# Untitled (19)

December 19, 2021

## 1 Analyzing Syrian Civil War Casualties

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## 2 Introduction

I want to analyze recorded Syrian Civil War Deaths and check certain relationships between categories. For example, I wanted to check the relationship between deaths of certain factions and civilains, combined with the locations or time of their deaths.

https://data.world/polymathic/casualties-of-the-syrian-civil-war

[164]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import datetime as dt
from sklearn.linear_model import LinearRegression
from statsmodels.formula.api import ols
```

Having downloaded the data for this tutorial, let's first read the data and preview some of the rows. This dataset is an overview of recorded individuals who were killed during the Syrian Civil War.

[23]:
```
data = pd.read_csv("Syr.csv")
data
```

[23]:
```
                                   name    status          gender province  \
0                            Ahmad Tomeh  Civilian    Adult - Male     Homs
1                      Bashar al-Haj Ali  Civilian    Adult - Male     Homs
2                       Hiba Riad Janoud  Civilian  Adult - Female     Hama
3                 Zahra Khaled al-Dabous  Civilian  Adult - Female     Hama
4                            Eyad Melhem  Civilian    Child - Male     Hama
…                                      …         …               …        …
168421                    Anas Al-Bakour  Civilian    Adult - Male     Hama
168422        Ibrahim Mohammad Al-Suleiman  Civilian    Adult - Male   Idlib
168423  Mohamad Ahmad Al-Yousef Al-Jarban  Civilian    Adult - Male     Hama
168424               Osama Mahmoud Haded  Civilian    Adult - Male     Homs
168425                     Nayef al-Daher  Civilian    Adult - Male     Homs
```

```
                  birthplace   deathdate          deathcause  \
0                  Telbeiseh  2019-02-18  Detention - Torture
1                  Telbeiseh  2019-02-18  Detention - Torture
2                      Tweni  2019-02-17            Shelling
3               Zakat village  2019-02-17            Shelling
4                   Lattamna  2019-02-16            Shelling
…                          …           …                   …
168421  Sahl Al-Ghab: Kafarnboudeh  2011-09-12         Shooting
168422                   Billion  2011-09-12            Shooting
168423              Soran - Hama  2011-07-31            Shooting
168424                  Talbiseh  2011-04-28            Shooting
168425                  Talbiseh  2011-03-29            Shooting

                                         actor
0       Syrian government and affiliated militias
1       Syrian government and affiliated militias
2       Syrian government and affiliated militias
3                                 Russian troops
4       Syrian government and affiliated militias
…                                            …
168421                                     NaN
168422                                     NaN
168423                                     NaN
168424                                     NaN
168425                                     NaN

[168426 rows x 8 columns]
```

We see that some of the values are NaN in the tail of the dataset. For our analysis, the main categories we are looking for is a relationship are between status, gender, province, date of death, cause of death, and actor categories. To find how many different types of values are between them, let's print all the unique values excluding date of death. Let's also check the datatypes of the columns, especially to see if the date of death is in date time.

[24]:
```
print("Gender Categories:")
print(data.gender.unique())
print("\n Province Categories:")
print(data.province.unique())
print("\n Cause of Death Categories:")
print(data.deathcause.unique())
print("\n Perpetrator Categories:")
print(data.actor.unique())
print("\n Status Categories:")
print(data.status.unique())
print("\n Data Types")
print(data.dtypes)
```

```
Gender Categories:
['Adult - Male' 'Adult - Female' 'Child - Male' 'Child - Female']

 Province Categories:
['Homs' 'Hama' 'Aleppo' 'Idlib' 'Unknown' 'Damascus' 'Raqqa' 'Daraa'
 'Deir Ezzor' 'Hasakeh' 'Lattakia' 'Other Nationalities'
 'Damascus Suburbs' 'Sweida' 'Quneitra' 'Tartous']

 Cause of Death Categories:
['Detention - Torture' 'Shelling' 'Explosion' 'Shooting' 'Other' 'Unknown'
 'Warplane shelling' 'Detention - Execution'
 'Un-allowed to seek Medical help' 'Siege' 'Field Execution'
 'Kidnapping - Execution' 'Kidnapping - Torture'
 'Kidnapping - Torture - Execution' 'Detention - Torture - Execution'
 'Chemical and toxic gases']

 Perpetrator Categories:
['Syrian government and affiliated militias' 'Russian troops'
 'Not identified' 'Al-Nusra Front' 'International coalition forces'
 'The organization of the Islamic State in Iraq and the Levant - ISIS'
 'Self administration forces' 'Armed opposition groups' nan]

 Status Categories:
['Civilian' 'Non-Civilian']

 Data Types
name          object
status        object
gender        object
province      object
birthplace    object
deathdate     object
deathcause    object
actor         object
dtype: object
```

## 3 Notes on the different categories

The category values are straight forward for the most part, but Actor categories interestingly have nan values. Whether the reason, we can assume this means the perpetrators were unidentified, but there is already a category for that called "Not identified". Despite looking like it's in datetime format, the date of deaths column is not actually in the type and all columns are "object" dtypes. Lets fill in the nan values in the "actor" column to "not identified", convert the "deathdate" column to datetime, and convert the other columns to string.

[34]:

```

```

```
data['actor'] = data['actor'].fillna('Not identified') # Fill in all nan values␣
↪in actor with "not identified"
data['deathdate']= pd.to_datetime(data['deathdate'])
data['name'] = data['name'].astype('str')
data['status'] = data['status'].astype('str')
data['gender'] = data['gender'].astype('str')
data['province'] = data['province'].astype('str')
data['birthplace'] = data['birthplace'].astype('str')
data['deathcause'] = data['deathcause'].astype('str')
data['actor'] = data['actor'].astype('str')
data.tail()
```

[34]:

```
                                     name    status         gender province  \
168421                     Anas Al-Bakour  Civilian  Adult - Male     Hama
168422        Ibrahim Mohammad Al-Suleiman  Civilian  Adult - Male    Idlib
168423  Mohamad Ahmad Al-Yousef Al-Jarban  Civilian  Adult - Male     Hama
168424                Osama Mahmoud Haded  Civilian  Adult - Male     Homs
168425                     Nayef al-Daher  Civilian  Adult - Male     Homs

                        birthplace  deathdate deathcause          actor
168421  Sahl Al-Ghab: Kafarnboudeh 2011-09-12   Shooting  Not identified
168422                     Billion 2011-09-12   Shooting  Not identified
168423                Soran - Hama 2011-07-31   Shooting  Not identified
168424                   Talbiseh 2011-04-28   Shooting  Not identified
168425                   Talbiseh 2011-03-29   Shooting  Not identified
```

# 4 Analysis

Let's get some basic data. First let's compile the amount of casualties and differentiate them by gender first.

[145]:

```
data_genderStat = data.groupby(['gender']).name.agg('count').to_frame('count').
↪reset_index()
data_genderStat
```

[145]:

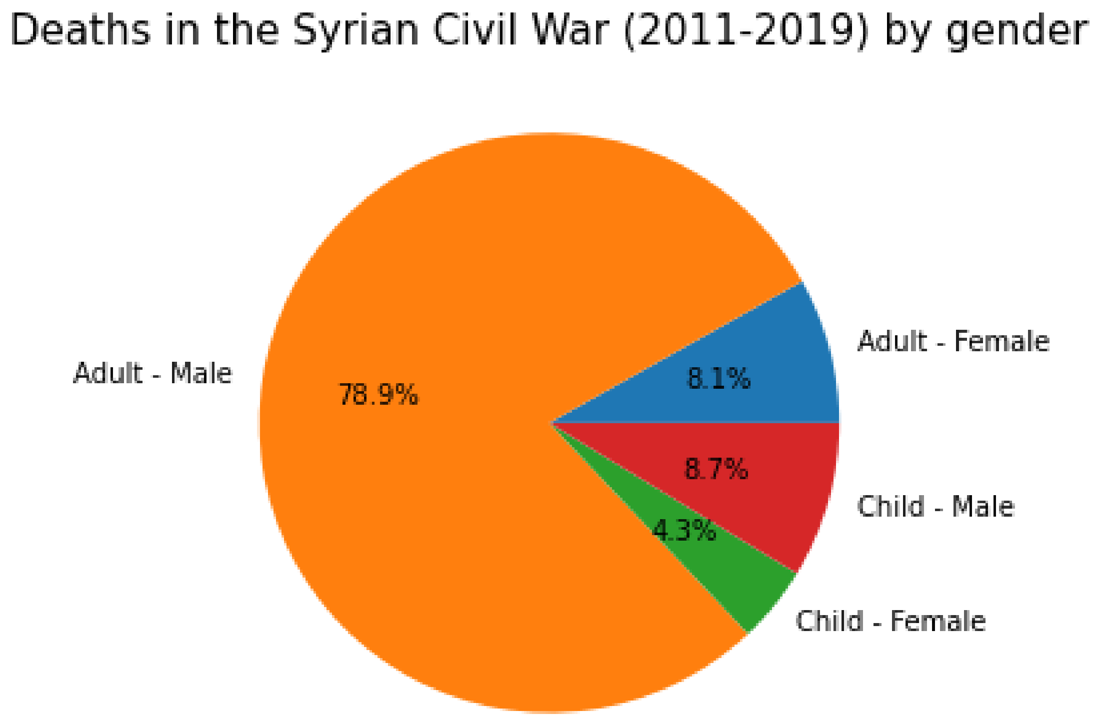
| | gender | count |
|---|---|---|
| 0 | Adult - Female | 13695 |
| 1 | Adult - Male | 132889 |
| 2 | Child - Female | 7191 |
| 3 | Child - Male | 14651 |

Let's turn that into a pie chart

[99]:

```
plt.figure(figsize=(5,5))
plt.title('Deaths in the Syrian Civil War (2011-2019) by gender', fontsize=15)
plt.pie(data_genderStat['count'],labels=data_genderStat['gender'],autopct='%1.
↪1f%%')
```

```
plt.show()
```




We can see here that most casualties in the Syrian Civil War are Adult males, with Male children taking second place, with females taking second place. We can assume that the reason for these proportions are because most combatants in the war are Adult males. To test that theory out lets make a plot that compares between gender and status with two pie charts. One shows the proportion of gender between civilians, and another between non-civilians.

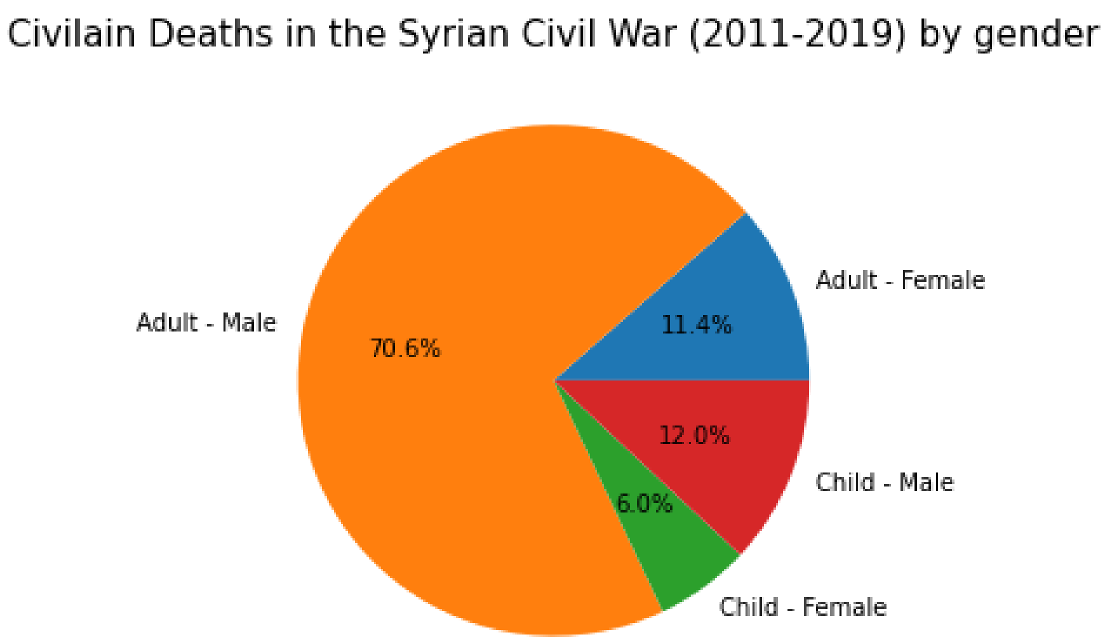
[141]:
```
StatusGender = data.groupby(['status','gender']).name.agg('count').
↪to_frame('count').reset_index()

Civilians = StatusGender.loc[StatusGender['status'] == "Civilian"]
NonCivilians = StatusGender.loc[StatusGender['status'] == "Non-Civilian"]

StatusGender
```

[141]:

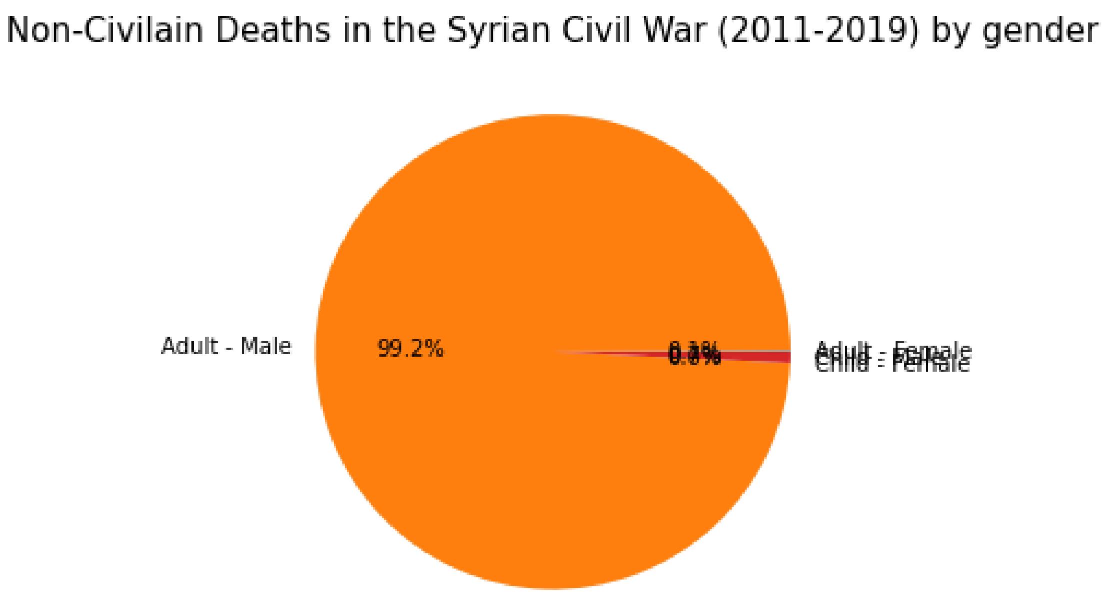
| | status | gender | count |
|---|---|---|---|
| 0 | Civilian | Adult - Female | 13656 |
| 1 | Civilian | Adult - Male | 84405 |
| 2 | Civilian | Child - Female | 7189 |
| 3 | Civilian | Child - Male | 14287 |
| 4 | Non-Civilian | Adult - Female | 39 |

```
5  Non-Civilian    Adult - Male  48484
6  Non-Civilian  Child - Female      2
7  Non-Civilian    Child - Male    364
```

[131]:
```
plt.figure(figsize=(5,5))
plt.title('Civilain Deaths in the Syrian Civil War (2011-2019) by gender',␣
↪fontsize=15)
plt.pie(Civilians['count'],labels=Civilians['gender'],autopct='%1.1f%%')
plt.show()
```

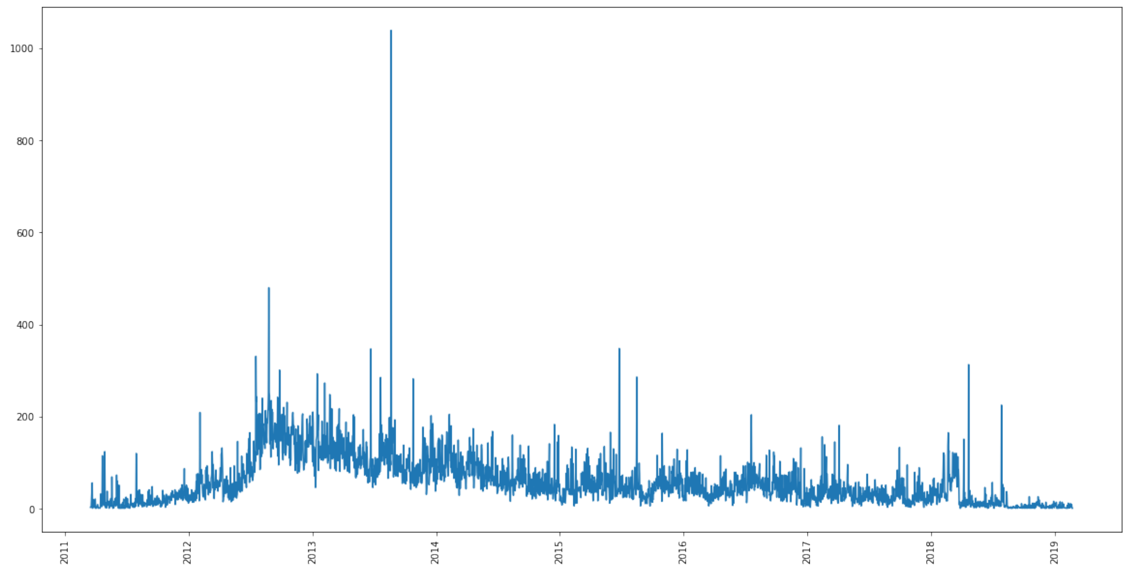



[133]:
```
plt.figure(figsize=(5,5))
plt.title('Non-Civilain Deaths in the Syrian Civil War (2011-2019) by gender',␣
↪fontsize=15)
plt.pie(NonCivilians['count'],labels=NonCivilians['gender'],autopct='%1.1f%%')
plt.show()
```




We can see that most of the deaths have affected males. While almost 100% of non-civilian deaths have been men, the table shows that the civilian body count vastly outnumbers the non-civilian body count.

[146]:
```
data_timeplot = data.groupby(['deathdate']).name.agg('count').to_frame('count').
↪reset_index()

# plot line graph
plt.figure(figsize=(20,10))
plt.plot(data_timeplot['deathdate'], data_timeplot['count'])
plt.xticks(rotation='vertical')
plt.show()
```




What we can observe from our eyes are two things. One, the number of deaths peaked between in the middle of 2012 to 2014. After that, the number of deaths seem to be in a slow but somewhat steady decline

[96]:
```
data_timeplot = data_timeplot.sort_values('count', ascending=False)
data_timeplot.head()
```

[96]:

| | deathdate | count |
|---|---|---|
| 870 | 2013-08-21 | 1039 |
| 509 | 2012-08-25 | 480 |
| 1543 | 2015-06-25 | 348 |
| 810 | 2013-06-22 | 347 |
| 471 | 2012-07-18 | 331 |

We check the date of August 21st, 2013 online and information shows thats the date of the Ghouta chemical attack allegedly by Syrian government forces against civilians. To visualize the effect of the attack, we can make three pie charts. One based on the statuses of casualties on that day, one based on the actors of those casualties aka perpetrators, and another based on the cause of death.

[111]:
```
GhoutaStats = data.loc[data['deathdate'] == "2013-08-21"]
GhoutaStats.head()
```

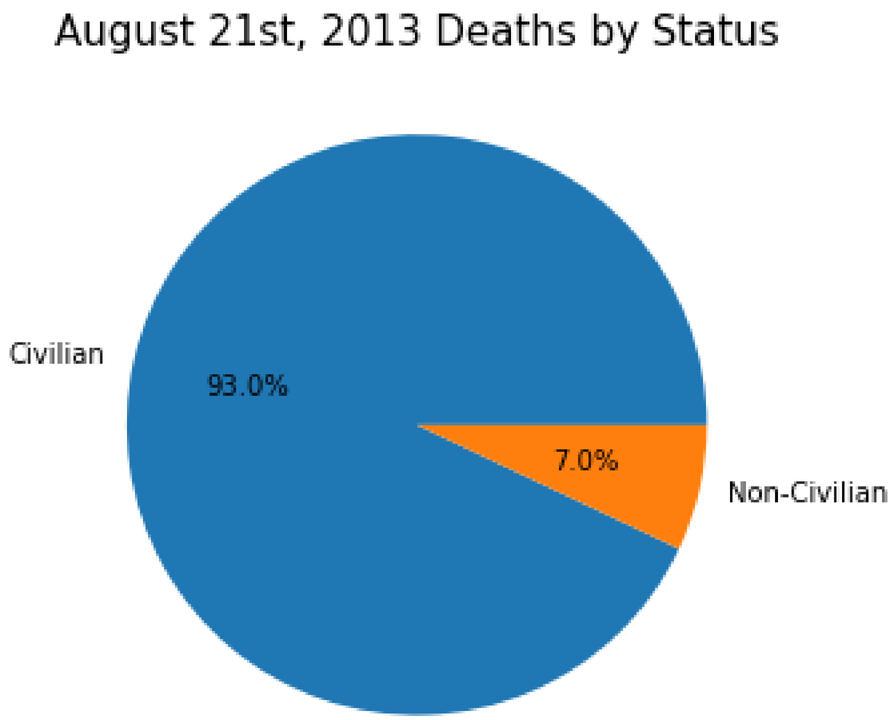
[111]:

| | name | status | gender | \ |
|---|---|---|---|---|
| 41857 | Ahmad Abdulhamed Balkash | Non-Civilian | Adult - Male | |
| 41858 | Tahseen Zoheir Mohammad Sendyan | Civilian | Adult - Male | |
| 41859 | Abd al-Salam Ahmad Gazal | Non-Civilian | Adult - Male | |
| 41860 | Fayez Dyab | Civilian | Adult - Male | |
| 41861 | Ahmad Abo al-Omer | Civilian | Adult - Male | |

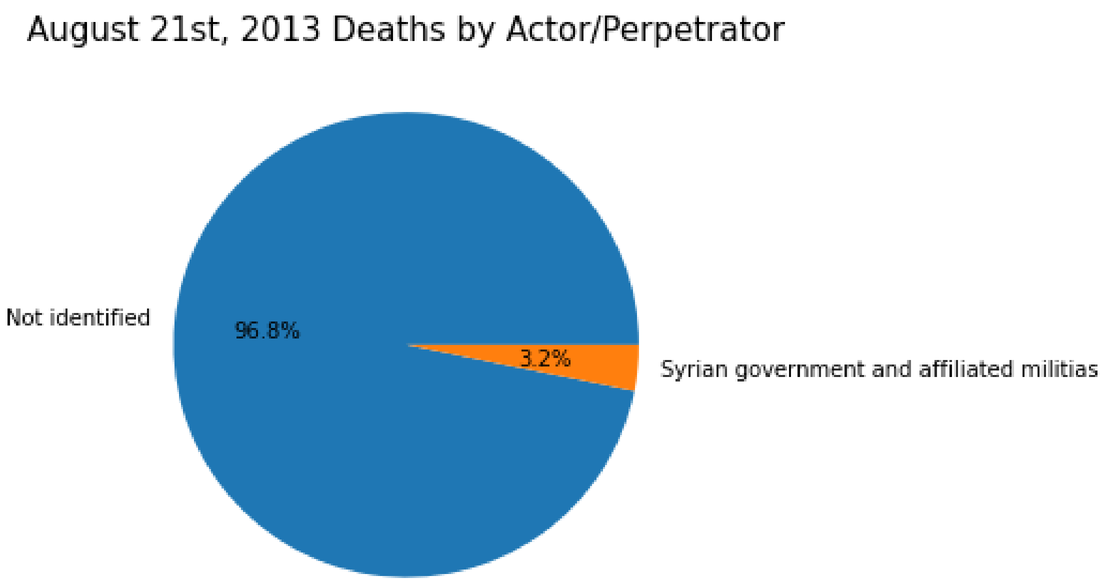
```
              province                    birthplace  deathdate  \
41857  Damascus Suburbs                   Mouadamiyeh 2013-08-21
41858          Damascus                        Mazzeh 2013-08-21
41859            Idlib                       Taftanaz 2013-08-21
41860              Hama  Al-Ghab Plain: Ramla village 2013-08-21
41861              Hama                 Karim village 2013-08-21

                    deathcause                                      actor
41857  Chemical and toxic gases  Syrian government and affiliated militias
41858  Chemical and toxic gases  Syrian government and affiliated militias
41859                  Shelling  Syrian government and affiliated militias
41860                  Shooting  Syrian government and affiliated militias
41861                  Shooting  Syrian government and affiliated militias
```

[149]:
```
# Compare by Status
GhoutaStatsOne = GhoutaStats.groupby(['status']).name.agg('count').
 ↪to_frame('count').reset_index()

# Compare by actor/perpetrator
GhoutaStatsTwo = GhoutaStats.groupby(['actor']).name.agg('count').
 ↪to_frame('count').reset_index()

# Compare by cause of death
GhoutaStatsThree = GhoutaStats.groupby(['deathcause']).name.agg('count').
 ↪to_frame('count').reset_index()
```

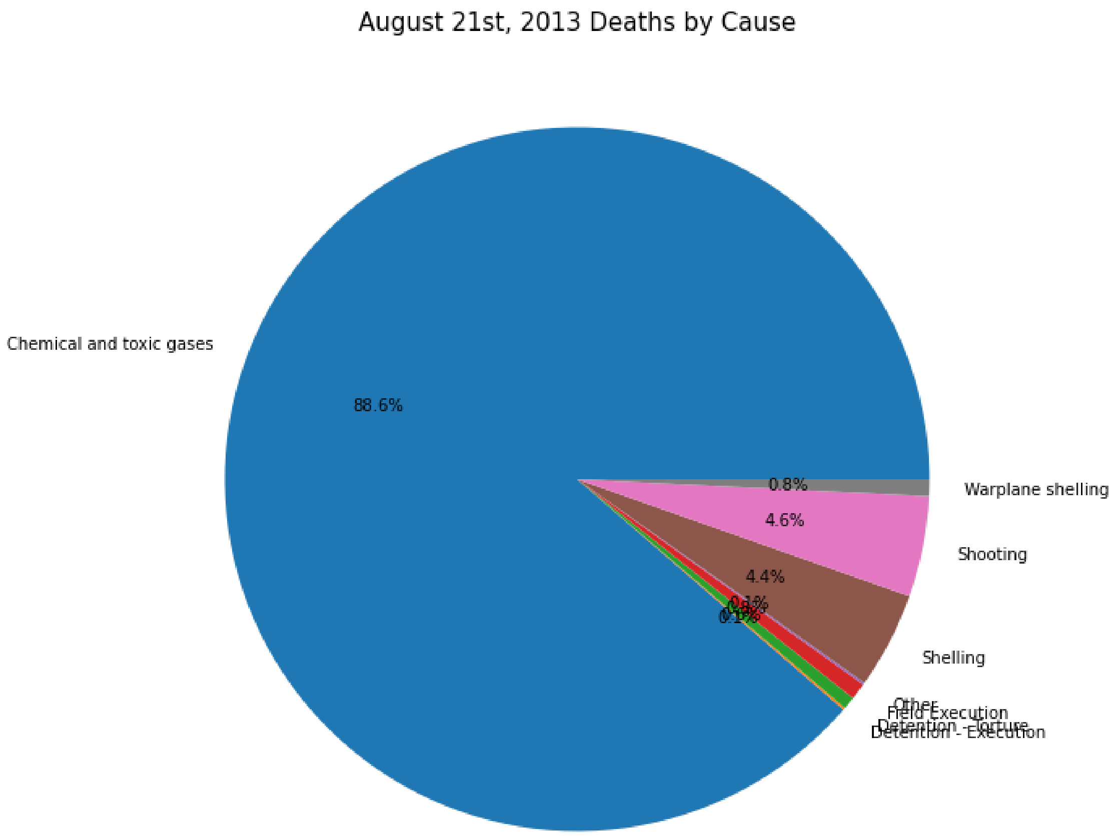
[148]:
```
plt.figure(figsize=(5,5))
plt.title('August 21st, 2013 Deaths by Status', fontsize=15)
plt.pie(GhoutaStatsOne['count'],labels=GhoutaStatsOne['status'],autopct='%1.
 ↪1f%%')
plt.show()
```




[150]:
```
plt.figure(figsize=(5,5))
plt.title('August 21st, 2013 Deaths by Actor/Perpetrator', fontsize=15)
plt.pie(GhoutaStatsTwo['count'],labels=GhoutaStatsTwo['actor'],autopct='%1.
 ↪1f%%')
plt.show()
```




[151]:
```
plt.figure(figsize=(10,10))
plt.title('August 21st, 2013 Deaths by Cause', fontsize=15)
plt.
 ↪pie(GhoutaStatsThree['count'],labels=GhoutaStatsThree['deathcause'],autopct='%1.
 ↪1f%%')
plt.show()
```




The three pie charts very interestingly shows the great significance of the chemical attack. The casualties were very predominantly civilian and indeed by a lethal gas. While the vast majority of deaths could not be attributed, the only other perpetrator identified on that day were Syrian government forces. The lack of any other identifiable perpetrator on that day may be the reason why the chemical attack has been attributed to the Syrian government.

That is just one incident however. Let's overall compare casualties caused by different factions.

[154]:
```
FactionKills = data.groupby(['actor']).name.agg('count').to_frame('count').
↪reset_index()
FactionKills
```

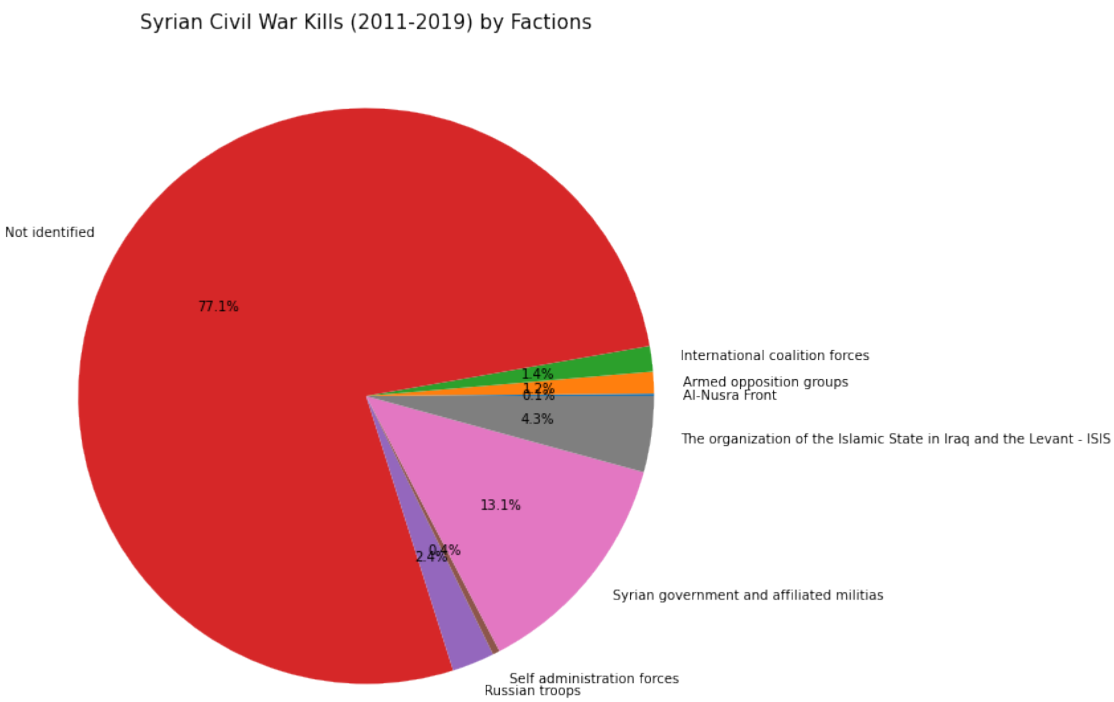
[154]:

| | actor | count |
|---|---|---|
| 0 | Al-Nusra Front | 229 |
| 1 | Armed opposition groups | 2059 |
| 2 | International coalition forces | 2404 |
| 3 | Not identified | 129862 |
| 4 | Russian troops | 4013 |
| 5 | Self administration forces | 672 |

```
6          Syrian government and affiliated militias   22007
7  The organization of the Islamic State in Iraq …    7180
```

[155]:

```python
plt.figure(figsize=(10,10))
plt.title('Syrian Civil War Kills (2011-2019) by Factions', fontsize=15)
plt.pie(FactionKills['count'],labels=FactionKills['actor'],autopct='%1.1f%%')
plt.show()
```




Most casualties have an unknown perpetrator, which is surprising. This may be because of civilians being the vast majority of the casualties as shown before. I hypothesize that civilians are more likely to have unidentified killers than non-civilians due to that reasoning, but let's test that out. Lets create two similar datasets, but between civilians and non-civilians.

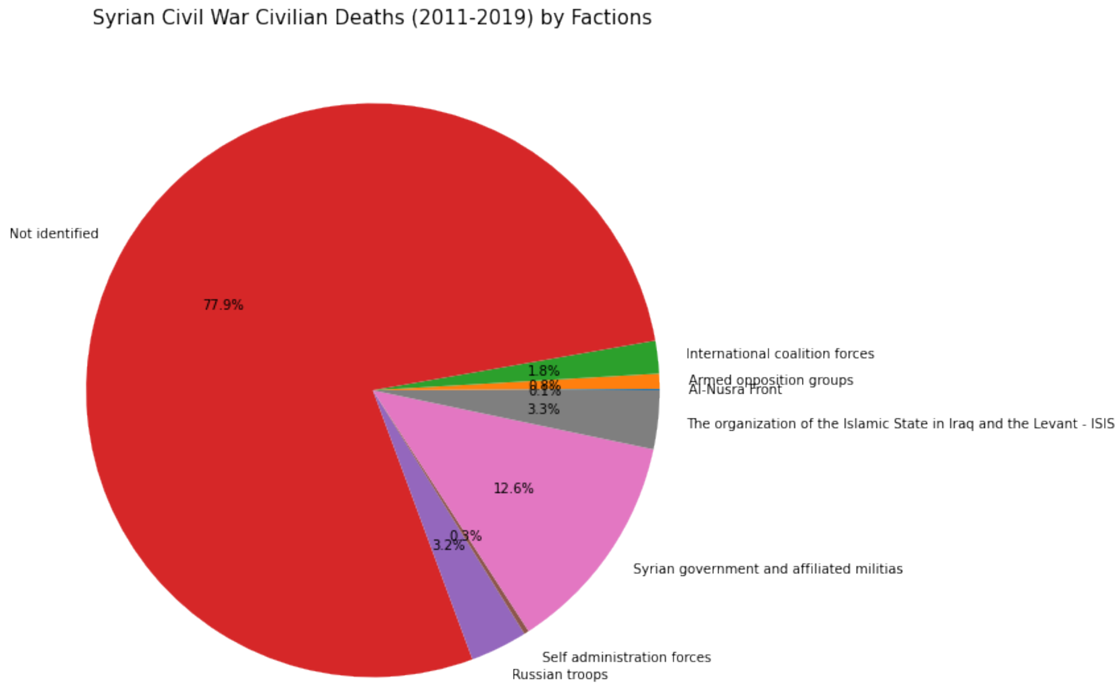
[156]:

```python
CivilianCas = data.loc[data['status'] == "Civilian"]
NonCivilianCas = data.loc[data['status'] == "Non-Civilian"]

CivilianCasActor = CivilianCas.groupby(['actor']).name.agg('count').
↪to_frame('count').reset_index()
NonCivilianCasActor = NonCivilianCas.groupby(['actor']).name.agg('count').
↪to_frame('count').reset_index()
```

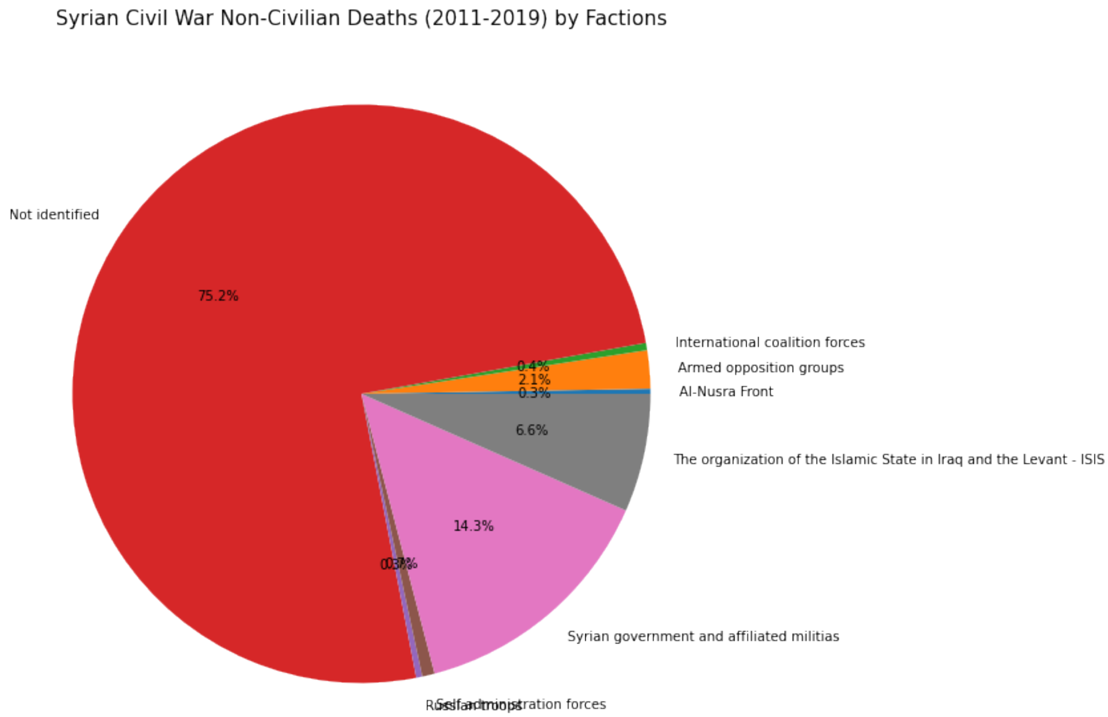
[158]:

```python
plt.figure(figsize=(10,10))
```

```
plt.title('Syrian Civil War Civilian Deaths (2011-2019) by Factions',␣
 ↪fontsize=15)
plt.pie(CivilianCasActor['count'],labels=CivilianCasActor['actor'],autopct='%1.
 ↪1f%%')
plt.show()
```




[160]:
```
plt.figure(figsize=(10,10))
plt.title('Syrian Civil War Non-Civilian Deaths (2011-2019) by Factions',␣
 ↪fontsize=15)
plt.
 ↪pie(NonCivilianCasActor['count'],labels=NonCivilianCasActor['actor'],autopct='%1.
 ↪1f%%')
plt.show()
```




To my own surprise, the distributions are quite similar to one another. With such a large proportion, we can't really check the differences between casualties where the actor was identified. Let's modify the datasets so they only take in identified data.

[ ]:

```
```

# 5 Machine Learning

Linear Regression line stuff

[170]:

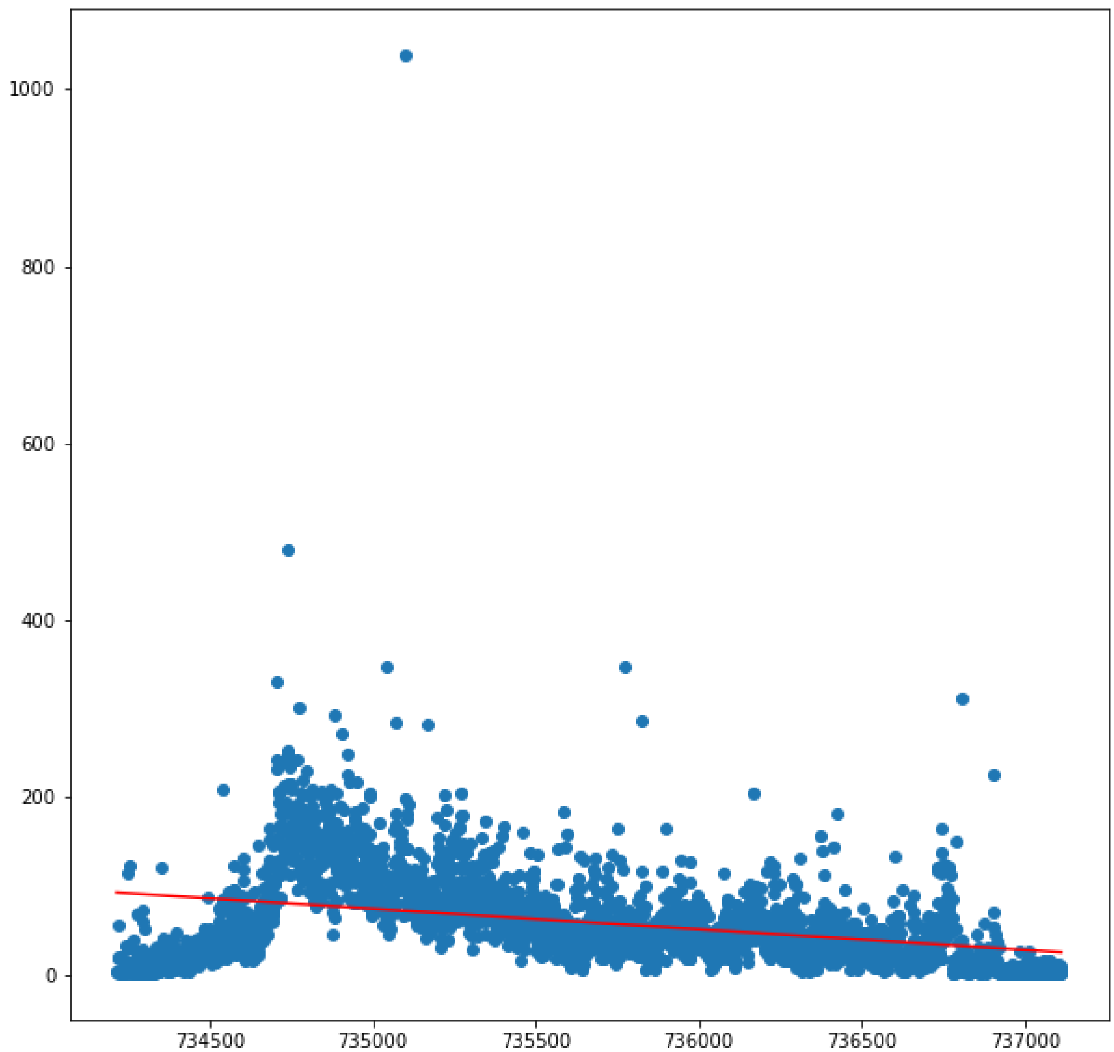
```
data_timeplot_regress = data_timeplot
data_timeplot_regress["deathdate"] = data_timeplot_regress['deathdate'].map(dt.
 ↪datetime.toordinal) # convert
est = ols(formula = 'deathdate ~ count', data = data_timeplot_regress).fit()
print(est.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              deathdate   R-squared:                       0.128
Model:                            OLS   Adj. R-squared:                  0.128
Method:                 Least Squares   F-statistic:                     421.1
Date:                Sun, 19 Dec 2021   Prob (F-statistic):           2.14e-87
Time:                        07:29:15   Log-Likelihood:                -23058.
```

```
No. Observations:                2858   AIC:                         4.612e+04
Df Residuals:                    2856   BIC:                         4.613e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept    7.36e+05     21.458   3.43e+04      0.000    7.36e+05    7.36e+05
count         -5.5259      0.269    -20.520      0.000      -6.054      -4.998
==============================================================================
Omnibus:                       66.347   Durbin-Watson:                   0.103
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               70.511
Skew:                          -0.383   Prob(JB):                     4.88e-16
Kurtosis:                       3.067   Cond. No.                         118.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

[172]:

```
X = data_timeplot_regress['deathdate'].values.reshape(-1, 1)
Y = data_timeplot_regress['count'].values.reshape(-1, 1)
linear_regressor = LinearRegression()
linear_regressor.fit(X, Y)
Y_pred = linear_regressor.predict(X)

plt.figure(figsize=(10,10))

plt.scatter(X, Y)
plt.plot(X, Y_pred, color='red') # plots regression line
plt.show()
```


1000
800
600
400
200
0
734500
735000
735500
736000
736500
737000

[ ]: