For my presentation I wanted to examine data about the opioid crisis in America. Initially I wanted to look at nation wide statistics, however I found that each state varied in their record keeping (if they kept records at all). Luckily I came across an article about Conneticut Open Data, and found the below data set that included race, gender, age, date of death, among other details from 2012-2017 for opioid deaths in Conneticut.

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

In [2]:
```
opioids=pd.read_csv(r"C:\Users\User\Desktop\Data Analysis\Accidental_Drug_Related_Deaths__2012-2017 CT 2.csv")
```

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

Out[3]:

	CaseNumber	Date	Sex	Race	Age	Residence City	Residence State	Residence County	Death City	Death State	...	Benzodiazepine	Methadone	Amphet	Tramad	Morphine (not heroin)	Other	Any Opioid
0	14-9876	6/28/2014	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	Y	NaN	NaN	NaN	NaN	NaN	NaN
1	12-16897	11/30/2012	Male	White	45.0	NaN	NaN	NaN	NEW HAVEN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	13-11849	8/12/2013	Male	White	30.0	NEW HAVEN	NaN	NaN	NEW HAVEN	NaN	...	NaN	Y	NaN	NaN	NaN	NaN	NaN
3	14-17578	11/23/2014	Male	White	27.0	NAUGATUCK	NaN	NaN	NEW MILFORD	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	12-11497	8/14/2012	Male	White	21.0	ENFIELD	NaN	NaN	ENFIELD	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN

5 rows × 32 columns

In [153]:
```
opioids2=pd.read_csv(r"C:\Users\User\Desktop\Data Analysis\Accidental_Drug_Related_Deaths__2012-2017 CT 3.csv")
opioids2.head()
```

Out[153]:

	CaseNumber	Date	Sex	Race	Age	Residence City	Residence State	Residence County	Death City	Death State	...	Other	Hydrocodone	Benzodiazepine	Methadone	Amphet	Tramad	Mo
0	14-9876	6/28/2014	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	0	1	1	0	0	0	
1	12-16897	11/30/2012	Male	White	45.0	NaN	NaN	NaN	NEW HAVEN	NaN	...	0	0	0	0	0	0	
2	13-11849	8/12/2013	Male	White	30.0	NEW HAVEN	NaN	NaN	NEW HAVEN	NaN	...	0	0	0	1	0	0	
3	14-17578	11/23/2014	Male	White	27.0	NAUGATUCK	NaN	NaN	NEW MILFORD	NaN	...	0	0	0	0	0	0	
4	12-11497	8/14/2012	Male	White	21.0	ENFIELD	NaN	NaN	ENFIELD	NaN	...	0	0	0	0	0	0	

5 rows × 30 columns

Questions I Focused On:

```
What effect does Race, Gender and Age have on deaths caused by opioids?

What opioids are causing the most deaths? What trends can be seen in the drugs used over the last 5 years?
```

Before analizing the dataset, I wanted to look at the general demographic statistics for Conneticut, which I have provided below.

General Conneticut Stats per the US Census Bureau

Total Population in 2017:

```
3,588,184
```

By Race:

```
White: 80.6%

Black: 11.8%

Latino/Hispanic: 15.7%

Other: 5.3%

More than one race: 2.3%
```

By Gender:

    Female: 51%

    Male: 49%

Populations change from 2011-2017:

    0.1% - 0.4%

Below you see the data for the age of individuals who died from opioids. I was surprised to find that the mean age was 41, as I expected it to be lower. The minimum age was 14, and the maximum age was 87.

In [4]:
```
opioids.describe()
```

Out[4]:

	Age
count	4080.000000
mean	41.755882
std	12.319208
min	14.000000
25%	31.000000
50%	42.000000
75%	52.000000
max	87.000000

Here we see that there are 4083 incidents recorded in the dataset.

In [5]:
```
opioids.shape
```

Out[5]:
```
(4083, 32)
```

Below are statistics regarding gender and race, which I will explain in more detail further down.

In [38]:
```
opioids['Sex'].value_counts()
```

Out[38]:
```
Male      2993
Female    1086
Name: Sex, dtype: int64
```

In [39]:
```
opioids.Sex.value_counts(normalize=True)
```

Out[39]:
```
Male      0.733758
Female    0.266242
Name: Sex, dtype: float64
```

In [40]:
```
opioids['Race'].value_counts()
```

Out[40]:
```
White       3244
Hispanic     432
Black        346
Other         50
Name: Race, dtype: int64
```

In [41]:
```
opioids.Race.value_counts(normalize=True)
```

Out[41]:
```
White       0.796660
Hispanic    0.106090
Black       0.084971
Other       0.012279
Name: Race, dtype: float64
```

Below are the value counts and percentages for each drug found in the dataset. In some cases more that one drug was found to be responsible for a death. Please note that I left out Cocaine when analyzing the data as that is not an opioid.

In [180]:
```
opioids2['Other'].value_counts()
```

Out[180]:
```
0    3078
1     987
       18
Name: Other, dtype: int64
```

24.17%

In [176]:
```
opioids2['Heroin'].value_counts()
```

Out[176]:
```
1    2149
0    1929
        5
Name: Heroin, dtype: int64
```

52.63%

In [177]:
```
opioids2['Fentanyl'].value_counts()
```

Out[177]:
```
0           2616
1           1463
1-A            2
1 (PTCH)       1
1 POPS         1
Name: Fentanyl, dtype: int64
```

35.93%

In [222]:
```
opioids2["Benzodiazepine"].value_counts()
```

Out[222]:
```
0    3005
1    1076
        2
Name: Benzodiazepine, dtype: int64
```

26.35%

In [178]:
```
opioids2["Oxycodone"].value_counts()
```

Out[178]:
```
0    3536
1     545
        2
Name: Oxycodone, dtype: int64
```

13.35%

In [223]:
```
opioids2["Methadone"].value_counts()
```

Out[223]:
```
0    3695
1     385
        3
Name: Methadone, dtype: int64
```

9.43%

In [179]:
```
opioids2["Oxymorphone"].value_counts()
```

Out[179]:
```
0    3986
1      96
        1
Name: Oxymorphone, dtype: int64
```

2.35%

In [181]:
```
opioids2["Hydrocodone"].value_counts()
```

Out[181]:
```
0    3977
1     104
        2
Name: Hydrocodone, dtype: int64
```

2.55%

In [186]:
```
opioids2["Amphet"].value_counts()
```

Out[186]:
```
0    3980
1     103
Name: Amphet, dtype: int64
```

2.52%

In [189]:
```
opioids2["Morphine (not heroin)"].value_counts()
```

Out[189]:
```
0                   4027
1                     35
                      18
STOLE MEDS             1
NO RX BUT STRAWS       1
PCP neg                1
Name: Morphine (not heroin), dtype: int64
```

0.93%

In [188]:
```
opioids2["Tramad"].value_counts()
```

Out[188]:
```
0    3993
1      90
Name: Tramad, dtype: int64
```

2.20%

Analysis of the different drugs show that Heroin, Fentanyl, Benzodiazepine, Oxycodone and Methadone were significant contributers. "Others" was also a significant contributer, however no further incite can be gained without knowing what is included in this category. The other identified drugs contributed less that 3% each.

In [8]:
```
#better, but we want to make sure that column is recorded as a date:WANT PYTHON TO RECOGNIZE AS A DATE AND STANDARDIZE
opioids.Date=pd.to_datetime(opioids.Date)
opioids.head()
```

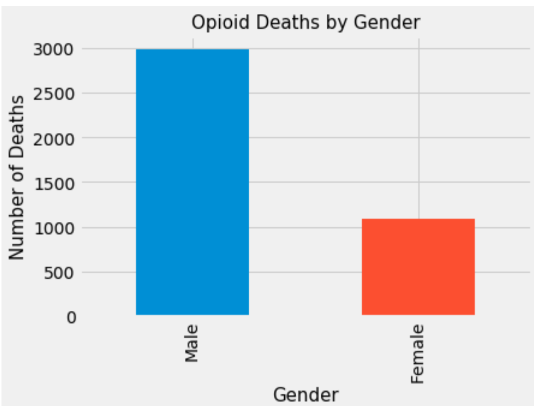
Out[8]:

	CaseNumber	Date	Sex	Race	Age	Residence City	Residence State	Residence County	Death City	Death State	...	Benzodiazepine	Methadone	Amphet	Tramad	Morphine (not heroin)	Other	Any Opioid	M
0	14-9876	2014-06-28	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	Y	NaN	NaN	NaN	NaN	NaN	NaN	
1	12-16897	2012-11-30	Male	White	45.0	NaN	NaN	NaN	NEW HAVEN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
2	13-11849	2013-08-12	Male	White	30.0	NEW HAVEN	NaN	NaN	NEW HAVEN	NaN	...	NaN	Y	NaN	NaN	NaN	NaN	NaN	
3	14-17578	2014-11-23	Male	White	27.0	NAUGATUCK	NaN	NaN	NEW MILFORD	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
4	12-11497	2012-08-14	Male	White	21.0	ENFIELD	NaN	NaN	ENFIELD	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

In the below two graphs you will see the distribution of deaths between males and females. It is apparent that men are affected at a much higher rate than women. This is particularly evident when considering that there are relatively equal numbers of men and women in Conneticut's general population.

In [108]:
```
opioids['Sex'].value_counts().plot(kind='bar')
plt.xlabel('Gender', fontsize=15)
plt.style.use('fivethirtyeight')
plt.ylabel('Number of Deaths', fontsize=15)
plt.title("Opioid Deaths by Gender", fontsize=15)
```

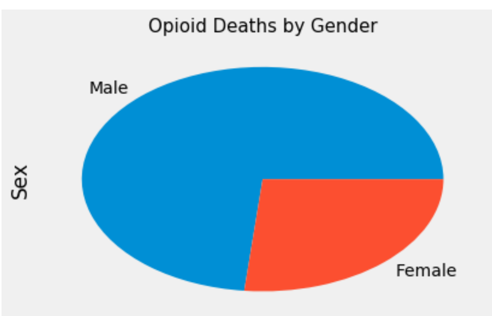
Out[108]: `Text(0.5,1,'Opioid Deaths by Gender')`



73% male, 27% female

In [107]:
```
opioids['Sex'].value_counts().plot(kind='pie')
plt.style.use('fivethirtyeight')
plt.title("Opioid Deaths by Gender", fontsize=15)
```

Out[107]: `Text(0.5,1,'Opioid Deaths by Gender')`

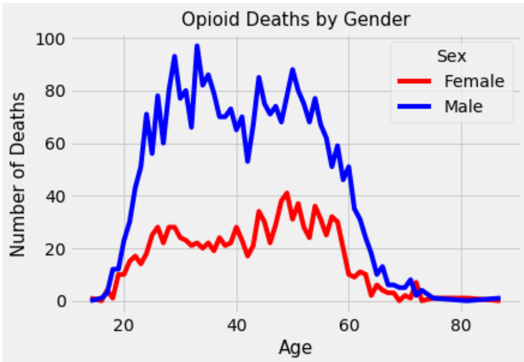


73% male, 27% female

Below you will see a graph of male and female deaths by age. You will see that male deaths spike in the 30s, before dipping down, and then raising again in the mid 40s and early 50s. Females raise to relatively stable levels from the late 20s until the mid 40s, but peak around 50. Both male and female rates drastically decline in the early 60s.

In [136]:
```
pd.crosstab(opioids['Age'], opioids['Sex']).plot(color=['red', 'blue'])
plt.style.use('fivethirtyeight')
plt.xlabel('Age', fontsize=15)
plt.ylabel('Number of Deaths', fontsize=15)
plt.title("Opioid Deaths by Gender", fontsize=15)
```

Out[136]:
```
Text(0.5,1,'Opioid Deaths by Gender')
```



In [243]:
```
opioids['Age'], opioids['Sex'].value_counts()
```

Out[243]:
```
(0        NaN
 1       45.0
 2       30.0
 3       27.0
 4       21.0
 5       25.0
 6       67.0
 7       32.0
 8       61.0
 9       37.0
 10      59.0
 11      22.0
 12      38.0
 13      40.0
 14      71.0
 15      54.0
 16      52.0
 17      55.0
 18      44.0
 19      26.0
 20      18.0
 21      36.0
 22      53.0
 23      61.0
 24      29.0
 25      48.0
 26      50.0
 27      49.0
 28      26.0
 29      53.0
         ...
 4053    32.0
 4054    37.0
 4055    26.0
 4056    65.0
 4057    50.0
 4058    26.0
 4059    22.0
 4060    30.0
 4061    33.0
 4062    39.0
 4063    31.0
 4064    50.0
 4065    61.0
 4066    38.0
 4067    26.0
 4068    68.0
 4069    39.0
 4070    34.0
 4071    52.0
 4072    46.0
 4073    69.0
 4074    38.0
 4075    26.0
 4076    50.0
 4077    36.0
 4078    36.0
 4079    48.0
 4080    50.0
 4081    48.0
 4082    25.0
 Name: Age, Length: 4083, dtype: float64, Male      2993
 Female    1086
 Name: Sex, dtype: int64)
```

In [167]:
```
heroin=opioids2[opioids2['Hydrocodone']=='1']
```

In [168]:
```
heroin.head()
```

Out[168]:

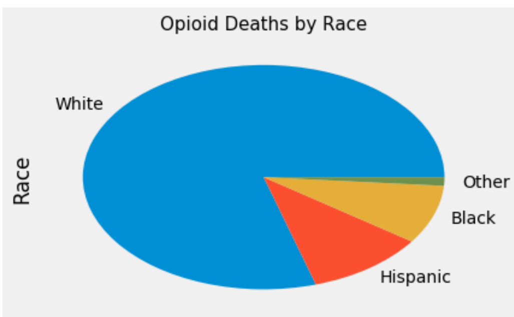
	CaseNumber	Date	Sex	Race	Age	Residence City	Residence State	Residence County	Death City	Death State	...	Other	Hydrocodone	Benzodiazepine	Methadone	Amphe
0	14-9876	6/28/2014	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	0	1	1	0	(
25	13-18762	12/23/2013	Male	Hispanic	48.0	BRIDGEPORT	NaN	FAIRFIELD	BRIDGEPORT	NaN	...	1	1	0	0	(
57	13-16639	11/14/2013	Female	White	56.0	WATERBURY	NaN	NEW HAVEN	WATERBURY	NaN	...	0	1	0	1	(
58	15-1042	1/18/2015	Female	White	72.0	ARLINGTON HEIGHTS	IL	COOK	EAST HAMPTON	CT	...	0	1	1	0	(
110	15-14704	9/14/2015	Male	White	51.0	MIDDLETOWN	CT	MIDDLESEX	MIDDLETOWN	CT	...	1	1	1	0	(

5 rows × 30 columns

Next, I wanted to examine the relationship between opioid deaths and race. The three graphs below show the number and percentage of opioids deaths by White, Hispanic, Black and Other (which includes individuals considered Asian, Native American, and other minorities). The percentages are very close to the general population percentages previously noted, indicating that race is not a significant contributing risk factor.

In [197]:
```
opioids['Race'].value_counts().plot(kind='pie')
plt.style.use('fivethirtyeight')
plt.title("Opioid Deaths by Race", fontsize=15)
```

Out[197]: `Text(0.5,1,'Opioid Deaths by Race')`



White 79.67%

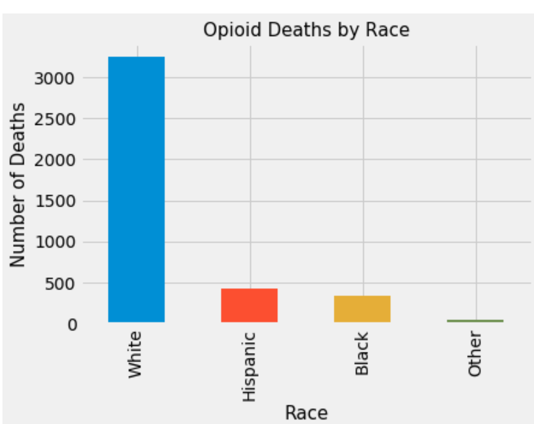
Hispanic 10.61%

Black 8.50%

Other 1.23%

In [194]:
```
opioids['Race'].value_counts().plot(kind='bar')
plt.style.use('fivethirtyeight')
plt.xlabel('Race', fontsize=15)
plt.ylabel('Number of Deaths', fontsize=15)
plt.title("Opioid Deaths by Race", fontsize=15)
```

Out[194]: `Text(0.5,1,'Opioid Deaths by Race')`



White 79.67%

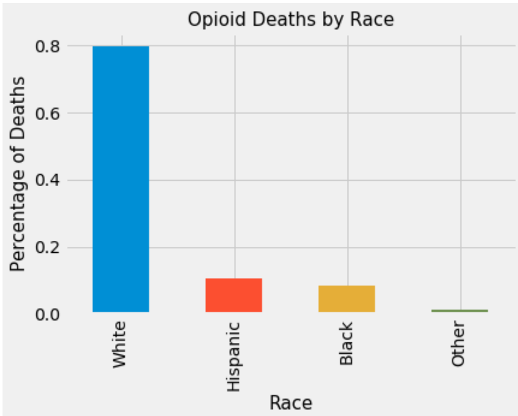
Hispanic 10.61%

Black 8.50%

Other 1.23%

In [196]:
```
opioids['Race'].value_counts(normalize=True).plot(kind='bar')
plt.style.use('fivethirtyeight')
plt.xlabel('Race', fontsize=15)
plt.ylabel('Percentage of Deaths', fontsize=15)
plt.title("Opioid Deaths by Race", fontsize=15)
```

Out[196]:
```
Text(0.5,1,'Opioid Deaths by Race')
```



White 79.67%

Hispanic 10.61%

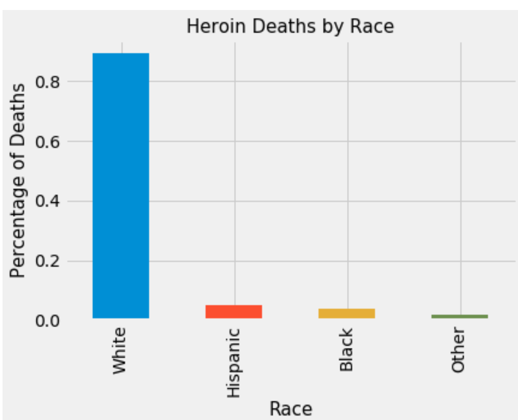
Black 8.50%

Other 1.23%

Next, I wanted to examine the relationship between race and the type of drug. Below you will see a graph of Heroin deaths by race. The overwhelming majority occured to Whites. Considering that the overall percentages for each Hispanic and Black are 10.61% and 8.5% respectively, they are under represented regarding Heroin deaths.

In [210]:
```
heroin['Race'].value_counts(normalize=True).plot(kind='bar')
plt.style.use('fivethirtyeight')
plt.xlabel('Race', fontsize=15)
plt.ylabel('Percentage of Deaths', fontsize=15)
plt.title("Heroin Deaths by Race", fontsize=15)
```

Out[210]:
```
Text(0.5,1,'Heroin Deaths by Race')
```



White 89.22%

Hispanic 4.90%

Black 3.92%

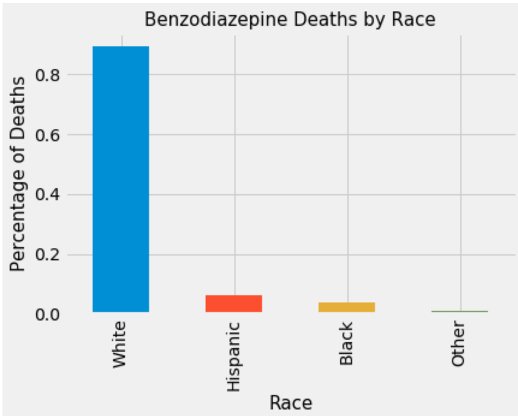
Other 1.96%

In [192]:
```
benzodiazepine=opioids2[opioids2['Benzodiazepine']=='1']
```

Below is graph showing the percentage of deaths by race for Benzodiazepine. Again, the overwhelming majority were White. The percentage for Black remained relatively the same as it did for Heroin, however for the Hispanic group it raised slightly from 4.9% to 6.25%. This shows that Hispanics are effected by Benzodiasepine more than Heroin, however the increase is slight. Overall, the White group is over represented again when looking at the overall statistics for total deaths.

In [208]:
```
benzodiazepine['Race'].value_counts(normalize=True).plot(kind='bar')
plt.style.use('fivethirtyeight')
plt.xlabel('Race', fontsize=15)
plt.ylabel('Percentage of Deaths', fontsize=15)
plt.title("Benzodiazepine Deaths by Race", fontsize=15)
```

Out[208]: `Text(0.5,1,'Benzodiazepine Deaths by Race')`



White 89.18%

Hispanic 6.25%

Black 3.64%

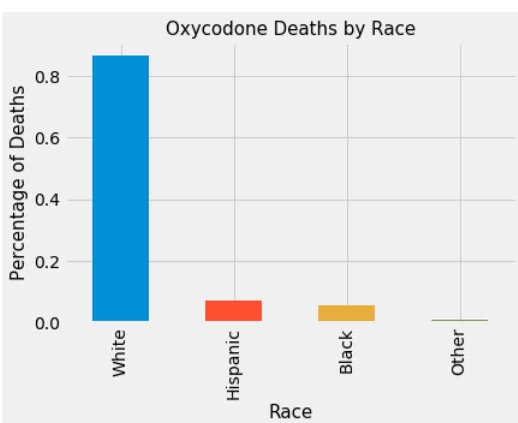
Other 0.93%

In [205]:
```
oxycodone=opioids2[opioids2['Oxycodone']=='1']
```

Below is graph showing the percentage of deaths by race for Oxycodone. Again, the majority were White. However for both the Hispanic and Black group the percentage raised in comparison to Heroin or Benzodiazepine. The Hispanic group makes up 7% of the overall deaths, and the Black group makes up 5.52%. While neither group shows a large increase from the previous two drugs examined, this is the highest percentage for both. Overall, the White group is still over represented when looking at the overall statistics for total deaths.

In [211]:
```
oxycodone['Race'].value_counts(normalize=True).plot(kind='bar')
plt.style.use('fivethirtyeight')
plt.xlabel('Race', fontsize=15)
plt.ylabel('Percentage of Deaths', fontsize=15)
plt.title("Oxycodone Deaths by Race", fontsize=15)
```

Out[211]: `Text(0.5,1,'Oxycodone Deaths by Race')`



White 86.56%

Hispanic 7.00%

Black 5.52%

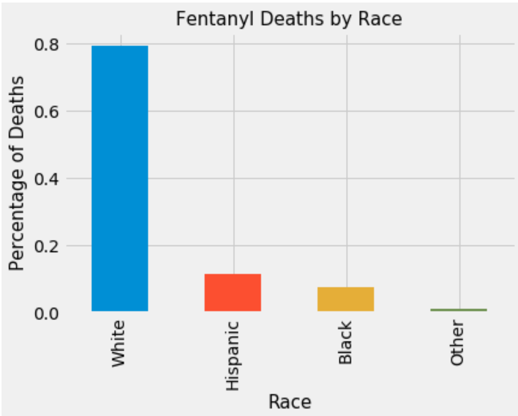
Other 0.92%

Finally, I examined the percentages of deaths for each race by Fentanyl. In this case, the percentages are in line with the overall percentages for deaths by race. Both the Hispanic group and Black group raise to 11.5% and 7.8% respectively. These are the highest percentages for these two groups of all of the previous drugs examined, and show that these two groups have the higests incidents of death by Fentanyl. In addition, this is the first instance where the percentage of White deaths is below 80%.

In [239]:
```
fentanyl=opioids2[opioids2['Fentanyl']=='1']
```

In [240]:
```
fentanyl['Race'].value_counts(normalize=True).plot(kind='bar')
plt.style.use('fivethirtyeight')
plt.xlabel('Race', fontsize=15)
plt.ylabel('Percentage of Deaths', fontsize=15)
plt.title("Fentanyl Deaths by Race", fontsize=15)
```

Out[240]: Text(0.5,1,'Fentanyl Deaths by Race')



White 79.33%

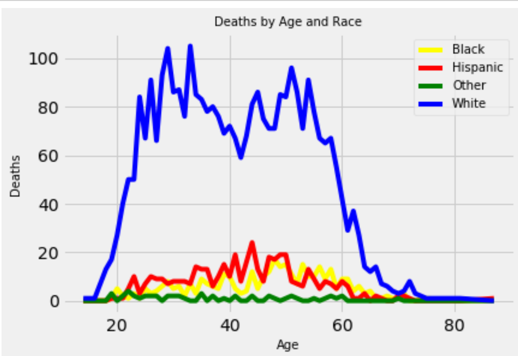
Hispanic 11.50%

Black 7.80%

Other 1.37%

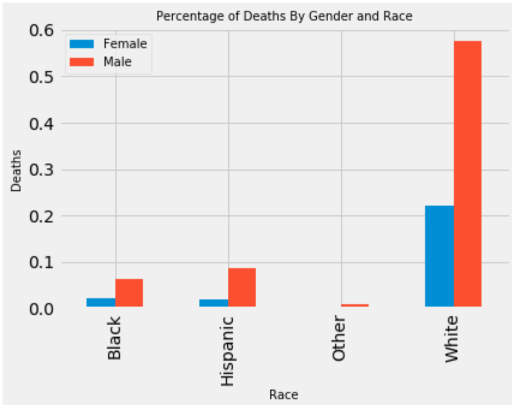
In the below graph you will see a comparison each race and the age at which death occurred. For the White population the age of death spikes from the late 20s until the mid 30s. There is then a downturn before spiking again from the late 40s to the late 50s. For the Hispanic group the rates of deaths remain relatively consistent from the early 20's until the late 50s, with a spike in the early to mid 40s. The Black group also remains relatively consistent, with a similar trajectory to the Hispanic group.

In [221]:
```
pd.crosstab(opioids['Age'], opioids['Race']).plot(color=['yellow', 'red', 'green', 'blue'])
plt.style.use('fivethirtyeight')
plt.xlabel('Age', fontsize=10)
plt.ylabel('Deaths', fontsize=10)
plt.legend(loc='upper right', fontsize=10, ncol=1)
plt.title('Deaths by Age and Race', fontsize=10)
plt.show()
```

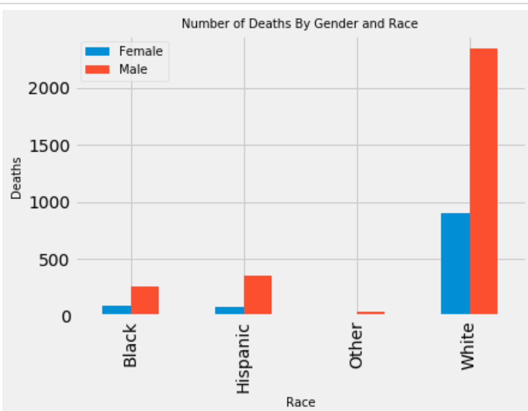


In the below two graphs you will see the number and percentage of deaths by the gender of each race. These graphs show that men are more than twice as likely to die from an opioid overdose than women in all racial categories. In all races the men make up 72.23% to 81.86% of the deaths for their racial category, and women make up 18.14% to 27.77%. The greatest disparity between the genders in within the Hispanic group, with less than 20% of all opioid deaths occuring in females. This is in comparison with the White group where roughly 30% of the total opioid deaths occcur in women.

In [233]:
```
pd.crosstab(opioids['Race'], opioids['Sex'], normalize=True ).plot.bar()
plt.style.use('fivethirtyeight')
plt.xlabel('Race', fontsize=10)
plt.ylabel('Deaths', fontsize=10)
plt.legend(loc='upper left', fontsize=10, ncol=1)
plt.title('Percentage of Deaths By Gender and Race', fontsize=10)
plt.show()
```



In [213]:
```
pd.crosstab(opioids['Race'], opioids['Sex'], normalize=False ).plot.bar()
plt.style.use('fivethirtyeight')
plt.xlabel('Race', fontsize=10)
plt.ylabel('Deaths', fontsize=10)
plt.legend(loc='upper left', fontsize=10, ncol=1)
plt.title('Number of Deaths By Gender and Race', fontsize=10)
plt.show()
```



In [245]:
```
pd.crosstab(opioids['Race'], opioids['Sex'], normalize=False )
```

Out[245]:

Sex	Female	Male
Race		
Black	90	256
Hispanic	78	352
Other	12	38
White	901	2343

Black Women: 26.01% ; Black Men: 73.99%

Hispanic Women: 18.14%; Hispanic Men: 81.86%

Other Women: 24%; Other Men: 76%

White Women: 27.77%; White Men: 72.23%

In [242]:
```
pd.crosstab(opioids['Race'], opioids['Sex'], normalize=True )
```

Out[242]:

Sex Race	Female	Male
Black	0.022113	0.062899
Hispanic	0.019165	0.086486
Other	0.002948	0.009337
White	0.221376	0.575676

In [20]:
```
daily=opioids.groupby(opioids['Date'])
```

In [24]:
```
type(daily)
```

Out[24]: `pandas.core.groupby.DataFrameGroupBy`

In [26]:
```
daily_count=daily.count()
daily_count.head(20)
```

Out[26]:

Date	CaseNumber	Sex	Race	Age	Residence City	Residence State	Residence County	Death City	Death State	Death County	...	Benzodiazepine	Methadone	Amphet	Tramad	Morphine (not heroin)	Other	Any Opioid	Ma
2012-01-01	1	1	1	1	1	0	1	1	0	1	...	0	0	0	0	0	0	0	
2012-01-03	1	1	1	1	1	0	1	1	0	1	...	1	0	0	0	0	0	0	
2012-01-04	1	1	1	1	1	0	1	1	0	1	...	0	0	0	0	0	0	0	
2012-01-05	1	1	1	1	1	0	1	1	0	1	...	0	1	0	0	0	0	0	
2012-01-07	1	1	1	1	1	0	1	1	0	1	...	0	0	0	0	0	0	0	
2012-	3	3	3	3	3	0	3	3	0	3		1	1	1	0	0	0	0	

In [46]:
```
X=daily[['Hydrocodone', 'Heroin',  'Fentanyl', 'Oxycodone', 'Oxymorphone']]
```

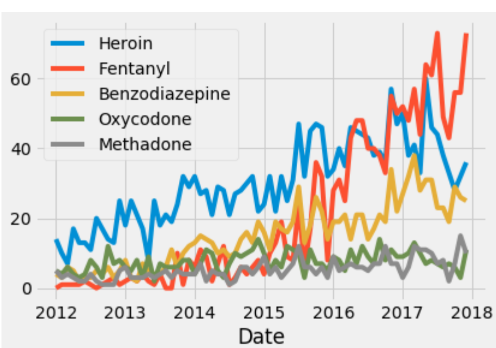
In [224]:
```
monthly=daily_count[['Heroin','Fentanyl','Benzodiazepine', "Oxycodone", "Methadone"]].resample('M', how='sum')
```

```
C:\Users\User\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: FutureWarning: how in .resample() is deprecated
the new syntax is .resample(...).sum()
  """Entry point for launching an IPython kernel.
```

Finally, I wanted to compare the number of deaths attributed to the top 5 drugs over time. I compared the monthly data from 2012 through 2017, and found that Methadone and Oxycodone had remained relatively steady over time. However, Heroin, Fentanyl and Benzodiazepine have all increased. Heroin went from less than 20 deaths a month, to peaking in 2017 and 60 per month. Benzodiazepine went from almost 0 deaths per month to peaking in 2017 at around 40 deaths per month. The most surprising result was the steep increase of Fentanyl starting in 2015. In 2012 Fentanyl had almost 0 deaths per month, and less deaths that Heroin or Benzodiazepine. By the end of 2017, the number of deaths had spiked to almost 80 deaths per month.

In [225]:
```
monthly.plot()
```

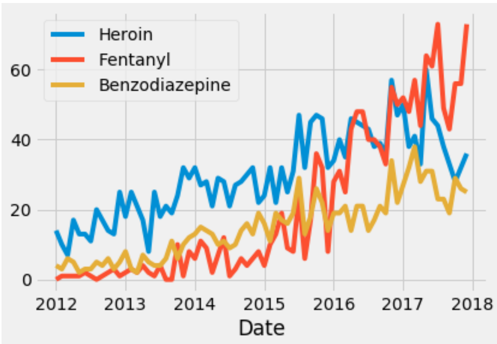
Out[225]: `<matplotlib.axes._subplots.AxesSubplot at 0x2e0d9f44d68>`



In [231]:
```
monthly2=daily_count[['Heroin','Fentanyl','Benzodiazepine']].resample('M', how='sum')
monthly2.plot()
```

```
C:\Users\User\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: FutureWarning: how in .resample() is deprecated
the new syntax is .resample(...).sum()
  """Entry point for launching an IPython kernel.
```

Out[231]: <matplotlib.axes._subplots.AxesSubplot at 0x2e0d8d15b38>



After analyzing my data, I found that the main demographic factor contributing to opioid deaths was Gender. Men died at over twice the rate of women across all racial categories. I also found that race was not a significannt factor contributing to opioid deaths. While there was some variation, over all the distribution of opioid deaths matched the racial demographic statistics of Conneticut as a whole. My data also showed that opioid related deaths increased over the 6 year period examined. Heroin, Fentanyl and Bezodiazepie contributed to the most deaths, and all three show a trend of increasing causing overdose deaths. The most striking finding was the steep increase in Fentanyl related deaths, going from almost 0 deaths per nonth in 2012 to roughly 80 deaths per month by the end of 2017. Hopefully the continued study of opioid related deaths will lead to solutions to this epedemic and assist in creating better treatment options and support for those afflicted with addiction.

In [ ]: