In [1]:

```python
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"

# import libraries

import numpy as np
import pandas as pd

# import the CSV
df = pd.read_csv("Traffic_Crashes_-_Crashes.csv")
```

In [2]:

```python
# split the date and time into two columns
df[['CRASH_DATE', 'CRASH_TIME']] = df.CRASH_DATE.str.split(expand=True)
df[['DATE_POLICE_NOTIFIED', 'TIME_POLICE_NOTIFIED']] = df.DATE_POLICE_NOTIFIED.str.spl


# Remove the ID because it provides no info
df = df.drop(columns=['CRASH_RECORD_ID'])
```

In [3]:

```python
df.head(5)
```

Out[3]:

	CRASH_DATE	POSTED_SPEED_LIMIT	TRAFFIC_CONTROL_DEVICE	DEVICE_CONDITION	WEATHER_CONDITION
0	7/10/19	35	NO CONTROLS	NO CONTROLS	CLEAR
1	6/30/17	35	STOP SIGN/FLASHER	FUNCTIONING PROPERLY	CLEAR
2	7/10/20	30	TRAFFIC SIGNAL	FUNCTIONING PROPERLY	CLEAR
3	7/11/20	30	NO CONTROLS	NO CONTROLS	CLEAR
4	7/8/20	20	NO CONTROLS	NO CONTROLS	CLEAR

5 rows × 28 columns

In [4]:

```python
# replace the white spaces and '' with Nan

df['INTERSECTION_RELATED_I'].replace(r'^\s*$', np.nan, regex=True)
#df['INTERSECTION_RELATED_I'].head(5)

df['NOT_RIGHT_OF_WAY'].replace(r'^\s*$', np.nan, regex=True)
#df['NOT_RIGHT_OF_WAY'].head(5)

df['HIT_AND_RUN_I'].replace(r'^\s*$', np.nan, regex=True)
#df['HIT_AND_RUN_I'].head(5)
```

Out[4]:

```
0         NaN
1           Y
2         NaN
3         NaN
4         NaN
         ...
481618    NaN
481619    NaN
481620    NaN
481621      Y
481622    NaN
Name: INTERSECTION_RELATED_I, Length: 481623, dtype: object
```

Out[4]:

```
0         NaN
1         NaN
2         NaN
3         NaN
4         NaN
         ...
481618    NaN
481619    NaN
481620    NaN
481621    NaN
481622    NaN
Name: NOT_RIGHT_OF_WAY, Length: 481623, dtype: object
```

Out[4]:

```
0         NaN
1         NaN
2         NaN
3           Y
4         NaN
         ...
481618      Y
481619      Y
481620    NaN
481621    NaN
481622      Y
Name: HIT_AND_RUN_I, Length: 481623, dtype: object
```

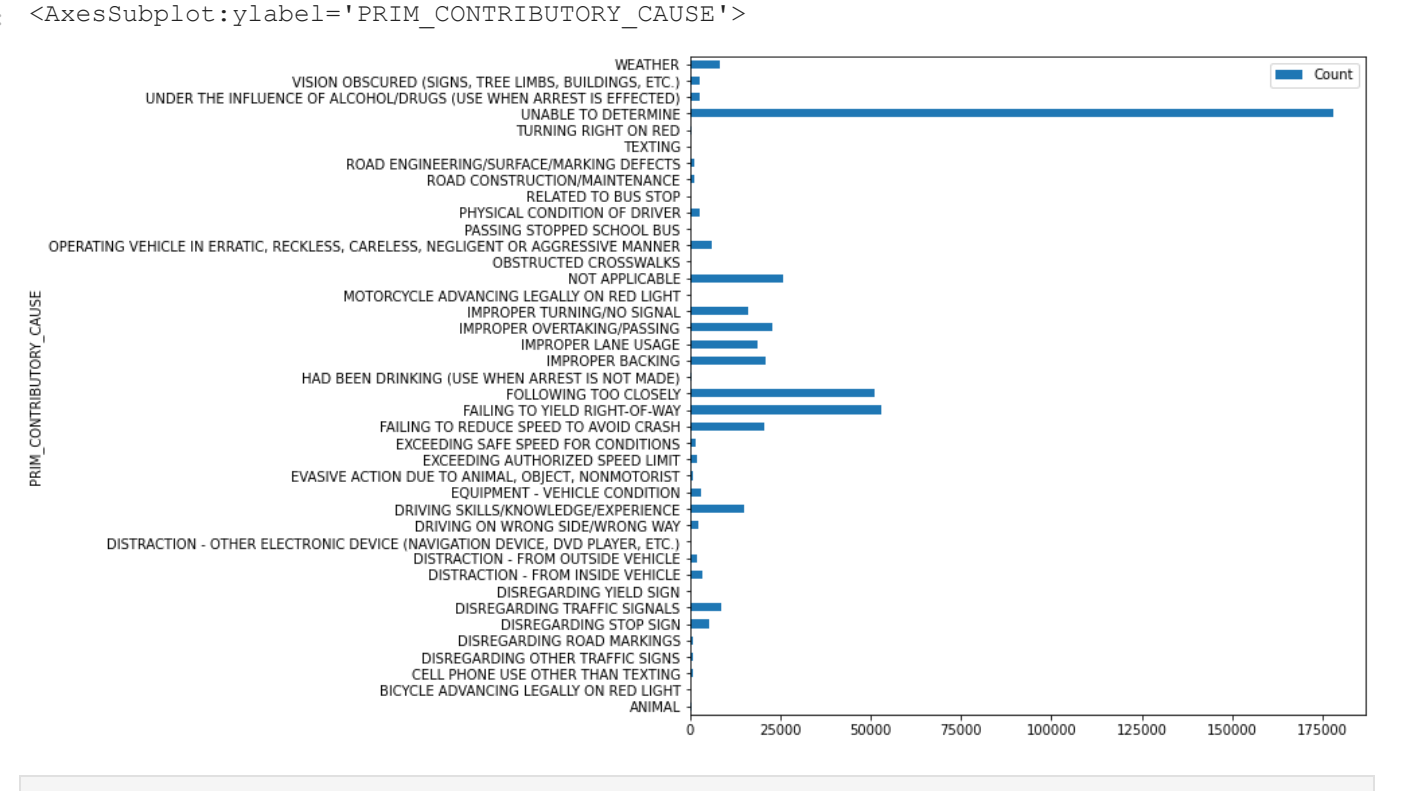
In [5]:

```python
# what are the reported primary top 10 causes of accidents
reasons = df.groupby(['PRIM_CONTRIBUTORY_CAUSE']).size().reset_index(name='Count')
reasons.sort_values(by='Count', ascending=False).head(10)

reasons.plot(x='PRIM_CONTRIBUTORY_CAUSE', y='Count', kind='barh', figsize = (9,9))

# seems like the vast majority of the accidents' reasons are "unable to determine"
# we will explore that deeper using other variables
```

Out[5]:

	PRIM_CONTRIBUTORY_CAUSE	Count
36	UNABLE TO DETERMINE	178010
18	FAILING TO YIELD RIGHT-OF-WAY	52982
19	FOLLOWING TOO CLOSELY	51238
26	NOT APPLICABLE	25849
23	IMPROPER OVERTAKING/PASSING	22858
21	IMPROPER BACKING	21096
17	FAILING TO REDUCE SPEED TO AVOID CRASH	20751
22	IMPROPER LANE USAGE	18637
24	IMPROPER TURNING/NO SIGNAL	15986
12	DRIVING SKILLS/KNOWLEDGE/EXPERIENCE	14968

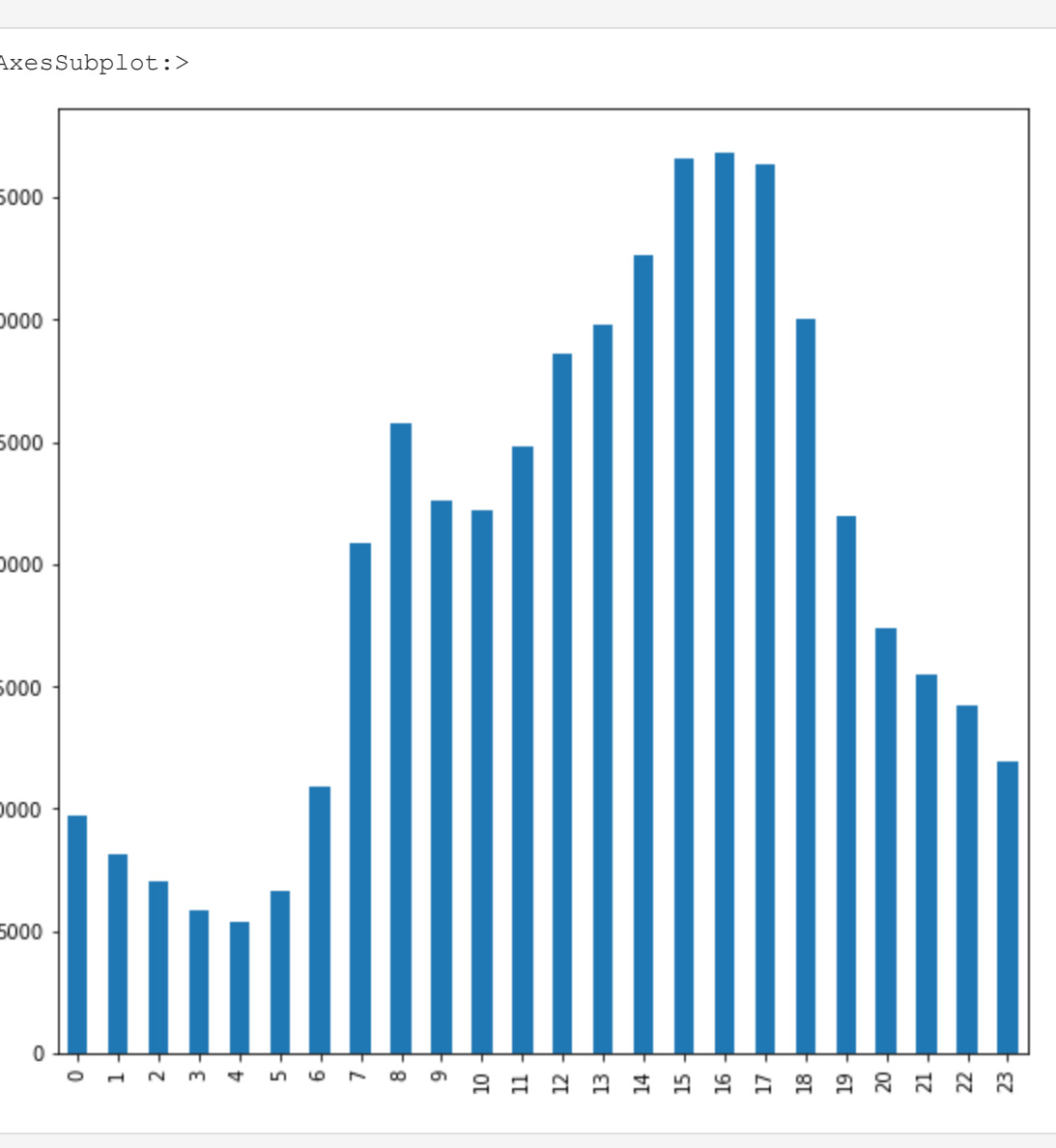
Out[5]: <AxesSubplot:ylabel='PRIM_CONTRIBUTORY_CAUSE'>



In [6]:

```python
# let us explore some more general statistics about the accidents
# what times do the accidents happen
time_hour = df.groupby(['CRASH_HOUR']).size().reset_index(name='Count')
time_hour['Count'].plot(kind='bar', figsize = (9,9))
```

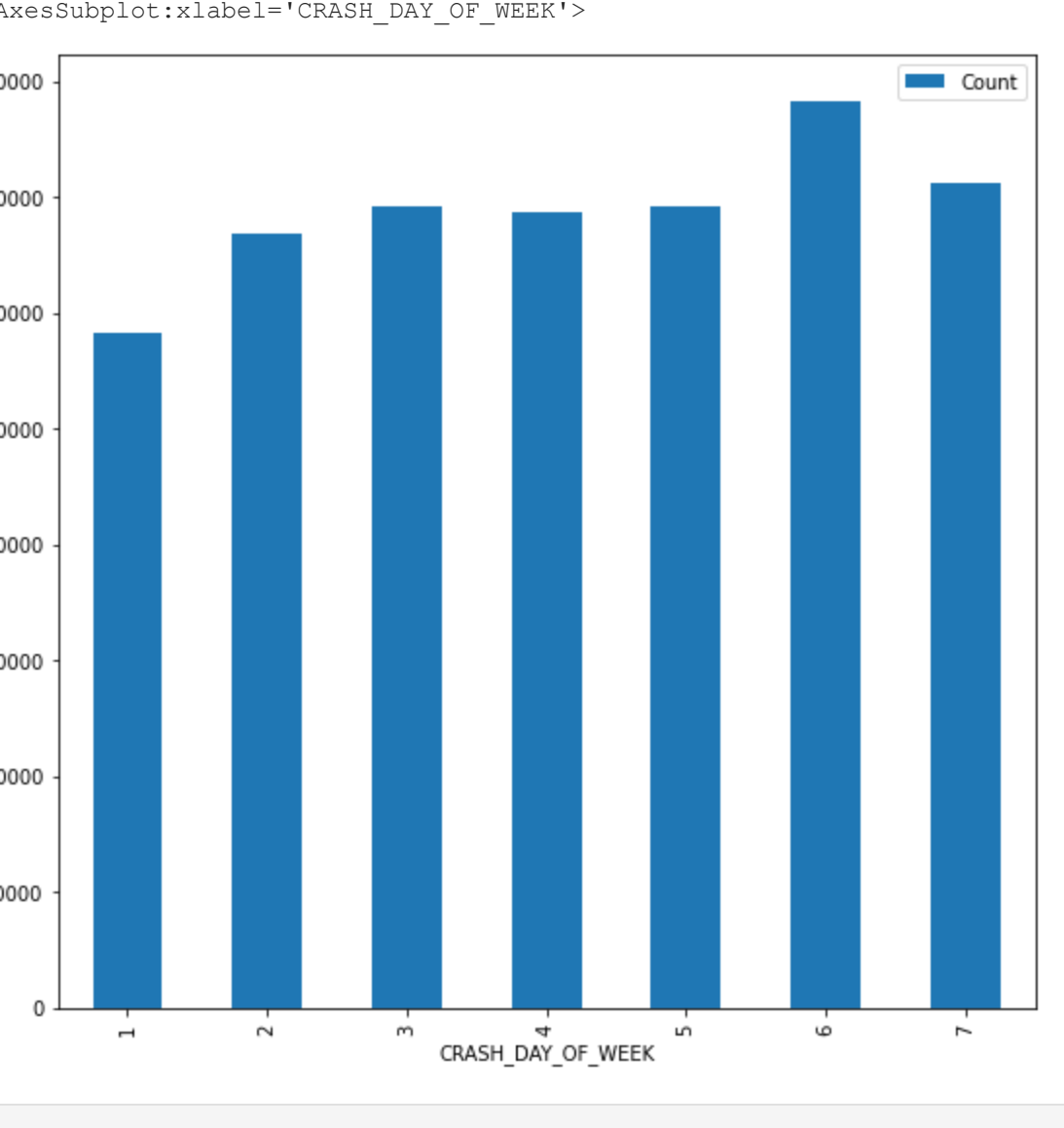
Out[6]: <AxesSubplot:>



In [7]:

```python
# see what day of the week
day_week = df.groupby(['CRASH_DAY_OF_WEEK']).size().reset_index(name='Count')
day_week.plot(x = 'CRASH_DAY_OF_WEEK' , y = 'Count', kind='bar', figsize = (9,9))
```

Out[7]: <AxesSubplot:xlabel='CRASH_DAY_OF_WEEK'>



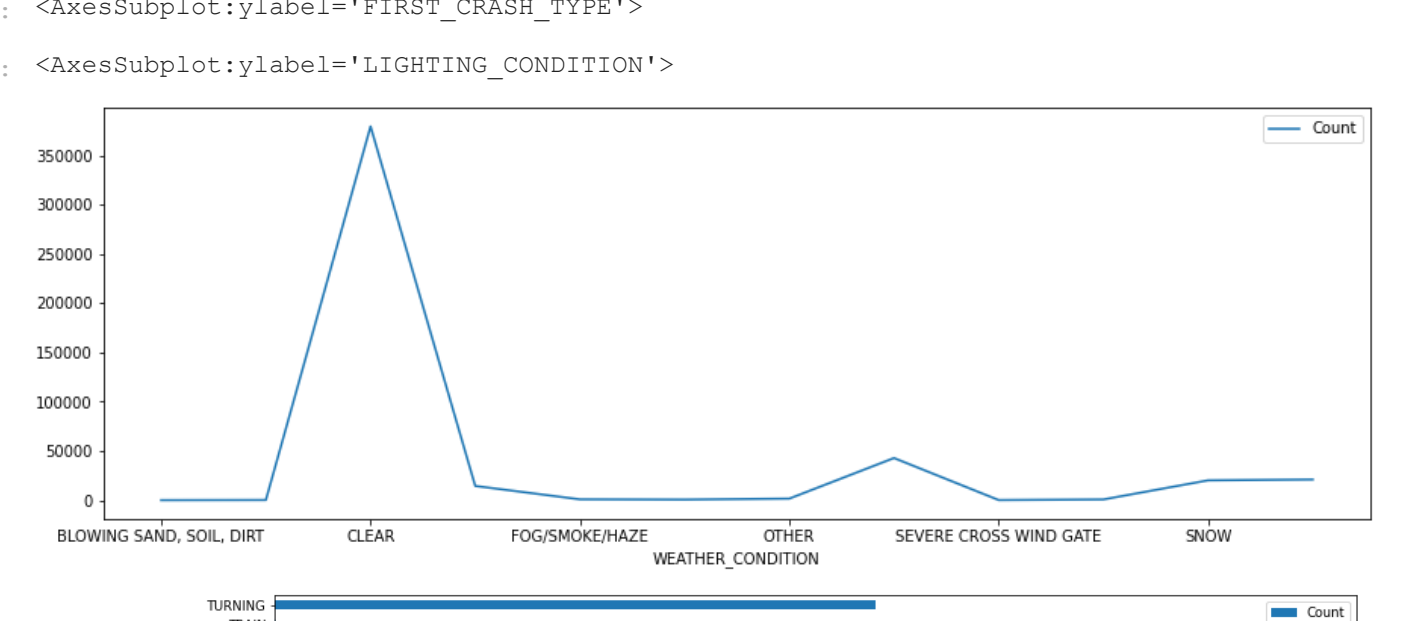
In [8]:

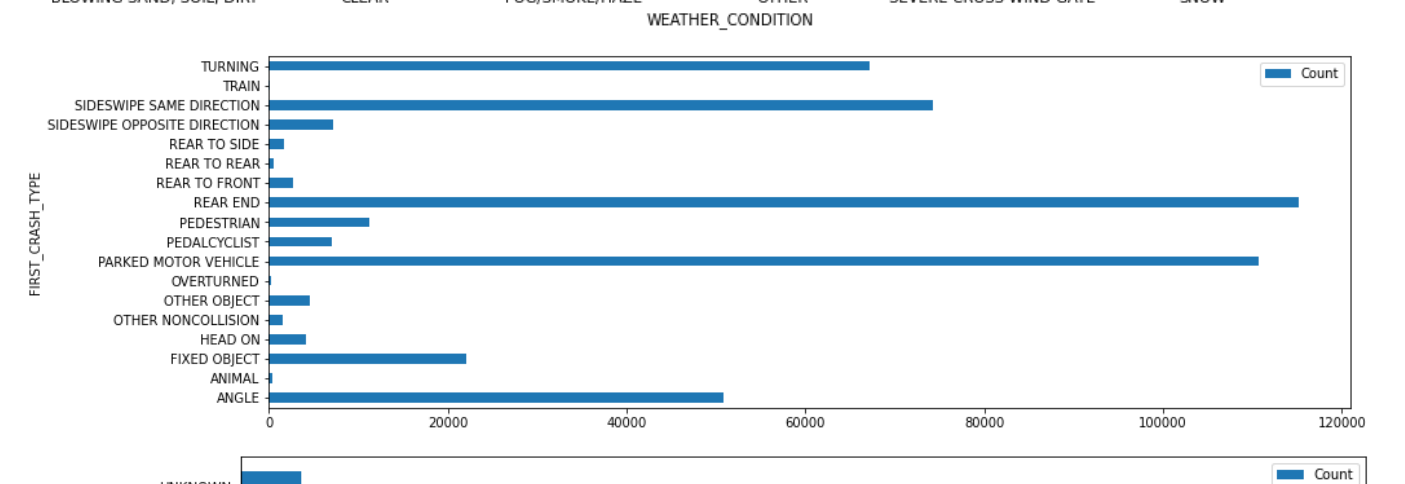
```python
# see what what weather
weather = df.groupby(['WEATHER_CONDITION']).size().reset_index(name='Count')
weather.plot(x = 'WEATHER_CONDITION', y = 'Count', figsize=(15,5))

# first crash type
crash_type = df.groupby(['FIRST_CRASH_TYPE']).size().reset_index(name='Count')
crash_type.plot(x = 'FIRST_CRASH_TYPE', y = 'Count', kind='barh', figsize=(15,5))

# lightning condition
light = df.groupby(['LIGHTING_CONDITION']).size().reset_index(name='Count')
light.plot(x = 'LIGHTING_CONDITION', y = 'Count', kind='barh', figsize=(15,5))
```

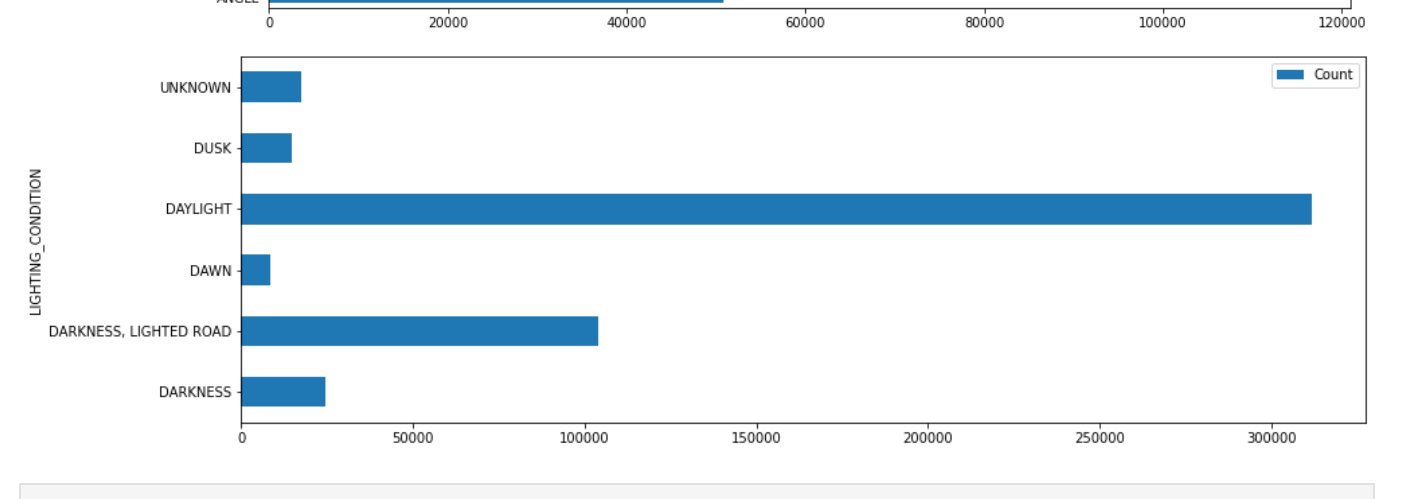
Out[8]: <AxesSubplot:xlabel='WEATHER_CONDITION'>

Out[8]: <AxesSubplot:ylabel='FIRST_CRASH_TYPE'>

Out[8]: <AxesSubplot:ylabel='LIGHTING_CONDITION'>



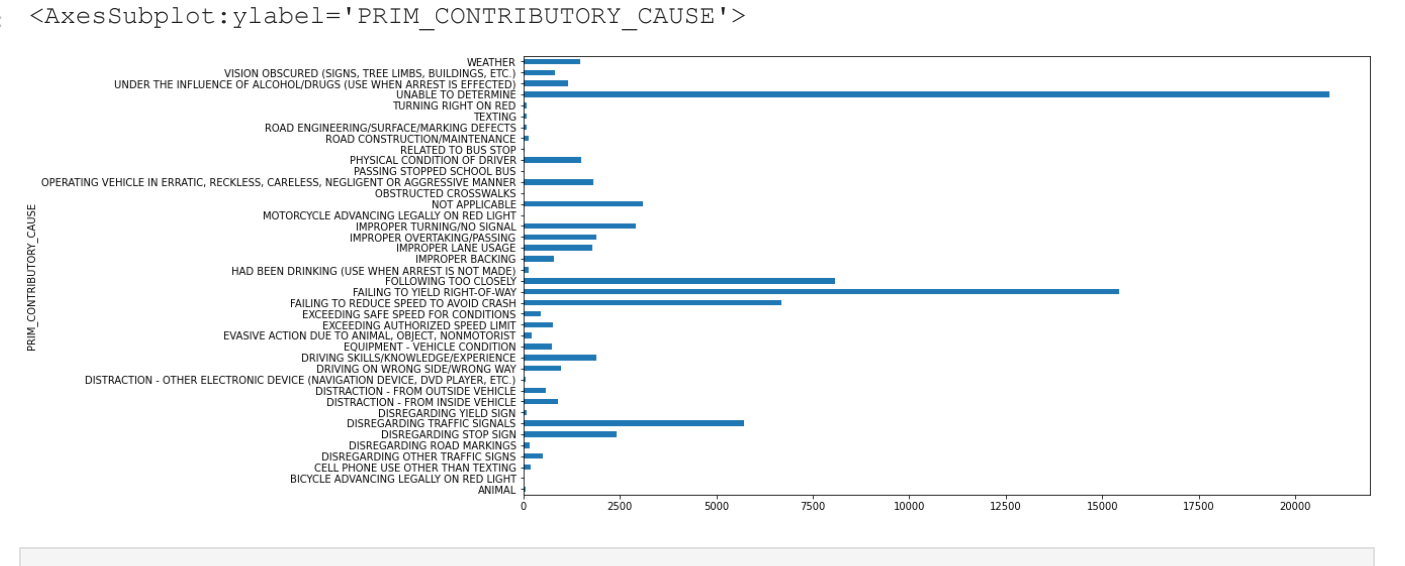




In [9]:

```python
import matplotlib.pyplot as plt

# see injuries total and fatal injuries per type of accident
inj = df.groupby(['PRIM_CONTRIBUTORY_CAUSE'])['INJURIES_TOTAL'].sum()
#inj
inj.plot(x = 'INJURIES_TOTAL', y = 'PRIM_CONTRIBUTORY_CAUSE', kind='barh', figsize=(15
```

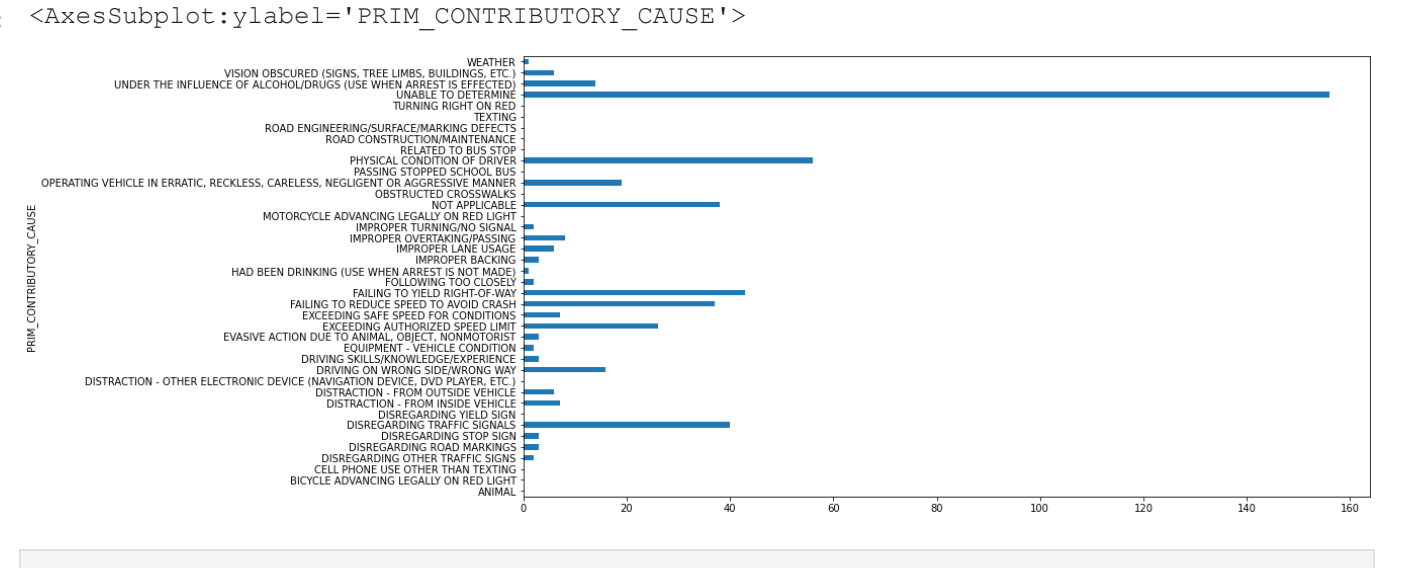
Out[9]: <AxesSubplot:ylabel='PRIM_CONTRIBUTORY_CAUSE'>



In [10]:

```python
# fatal accidents by type
inj_f = df.groupby(['PRIM_CONTRIBUTORY_CAUSE'])['INJURIES_FATAL'].sum()
#inj_f
inj_f.plot(x = 'INJURIES_FATAL', y = 'PRIM_CONTRIBUTORY_CAUSE', kind='barh', figsize=
```

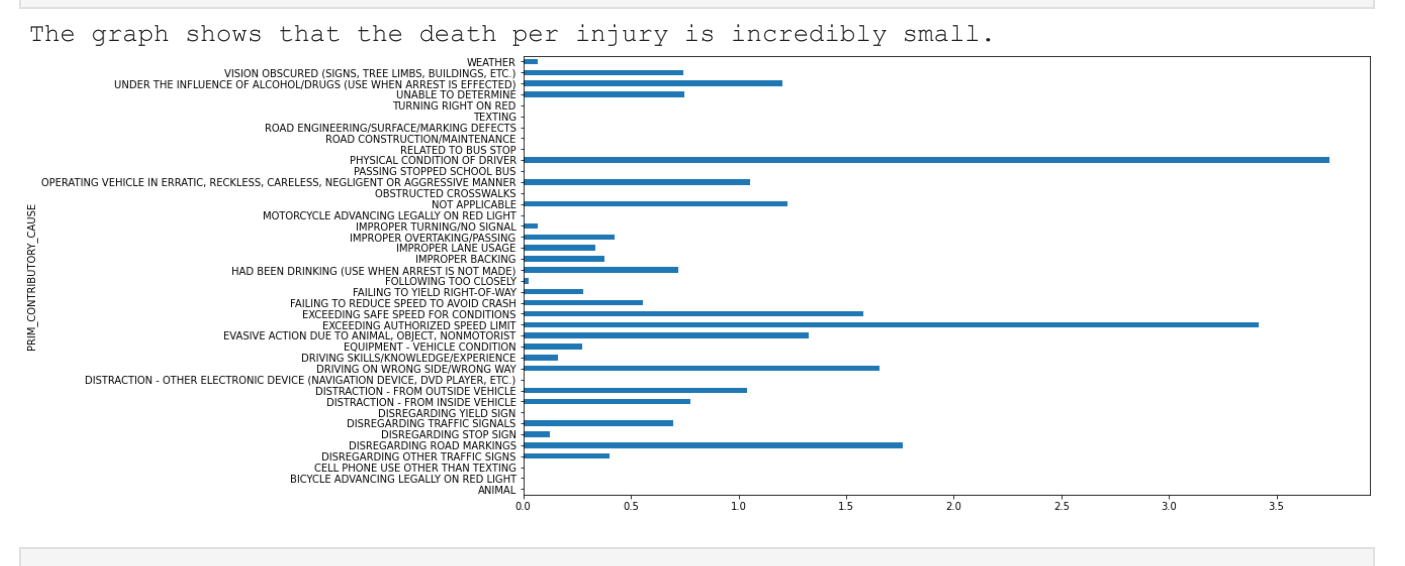
Out[10]: <AxesSubplot:ylabel='PRIM_CONTRIBUTORY_CAUSE'>



In [11]:

```python
# change to die based on type of accident
death_rate = (inj_f / inj)
d_r = (death_rate*100).plot(kind='barh', figsize=(15,8))

#frames_inj = [inj, inj_f]

#r = pd.concat(frames_inj, axis=1)
#r.plot(kind='barh', figsize=(15,8), xticks = range(0,25000,1000))

print('The graph shows that the death per injury is incredibly small.')
```

```
The graph shows that the death per injury is incredibly small.
```



In [12]:

```python
# convert date string to date format
df['CRASH_DATE'] = pd.to_datetime(df['CRASH_DATE'], errors='coerce')
df['CRASH_DATE'].head(2)

# create a column with years only
df['YEAR'] = df['CRASH_DATE'].dt.year
df.YEAR.head(2)
```

Out[12]:

```
0   2019-07-10
1   2017-06-30
Name: CRASH_DATE, dtype: datetime64[ns]
```

Out[12]:

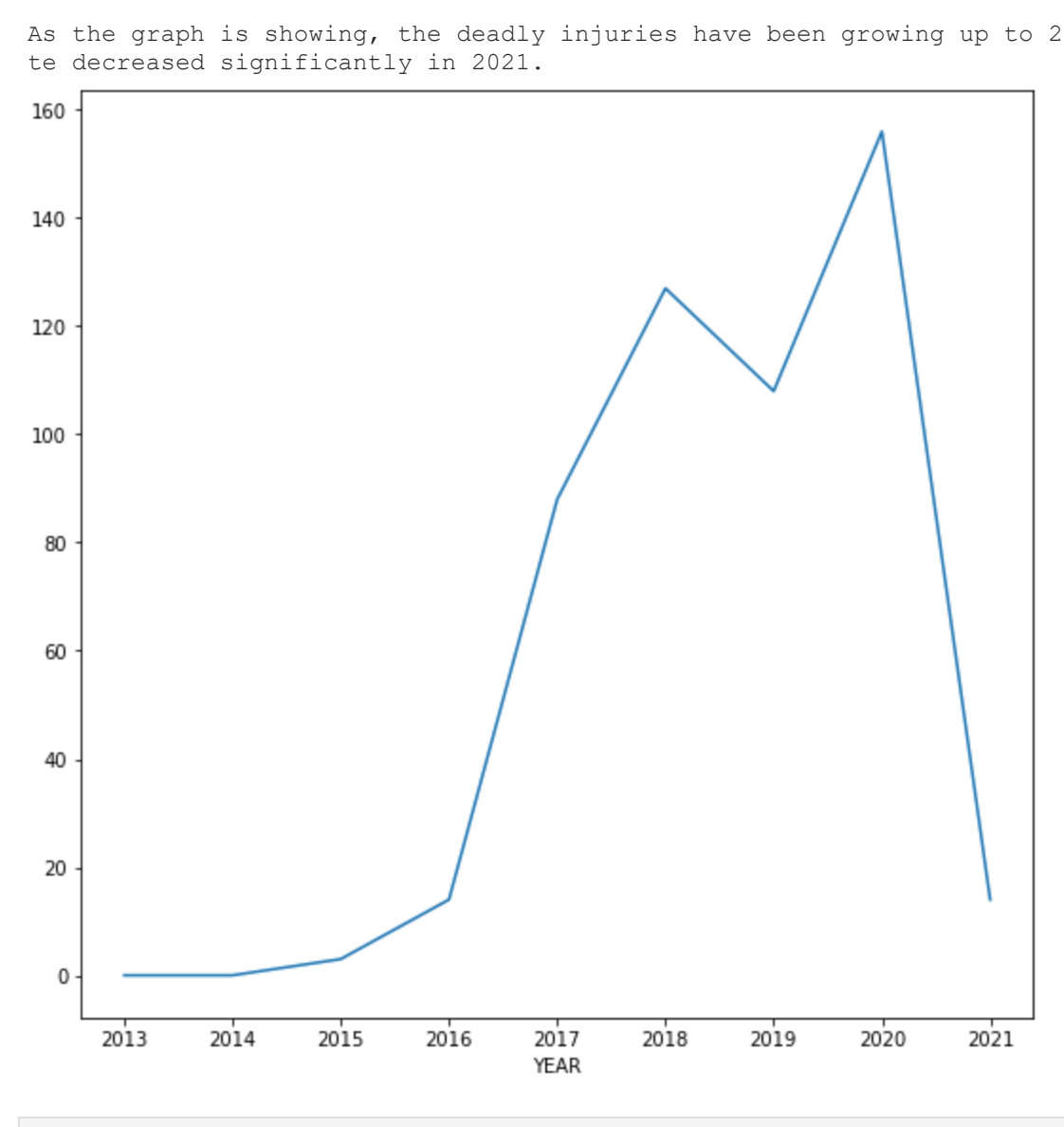
```
0    2019
1    2017
Name: YEAR, dtype: int64
```

In [13]:

```python
# deadly accidents by year
fatal_year = df.groupby('YEAR')['INJURIES_FATAL'].sum()
fatal_year.plot(figsize=(9,9))
print('As the graph is showing, the deadly injuries have been growing up to 2020, the
```

Out[13]: <AxesSubplot:xlabel='YEAR'>

```
As the graph is showing, the deadly injuries have been growing up to 2020, then the ra
te decreased significantly in 2021.
```



In [14]:

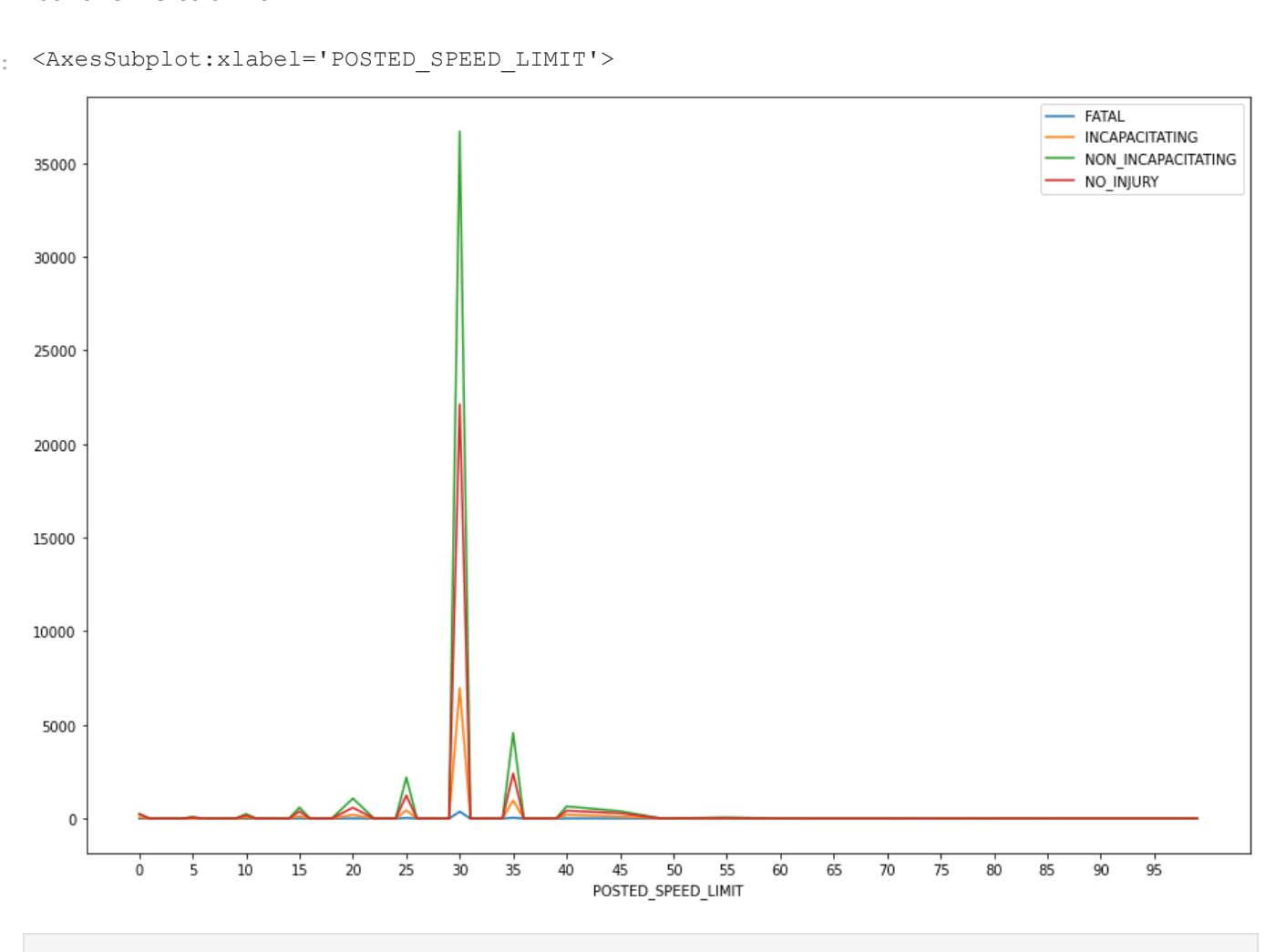
```python
# let's see the number and type of injuries based on the speed limit
# create subsets and join them
tot_inj_speed = df.groupby('POSTED_SPEED_LIMIT')['INJURIES_TOTAL'].sum().reset_index(
n_inj_speed = df.groupby('POSTED_SPEED_LIMIT')['INJURIES_FATAL'].sum().reset_index(na
n_inj2_speed = df.groupby('POSTED_SPEED_LIMIT')['INJURIES_INCAPACITATING'].sum().rese
n_inj3_speed = df.groupby('POSTED_SPEED_LIMIT')['INJURIES_NON_INCAPACITATING'].sum().
n_inj4_speed = df.groupby('POSTED_SPEED_LIMIT')['INJURIES_REPORTED_NOT_EVIDENT'].sum(

frames_inj = [n_inj_speed, n_inj2_speed, n_inj3_speed, n_inj4_speed]
r = pd.concat(frames_inj)
r
# plot is very big with very small numbers
r.plot(x = 'POSTED_SPEED_LIMIT', figsize=(15,10), xticks = range(0,100,5))
```

Out[14]:

	POSTED_SPEED_LIMIT	FATAL	INCAPACITATING	NON_INCAPACITATING	NO_INJURY
0	0	3.0	NaN	NaN	NaN
1	1	0.0	NaN	NaN	NaN
2	2	0.0	NaN	NaN	NaN
3	3	0.0	NaN	NaN	NaN
4	4	0.0	NaN	NaN	NaN
...	...	...	...	...	...
37	60	NaN	NaN	NaN	5.0
38	63	NaN	NaN	NaN	0.0
39	65	NaN	NaN	NaN	2.0
40	70	NaN	NaN	NaN	0.0
41	99	NaN	NaN	NaN	5.0

168 rows × 5 columns

Out[14]: <AxesSubplot:xlabel='POSTED_SPEED_LIMIT'>



In [15]:

```python
import math
# Is there a relationship between hit and run crashes and number of fatal injuries?
hit_run = df.groupby('POSTED_SPEED_LIMIT')['HIT_AND_RUN_I'].count().reset_index(name =

ratio = (sum(n_inj_speed['FATAL']) / sum(hit_run['COUNT']))*100

print('It appears that hit and run accidents are not strongly correlated with fatal ac
print("There's an overall ratio of {:.2f}% of fatal incidents to hit-and-run accidents

hit_run_tot = df.groupby(['HIT_AND_RUN_I']).size().reset_index(name='COUNT')
hit_run_fatal = df.groupby('HIT_AND_RUN_I')['INJURIES_FATAL'].sum().reset_index(name =

ratio2 = (sum(hit_run_fatal['SUM']) / sum(hit_run_tot['COUNT']))*100

print("There's an overall chance of {:.2f}% to die if involved in a hit-and-run accid

# lets calculate the correlation coefficient

N = len(df) # total number of cases

# x is count of all hit and run
x = hit_run_tot.iloc[int(hit_run_tot[['COUNT']].idxmax())]['COUNT']

# y is count of all fatal injuries
tot_fat = df.groupby(['INJURIES_FATAL']).size().reset_index(name='COUNT')
y = tot_fat.iloc[int(hit_run_tot[['COUNT']].idxmax())]['COUNT']

# sum(xy) = sum(1*1) = sum(y). x and y are 1 because we count them as 1 if Y, 0 if N
numerator = (N*sum(hit_run_fatal['SUM'])) - (x*y)    # sigma x*y -> x*y will be 1 only
denominator = math.sqrt(((N*x) - (x**2))*((N*y) - (y**2)))
r = numerator / denominator
print("The correlation coefficient p is {:.4f} which is a weak correlation.".format(r)
```

```
It appears that hit and run accidents are not strongly correlated with fatal accident
s.
There's an overall ratio of 0.36% of fatal incidents to hit-and-run accidents
There's an overall chance of 0.06% to die if involved in a hit-and-run accident
The correlation coefficient p is -0.0052 which is a weak correlation.
```

In [16]:

```python
# Do intersection-related crashes result in more fatal injuries?
# compare intersection deaths to non-intersection deaths
intersection_deaths = df[df.INTERSECTION_RELATED_I == 'Y']
sum_deaths = intersection_deaths['INJURIES_FATAL'].sum()
#sum_deaths

sum_deaths_tot = df['INJURIES_FATAL'].sum()
#sum_deaths_tot

ratio = sum_deaths / sum_deaths_tot
#ratio

print("There's a {:.2f} ratio intersection-deaths to total-deaths, which is quite sign
print("{:.2f}% of deadly injuries are related to intersections, we can conclude that
```

```
There's a 0.33 ratio intersection-deaths to total-deaths, which is quite significant.
32.75% of deadly injuries are related to intersections, we can conclude that intersect
ions result in more deaths.
```

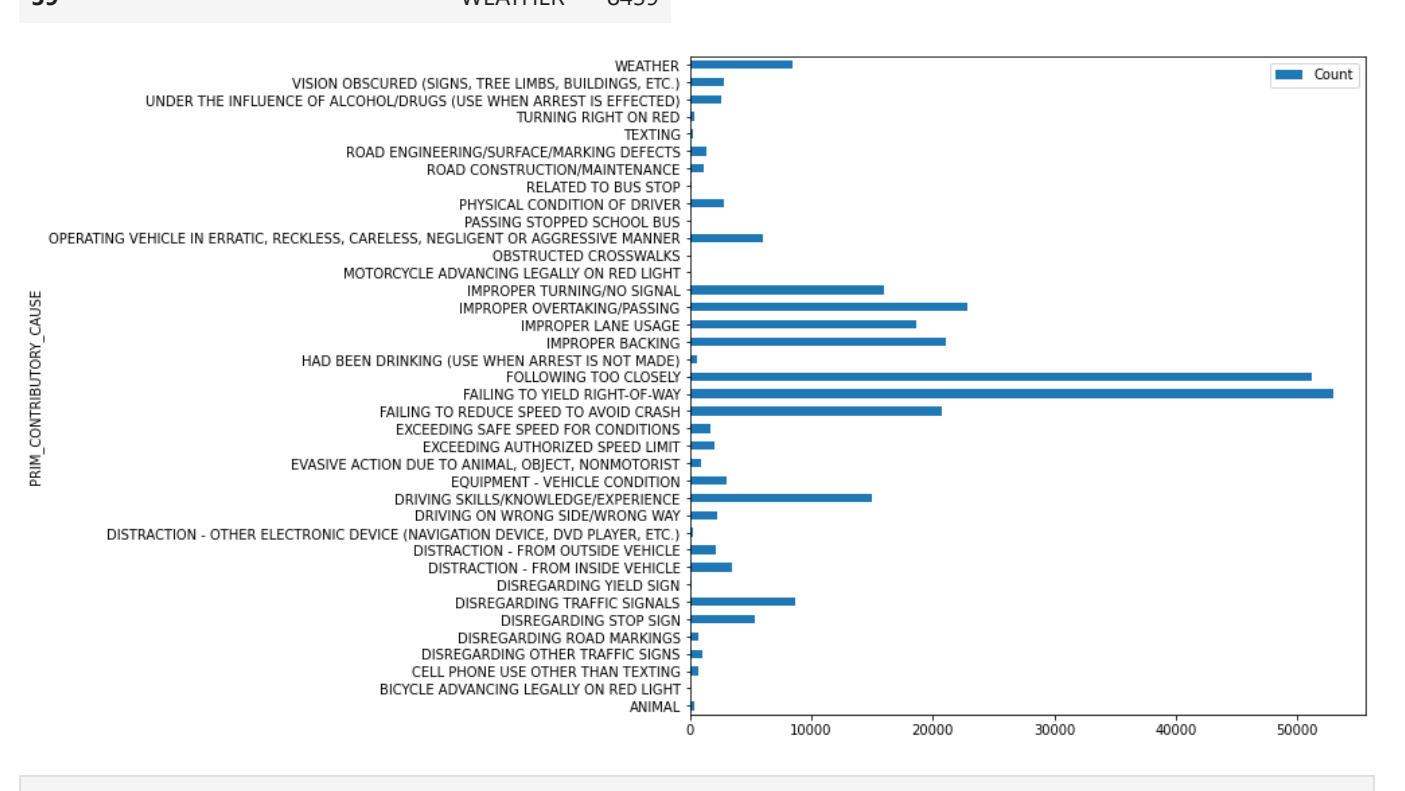
In [17]:

```python
# let's see how the accidents graph looks like for reasons we actually know
# remove the unable to determine and non applicable
clear_reasons = reasons[reasons.PRIM_CONTRIBUTORY_CAUSE != 'UNABLE TO DETERMINE']
clear_reasons = clear_reasons[clear_reasons.PRIM_CONTRIBUTORY_CAUSE != 'NOT APPLICABLE

#plot the data
clear_reasons.plot(x='PRIM_CONTRIBUTORY_CAUSE', y='Count', kind='barh', figsize = (9,
clear_reasons.sort_values(by='Count', ascending=False).head(10)
```

Out[17]: <AxesSubplot:ylabel='PRIM_CONTRIBUTORY_CAUSE'>

Out[17]:

	PRIM_CONTRIBUTORY_CAUSE	Count
18	FAILING TO YIELD RIGHT-OF-WAY	52982
19	FOLLOWING TOO CLOSELY	51238
23	IMPROPER OVERTAKING/PASSING	22858
21	IMPROPER BACKING	21096
17	FAILING TO REDUCE SPEED TO AVOID CRASH	20751
22	IMPROPER LANE USAGE	18637
24	IMPROPER TURNING/NO SIGNAL	15986
12	DRIVING SKILLS/KNOWLEDGE/EXPERIENCE	14968
6	DISREGARDING TRAFFIC SIGNALS	8713
39	WEATHER	8439



In [18]:

```python
# let us explore what other details the top 2 most popular accidents reasons have
# failing to yeld right-of-way
right_of_way = df[df.PRIM_CONTRIBUTORY_CAUSE == 'FAILING TO YIELD RIGHT-OF-WAY']
#right_of_way.head(5)

# let us see how many of these are actually reported to be intersaction related, no r
intersection = right_of_way.groupby(['INTERSECTION_RELATED_I']).size().reset_index(na
print(intersection)

not_r_o_w = right_of_way.groupby(['NOT_RIGHT_OF_WAY']).size().reset_index(name='Count
print(not_r_o_w)
```

```
  INTERSECTION_RELATED_I  Count
0                      N    618
1                      Y  21090
  NOT_RIGHT_OF_WAY  Count
0                N    108
1                Y   1077
```

In [19]:

```python
# so far we know that most of the accidents reported are caused by a fail of yelding
percent = intersection.iloc[int(intersection[['Count']].idxmax())]['Count']/clear_rea

print('{:.2f}% of accidents that fail to yeld right-of-way are reported on an interse
print('It appears that the places of the accidents underreported because the yelding

# let's see how many deaths are caused by the fail of yelding right-of-way
sum_deaths = right_of_way['INJURIES_FATAL'].sum()
#sum_deaths

sum_deaths_tot = df['INJURIES_FATAL'].sum()
#sum_deaths_tot

ratio2 = sum_deaths / sum_deaths_tot
#ratio

print("The ratio of fatal injuries due failing to yelding right-of-way to total fatal
print("Although deaths due intersection amount to {:.2f}%, deaths on intersections du
```

```
39.81% of accidents that fail to yeld right-of-way are reported on an intersection.
It appears that the places of the accidents underreported because the yelding right-of
-way happens mostly on an intersection.
The ratio of fatal injuries due failing to yelding right-of-way to total fatal injurie
s is 0.08
Although deaths due intersection amount to 32.75%, deaths on intersections due to fail
ing to yeld right-of-way is 8.43%
```

In [20]:

```python
# let's look now at the second most popular type of accident
# following too closely, this might happen for multiple reasons. Let's explore some o
follow_too_close = df[df.PRIM_CONTRIBUTORY_CAUSE == 'FOLLOWING TOO CLOSELY']

# let's see what type of trafficway, time of the day, weather condition and roadway c
traffic_way = follow_too_close.groupby(['TRAFFICWAY_TYPE']).size().reset_index(name='
#traffic_way.sort_values(by='Count', ascending=False).head(10)

time_hour = follow_too_close.groupby(['CRASH_HOUR']).size().reset_index(name='Count')
#time_hour.sort_values(by='Count', ascending=False).head(10)

weather_cond = follow_too_close.groupby(['WEATHER_CONDITION']).size().reset_index(nam
#weather_cond.sort_values(by='Count', ascending=False).head(10)

road_cond = follow_too_close.groupby(['ROADWAY_SURFACE_COND']).size().reset_index(nam
#road_cond.sort_values(by='Count', ascending=False).head(10)
```

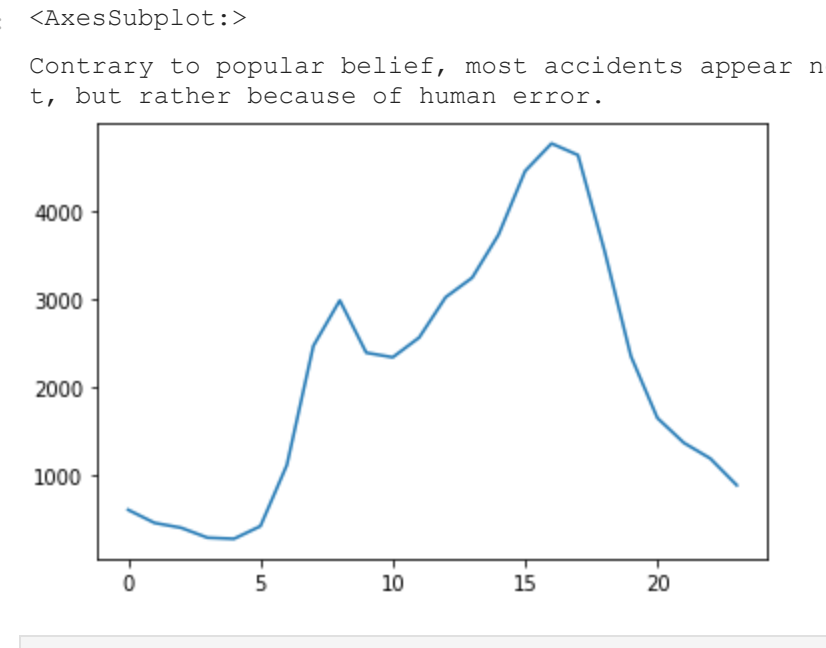
In [21]:

```python
print('It appears that most accidents of type "Follow too close" happen under these co
t = traffic_way.sort_values(by='Count', ascending=False)
tt = t.iloc[0]['TRAFFICWAY_TYPE']
tn = t.iloc[0]['Count']
tpercent = tn/sum(traffic_way['Count'])*100
print('Trafficway: {}, with {} accidents, amounting to {:.2f}% of total accidents of

w = weather_cond.sort_values(by='Count', ascending=False)
ww = w.iloc[0]['WEATHER_CONDITION']
wn = w.iloc[0]['Count']
wpercent = wn/sum(weather_cond['Count'])*100
print('Weather: {}, with {} accidents, amounting to {:.2f}% of total accidents of thi

r = road_cond.sort_values(by='Count', ascending=False)
rr = r.iloc[0]['ROADWAY_SURFACE_COND']
rn = r.iloc[0]['Count']
rpercent = rn/sum(weather_cond['Count'])*100
print('Road Condition: {}, with {} accidents, amounting to {:.2f}% of total accidents

print('Time of accidents:')
time_hour['Count'].plot()

print('Contrary to popular belief, most accidents appear not to be because of the env
```

```
It appears that most accidents of type "Follow too close" happen under these condition
s:
Trafficway: NOT DIVIDED, with 26991 accidents, amounting to 52.68% of total accidents
of this type.
Weather: CLEAR, with 41507 accidents, amounting to 81.01% of total accidents of this t
ype.
Road Condition: DRY, with 39133 accidents, amounting to 76.37% of total accidents of t
his type.
Time of accidents:
```

Out[21]: <AxesSubplot:>

```
Contrary to popular belief, most accidents appear not to be because of the environmen
t, but rather because of human error.
```



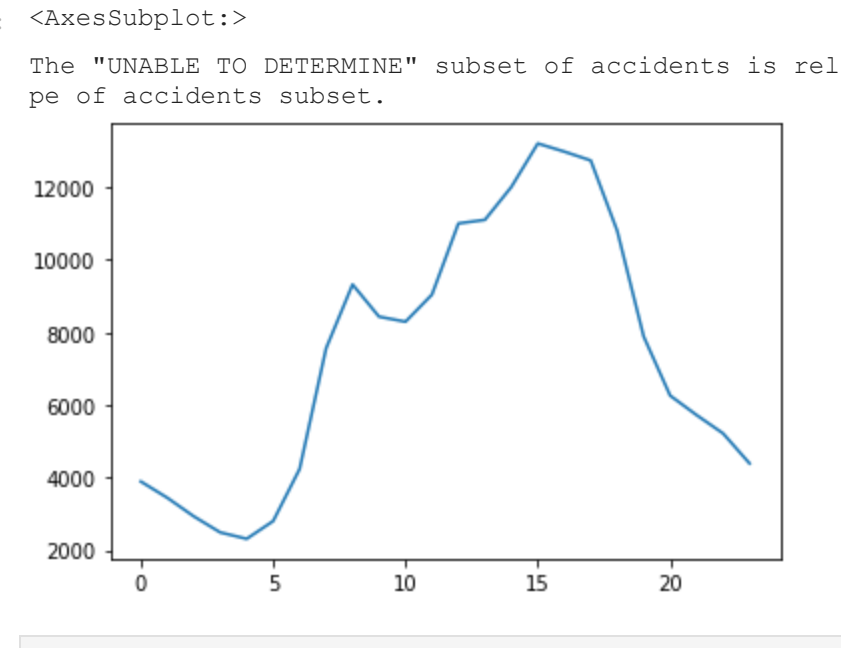
In [22]:

```python
# let's now explore the 'unable to determine' and 'non applicable' types of accident

non_det_df = df[df.PRIM_CONTRIBUTORY_CAUSE == 'UNABLE TO DETERMINE']
#non_det_df.head(5)

# lets compare the non_determined to the determined accident types

traffic_way_nd = non_det_df.groupby(['TRAFFICWAY_TYPE']).size().reset_index(name='Cou
#traffic_way_nd.sort_values(by='Count', ascending=False).head(20)

time_hour_nd = non_det_df.groupby(['CRASH_HOUR']).size().reset_index(name='Count')
#time_hour.sort_values(by='Count', ascending=False).head(10)

weather_cond_nd = non_det_df.groupby(['WEATHER_CONDITION']).size().reset_index(name='
#weather_cond.sort_values(by='Count', ascending=False).head(10)

road_cond_nd = non_det_df.groupby(['ROADWAY_SURFACE_COND']).size().reset_index(name='
#road_cond.sort_values(by='Count', ascending=False).head(10)

print('It appears that most accidents of type "UNABLE TO DETERMINE" happen under these
tnd = traffic_way_nd.sort_values(by='Count', ascending=False)
ttnd = tnd.iloc[0]['TRAFFICWAY_TYPE']
tnnd = tnd.iloc[0]['Count']
tndpercent = tnnd/sum(traffic_way_nd['Count'])*100
print('Trafficway: {}, with {} accidents, amounting to {:.2f}% of total accidents of

wnd = weather_cond_nd.sort_values(by='Count', ascending=False)
wwnd = wnd.iloc[0]['WEATHER_CONDITION']
wnnd = wnd.iloc[0]['Count']
wndpercent = wnnd/sum(weather_cond_nd['Count'])*100
print('Weather: {}, with {} accidents, amounting to {:.2f}% of total accidents of thi

rnd = road_cond_nd.sort_values(by='Count', ascending=False)
rrnd = rnd.iloc[0]['ROADWAY_SURFACE_COND']
rnnd = rnd.iloc[0]['Count']
rndpercent = rnnd/sum(road_cond_nd['Count'])*100
print('Road Condition: {}, with {} accidents, amounting to {:.2f}% of total accidents

print('Time of accidents:')
time_hour_nd['Count'].plot()

print('The "UNABLE TO DETERMINE" subset of accidents is relatively similtar to the de
```

```
It appears that most accidents of type "UNABLE TO DETERMINE" happen under these condit
ions:
Trafficway: NOT DIVIDED, with 79462 accidents, amounting to 44.64% of total accidents
of this type.
Weather: CLEAR, with 138237 accidents, amounting to 77.66% of total accidents of this
type.
Road Condition: DRY, with 129209 accidents, amounting to 72.59% of total accidents of
this type.
Time of accidents:
```

Out[22]: <AxesSubplot:>

```
The "UNABLE TO DETERMINE" subset of accidents is relatively similtar to the defined ty
pe of accidents subset.
```



In [23]:

```python
# as a final thought, let us see how death rate of this specific type of accident is
# device condition and damage

tot_d_nd = non_det_df['INJURIES_FATAL'].sum()

tot_d = df['INJURIES_FATAL'].sum()

percent_d_nd = (tot_d_nd / tot_d)*100

traffic_dev_death_nd = non_det_df.groupby('TRAFFIC_CONTROL_DEVICE')['INJURIES_FATAL']
#traffic_dev_death_nd

tdd_nd = traffic_dev_death_nd.sort_values(by='DEATHS', ascending=False)
a = tdd_nd.iloc[0]['TRAFFIC_CONTROL_DEVICE']
b = tdd_nd.iloc[0]['DEATHS']

dev_death_nd = non_det_df.groupby('DEVICE_CONDITION')['INJURIES_FATAL'].sum().reset_i
#dev_death_nd

tdd_nd2 = dev_death_nd.sort_values(by='DEATHS', ascending=False)
a2 = tdd_nd2.iloc[1]['DEVICE_CONDITION']
b2 = tdd_nd2.iloc[1]['DEATHS']

dmg_death_nd = non_det_df.groupby('DAMAGE')['INJURIES_FATAL'].sum().reset_index(name=
#dmg_death_nd

tdd_nd3 = dmg_death_nd.sort_values(by='DEATHS', ascending=False)
a3 = tdd_nd3.iloc[0]['DAMAGE']
b3 = tdd_nd3.iloc[0]['DEATHS']

print("There's been {} deaths by unspecified accident type out of {} total deaths. A
print("Most of the accidents use traffic control: {}, total deaths: {}.".format(a, b)
print("Second type of most accidents' devices: {}, total deaths: {}.".format(a2, b2))
print("Most of the accidents causing death also do damages: {}, {:.2f}% of the time."
```

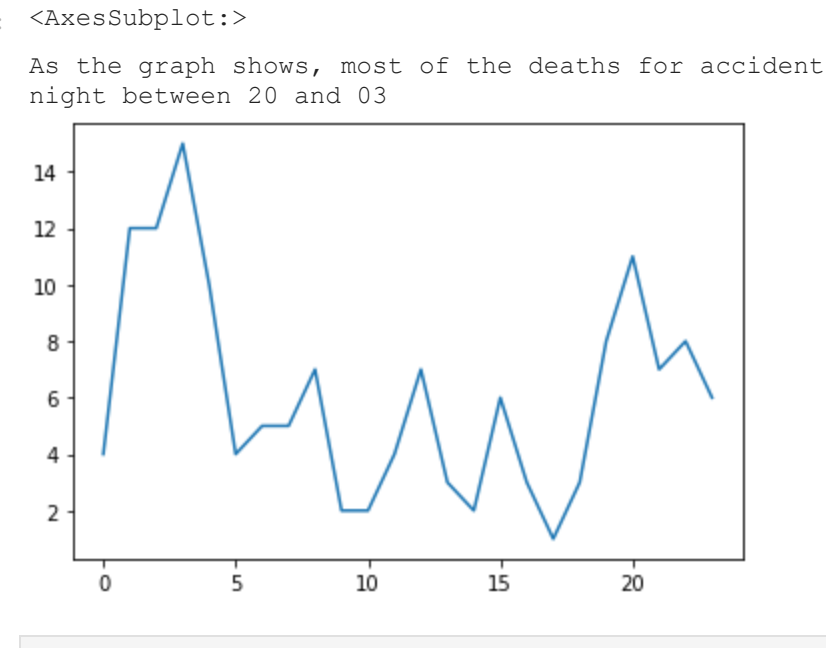
```
There's been 156.0 deaths by unspecified accident type out of 510.0 total deaths. A 3
0.59% of the total.
Most of the accidents use traffic control: NO CONTROLS, total deaths: 106.0.
Second type of most accidents' devices: FUNCTIONING PROPERLY, total deaths: 45.0.
Most of the accidents causing death also do damages: OVER $1,500, 85.90% of the time.
```

In [24]:

```python
# let us see what are the times most deaths happen in this subset of accidents
fatal_nd = non_det_df[non_det_df['INJURIES_FATAL'] > 0]
fatal_nd_time = fatal_nd.groupby(['CRASH_HOUR']).size().reset_index(name='Count')
fatal_nd_time['Count'].plot()

print("As the graph shows, most of the deaths for accidents of unspecified reasons hap
```

Out[24]: <AxesSubplot:>

```
As the graph shows, most of the deaths for accidents of unspecified reasons happen at
night between 20 and 03
```



In [ ]: