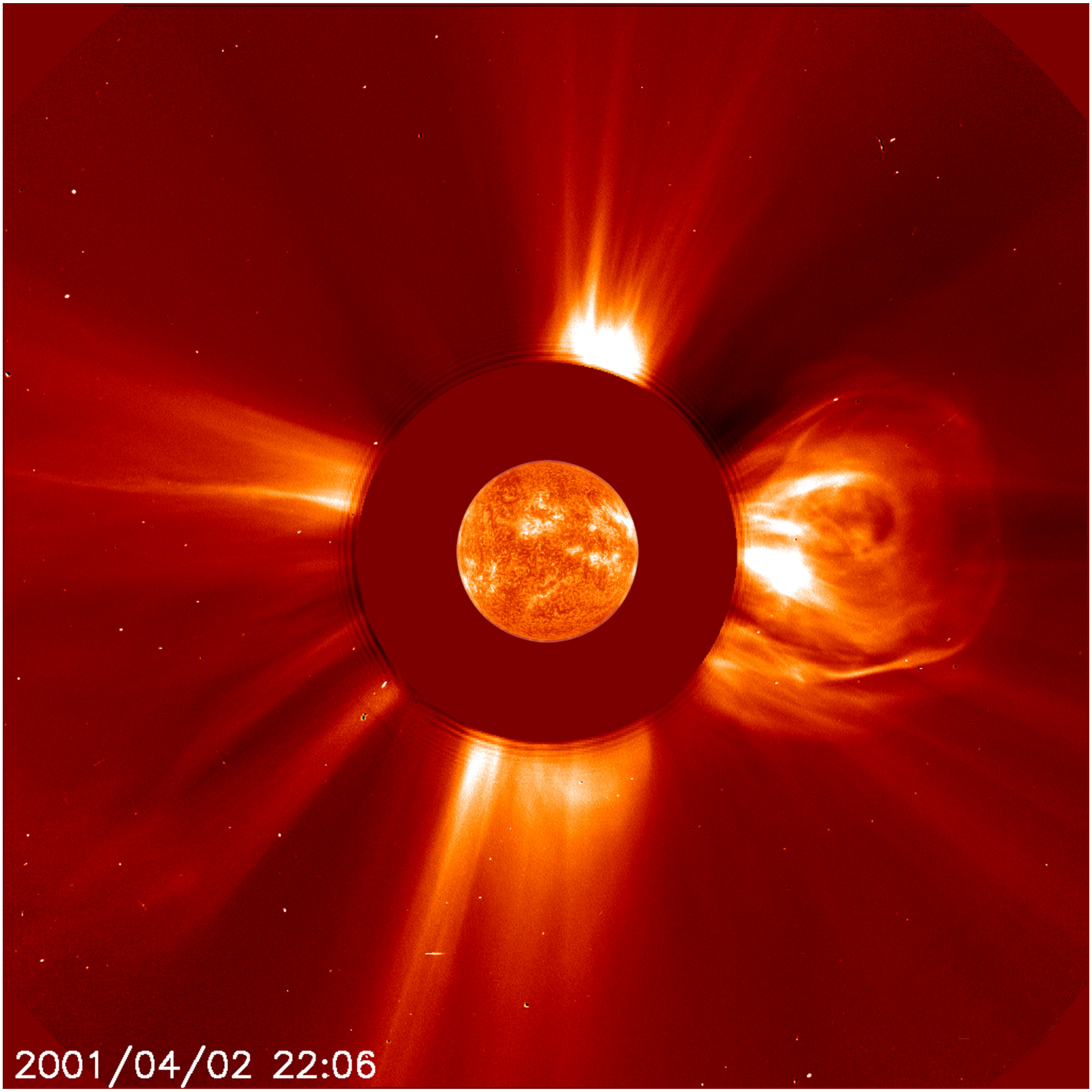
- plotting the `importance` / `X_class` of **Flare Events** over years

Analysis

First

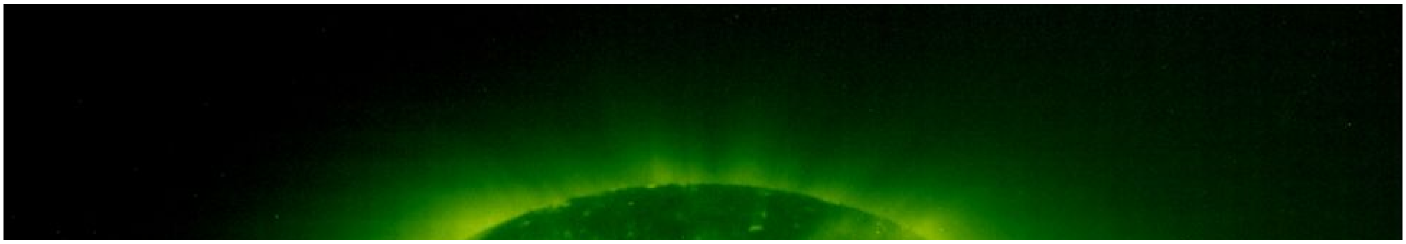
- The last 10 years [2005 to 2015], all solar flares were relatively small as no solar flare approached `X10`
- and **X_class Solar Flares** occured every year without stopping from `1998` to `2015` ### Second
- The most powerfull events occured between `2001` and `2005`

[Biggest Ever recorded at its time (https://visibleearth.nasa.gov/images/55580/biggest-solar-flare-on-record)](https://visibleearth.nasa.gov/images/55580/biggest-solar-flare-on-record) (2001)



> At 4:51 p.m. EDT, on Monday, April 2, 2001, the sun unleashed the biggest solar flare ever recorded, as observed by the Solar and Heliospheric Observatory (SOHO) satellite. The flare was definitely more powerful than the famous solar flare on March 6, 1989, which was related to the disruption of power grids in Canada.

[Giant Halloween (https://www.space.com/23396-scary-halloween-solar-storm-2003-anniversary.html)](https://www.space.com/23396-scary-halloween-solar-storm-2003-anniversary.html) (late 2003)



In [41]:

```
fig = plt.figure(figsize=(11, 6))
ax = fig.add_axes([0, 0, 1, 1])
ax.plot(nasa_50_sorted.Start_Datetime,  nasa_50_sorted.importance_2,
lw=3, color=colors_list[0])
ax.set_title("The Top 50 Solar Flares over time", fontsize=18)
ax.set_xlabel("Years", fontsize=16)
ax.set_ylabel("$X$-class", fontsize=16)
ax.set_yticks(range(0, 30, 2))
ax.grid(True)
plt.show()
```