Housing Blight Analysis

==

Import Libraries

In [1]:

```
import numpy as np
from numpy import count_nonzero, median, mean
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import random
#import squarify

# Plotly
# import plotly.express as px
# import plotly.offline as py
# import plotly.graph_objs as go

#import pandas_profiling
# from pandas_profiling import ProfileReport
# import sweetviz

#import statsmodels.api as sm
#import statsmodels.formula.api as smf
# from statsmodels.formula.api import ols
# Import variance_inflation_factor from statsmodels
#from statsmodels.stats.outliers_influence import variance_inflation_factor
# Import Tukey's HSD function
#from statsmodels.stats.multicomp import pairwise_tukeyhsd

import datetime
from datetime import datetime, timedelta, date


#import os
#import zipfile
import scipy
from scipy import stats
from scipy.stats.mstats import normaltest # D'Agostino K^2 Test
from scipy.stats import boxcox
from collections import Counter

# Use Folium library to plot values on a map.
#import folium

%matplotlib inline
#sets the default autosave frequency in seconds
%autosave 60
sns.set_style('dark')
sns.set(font_scale=1.2)
```

```python
#sns.set(rc={'figure.figsize':(14,10)})

plt.rc('axes', titlesize=9)
plt.rc('axes', labelsize=14)
plt.rc('xtick', labelsize=12)
plt.rc('ytick', labelsize=12)

import warnings
warnings.filterwarnings('ignore')

pd.set_option('display.max_columns',None)
#pd.set_option('display.max_rows',None)
pd.set_option('display.width', 1000)
pd.set_option('display.float_format','{:.2f}'.format)

random.seed(0)
np.random.seed(0)
np.set_printoptions(suppress=True)
```

```
Autosaving every 60 seconds
```

==

Import Data

In [2]:
```python
df = pd.read_csv("blight.csv", low_memory=False)
```

==

Data Quick Glance

In [3]:
```python
df.head()
```

Out[3]:

	building_id	blighted	violation_count	violation_judgement_amount	violation_category_(
0	91	1	2.00	225.00	
1	96	1	1.00	140.00	
2	275	1	0.00	0.00	
3	391	1	0.00	0.00	
4	392	1	0.00	0.00	

In [4]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11076 entries, 0 to 11075
Data columns (total 68 columns):
 #   Column                                                Non-Null Count  Dtype

---  ------                                                --------------  -----

 0   building_id                                           11076 non-null  int64

 1   blighted                                              11076 non-null  int64

 2   violation_count                                       11076 non-null  float6
4
 3   violation_judgement_amount                            11076 non-null  float6
4
 4   violation_category_0_count                            11076 non-null  float6
4
 5   violation_category_1_count                            11076 non-null  float6
4
 6   violation_no_pay_applied_count                        11076 non-null  float6
4
 7   violation_full_pay_count                              11076 non-null  float6
4
 8   violation_no_pay_on_rec_count                         11076 non-null  float6
4
 9   violation_partial_pay_count                           11076 non-null  float6
4
 10  call_count                                            11076 non-null  float6
4
 11  call_avg_rating                                       11076 non-null  float6
4
 12  call_ticket_open_count                                11076 non-null  float6
4
 13  call_ticket_archived_count                            11076 non-null  float6
4
 14  call_ticket_acknowledged_count                        11076 non-null  float6
4
 15  call_ticket_closed_count                              11076 non-null  float6
4
 16  call_res_snow_removal_count                           11076 non-null  float6
4
 17  call_illegal_dumping_count                            11076 non-null  float6
4
 18  call_trash_improper_placement_count                   11076 non-null  float6
4
 19  call_running_water_count                              11076 non-null  float6
4
 20  call_water_main_break_count                           11076 non-null  float6
4
 21  call_traffic_sign_count                               11076 non-null  float6
4
 22  call_trash_bulk_waste_count                           11076 non-null  float6
4
 23  call_abandoned_vehicle_count                          11076 non-null  float6
4
 24  call_manhole_cover_count                              11076 non-null  float6
```

```
4
 25  call_curbside_solid_waste_count                         11076 non-null  float6
4
 26  call_dpw_others_count                                   11076 non-null  float6
4
 27  call_dpw_debris_removal_count                           11076 non-null  float6
4
 28  call_graffiti_count                                     11076 non-null  float6
4
 29  call_st_light_pole_down_count                           11076 non-null  float6
4
 30  call_potholes_count                                     11076 non-null  float6
4
 31  call_traffic_signal_count                               11076 non-null  float6
4
 32  call_tree_count                                         11076 non-null  float6
4
 33  call_fire_hydrant_count                                 11076 non-null  float6
4
 34  call_clogged_drain_count                                11076 non-null  float6
4
 35  call_other_type_count                                   11076 non-null  float6
4
 36  crime_count                                             11076 non-null  float6
4
 37  crime_other_crime_count                                 11076 non-null  float6
4
 38  crime_environment_count                                 11076 non-null  float6
4
 39  crime_fraud_count                                       11076 non-null  float6
4
 40  crime_aggravated_assault_count                          11076 non-null  float6
4
 41  crime_robbery_count                                     11076 non-null  float6
4
 42  crime_burglary_count                                    11076 non-null  float6
4
 43  crime_other_burglary_count                              11076 non-null  float6
4
 44  crime_homicide_count                                    11076 non-null  float6
4
 45  crime_assault_count                                     11076 non-null  float6
4
 46  crime_weapons_offenses_count                            11076 non-null  float6
4
 47  crime_kidnaping_count                                   11076 non-null  float6
4
 48  crime_traffic_violations-driving_on_suspended_count     11076 non-null  float6
4
 49  crime_obstructing_the_police_count                      11076 non-null  float6
4
 50  crime_obstructing_judiciary_count                       11076 non-null  float6
4
 51  crime_dangerous_drugs_count                             11076 non-null  float6
4
 52  crime_stolen_vehicle_count                              11076 non-null  float6
```

```
4
 53  crime_arson_count                                     11076 non-null  float6
4
 54  crime_damage_to_property_count                        11076 non-null  float6
4
 55  crime_family_offense_count                            11076 non-null  float6
4
 56  crime_larceny_count                                   11076 non-null  float6
4
 57  crime_health-safety_count                             11076 non-null  float6
4
 58  crime_ouil_dispose_of_vehicle_to_avoid_forfeiture_count  11076 non-null  float6
4
 59  crime_escape_count                                    11076 non-null  float6
4
 60  crime_extortion_count                                 11076 non-null  float6
4
 61  crime_solicitation_count                              11076 non-null  float6
4
 62  crime_forgery_count                                   11076 non-null  float6
4
 63  crime_public_peace_count                              11076 non-null  float6
4
 64  crime_stolen_property_count                           11076 non-null  float6
4
 65  crime_bribery_count                                   11076 non-null  float6
4
 66  crime_traffic_violations-motorcycle_violations_count     11076 non-null  float6
4
 67  crime_runaway_count                                   11076 non-null  float6
4
dtypes: float64(66), int64(2)
memory usage: 5.7 MB
```

In [5]:
```
df.dtypes.value_counts()
```

Out[5]:
```
float64    66
int64       2
dtype: int64
```

In [6]:
```
# Descriptive Statistical Analysis
df.describe(include="all")
```

Out[6]:

	building_id	blighted	violation_count	violation_judgement_amount	violation_catego
count	11076.00	11076.00	11076.00	11076.00	
mean	76369.21	0.50	1.83	831.17	
std	47086.72	0.50	2.76	1921.39	
min	80.00	0.00	0.00	0.00	
25%	34152.00	0.00	0.00	0.00	
50%	75662.00	0.50	1.00	170.00	
75%	117703.50	1.00	3.00	915.00	
max	159448.00	1.00	94.00	36685.00	

In [7]:

```
# Descriptive Statistical Analysis
df.describe(include=["int", "float"])
```

Out[7]:

	building_id	blighted	violation_count	violation_judgement_amount	violation_catego
count	11076.00	11076.00	11076.00	11076.00	
mean	76369.21	0.50	1.83	831.17	
std	47086.72	0.50	2.76	1921.39	
min	80.00	0.00	0.00	0.00	
25%	34152.00	0.00	0.00	0.00	
50%	75662.00	0.50	1.00	170.00	
75%	117703.50	1.00	3.00	915.00	
max	159448.00	1.00	94.00	36685.00	

In [8]:

```
df.columns
```

```
Out[8]: Index(['building_id', 'blighted', 'violation_count', 'violation_judgement_amount',
'violation_category_0_count', 'violation_category_1_count', 'violation_no_pay_appl
ied_count', 'violation_full_pay_count', 'violation_no_pay_on_rec_count', 'violatio
n_partial_pay_count', 'call_count', 'call_avg_rating', 'call_ticket_open_count',
'call_ticket_archived_count', 'call_ticket_acknowledged_count', 'call_ticket_close
d_count', 'call_res_snow_removal_count', 'call_illegal_dumping_count', 'call_trash
_improper_placement_count', 'call_running_water_count', 'call_water_main_break_cou
nt', 'call_traffic_sign_count', 'call_trash_bulk_waste_count', 'call_abandoned_veh
icle_count', 'call_manhole_cover_count', 'call_curbside_solid_waste_count', 'call_
dpw_others_count', 'call_dpw_debris_removal_count', 'call_graffiti_count', 'call_s
t_light_pole_down_count', 'call_potholes_count', 'call_traffic_signal_count', 'cal
l_tree_count', 'call_fire_hydrant_count', 'call_clogged_drain_count', 'call_other_
type_count',
       'crime_count', 'crime_other_crime_count', 'crime_environment_count', 'crime
_fraud_count', 'crime_aggravated_assault_count', 'crime_robbery_count', 'crime_bur
glary_count', 'crime_other_burglary_count', 'crime_homicide_count', 'crime_assault
_count', 'crime_weapons_offenses_count', 'crime_kidnaping_count', 'crime_traffic_v
iolations-driving_on_suspended_count', 'crime_obstructing_the_police_count', 'crim
e_obstructing_judiciary_count', 'crime_dangerous_drugs_count', 'crime_stolen_vehic
le_count', 'crime_arson_count', 'crime_damage_to_property_count', 'crime_family_of
fense_count', 'crime_larceny_count', 'crime_health-safety_count', 'crime_ouil_disp
ose_of_vehicle_to_avoid_forfeiture_count', 'crime_escape_count', 'crime_extortion_
count', 'crime_solicitation_count', 'crime_forgery_count', 'crime_public_peace_cou
nt', 'crime_stolen_property_count', 'crime_bribery_count', 'crime_traffic_violatio
ns-motorcycle_violations_count', 'crime_runaway_count'],
      dtype='object')
```

```
In [9]: df.shape
```

```
Out[9]: (11076, 68)
```

```
In [10]: df.isnull().sum()
```

```
Out[10]: building_id                                        0
blighted                                           0
violation_count                                    0
violation_judgement_amount                         0
violation_category_0_count                         0
                                                  ..
crime_public_peace_count                           0
crime_stolen_property_count                        0
crime_bribery_count                                0
crime_traffic_violations-motorcycle_violations_count    0
crime_runaway_count                                0
Length: 68, dtype: int64
```

```
In [11]: df.duplicated().sum()
```

```
Out[11]: 0
```

```
In [12]: df.drop(['building_id', 'violation_judgement_amount', 'violation_category_0_count',
         'violation_no_pay_applied_count', 'violation_full_pay_count', 'violation_n
```

```
In [13]: df.columns
```

Out[13]:
```
Index(['blighted', 'violation_count', 'call_count', 'call_avg_rating', 'call_ticke
t_open_count', 'call_ticket_archived_count', 'call_ticket_acknowledged_count', 'ca
ll_ticket_closed_count', 'call_res_snow_removal_count', 'call_illegal_dumping_coun
t', 'call_trash_improper_placement_count', 'call_running_water_count', 'call_water
_main_break_count', 'call_traffic_sign_count', 'call_trash_bulk_waste_count', 'cal
l_abandoned_vehicle_count', 'call_manhole_cover_count', 'call_curbside_solid_waste
_count', 'call_dpw_others_count', 'call_dpw_debris_removal_count', 'call_graffiti_
count', 'call_st_light_pole_down_count', 'call_potholes_count', 'call_traffic_sign
al_count', 'call_tree_count', 'call_fire_hydrant_count', 'call_clogged_drain_coun
t', 'call_other_type_count', 'crime_count', 'crime_other_crime_count', 'crime_envi
ronment_count', 'crime_fraud_count', 'crime_aggravated_assault_count', 'crime_robb
ery_count', 'crime_burglary_count', 'crime_other_burglary_count', 'crime_homicide_
count',
       'crime_assault_count', 'crime_weapons_offenses_count', 'crime_kidnaping_cou
nt', 'crime_traffic_violations-driving_on_suspended_count', 'crime_obstructing_the
_police_count', 'crime_obstructing_judiciary_count', 'crime_dangerous_drugs_coun
t', 'crime_stolen_vehicle_count', 'crime_arson_count', 'crime_damage_to_property_c
ount', 'crime_family_offense_count', 'crime_larceny_count', 'crime_health-safety_c
ount', 'crime_ouil_dispose_of_vehicle_to_avoid_forfeiture_count', 'crime_escape_co
unt', 'crime_extortion_count', 'crime_solicitation_count', 'crime_forgery_count',
'crime_public_peace_count', 'crime_stolen_property_count', 'crime_bribery_count',
'crime_traffic_violations-motorcycle_violations_count', 'crime_runaway_count'],
      dtype='object')
```

In [14]:
```
df.drop(['call_avg_rating', 'call_ticket_open_count', 'call_ticket_archived_count',
         'call_ticket_closed_count', 'call_res_snow_removal_count', 'call_illegal_d
         'call_trash_improper_placement_count', 'call_running_water_count', 'call_w
         'call_traffic_sign_count', 'call_trash_bulk_waste_count', 'call_abandoned_
         'call_manhole_cover_count', 'call_curbside_solid_waste_count', 'call_dpw_o
         'call_dpw_debris_removal_count', 'call_graffiti_count', 'call_st_light_pol
         'call_traffic_signal_count', 'call_tree_count', 'call_fire_hydrant_count',
         'call_other_type_count'], axis=1, inplace=True)
```

In [15]:
```
df.columns
```

Out[15]:
```
Index(['blighted', 'violation_count', 'call_count', 'crime_count', 'crime_other_cr
ime_count', 'crime_environment_count', 'crime_fraud_count', 'crime_aggravated_assa
ult_count', 'crime_robbery_count', 'crime_burglary_count', 'crime_other_burglary_c
ount', 'crime_homicide_count', 'crime_assault_count', 'crime_weapons_offenses_coun
t', 'crime_kidnaping_count', 'crime_traffic_violations-driving_on_suspended_coun
t', 'crime_obstructing_the_police_count', 'crime_obstructing_judiciary_count', 'cr
ime_dangerous_drugs_count', 'crime_stolen_vehicle_count', 'crime_arson_count', 'cr
ime_damage_to_property_count', 'crime_family_offense_count', 'crime_larceny_coun
t', 'crime_health-safety_count', 'crime_ouil_dispose_of_vehicle_to_avoid_forfeitur
e_count', 'crime_escape_count', 'crime_extortion_count', 'crime_solicitation_coun
t', 'crime_forgery_count', 'crime_public_peace_count', 'crime_stolen_property_coun
t', 'crime_bribery_count', 'crime_traffic_violations-motorcycle_violations_count',
       'crime_runaway_count'],
      dtype='object')
```

In [16]:
```
df.drop(['crime_other_crime_count', 'crime_environment_count', 'crime_fraud_count',
         'crime_aggravated_assault_count', 'crime_robbery_count', 'crime_burglary_c
         'crime_other_burglary_count', 'crime_homicide_count', 'crime_assault_count
         'crime_weapons_offenses_count', 'crime_kidnaping_count',
         'crime_traffic_violations-driving_on_suspended_count', 'crime_obstructing_
```

```
            'crime_obstructing_judiciary_count', 'crime_dangerous_drugs_count',
            'crime_stolen_vehicle_count', 'crime_arson_count', 'crime_damage_to_proper
            'crime_family_offense_count', 'crime_larceny_count', 'crime_health-safety_
            'crime_ouil_dispose_of_vehicle_to_avoid_forfeiture_count', 'crime_escape_c
            'crime_extortion_count', 'crime_solicitation_count', 'crime_forgery_count'
            'crime_public_peace_count', 'crime_stolen_property_count', 'crime_bribery_
            'crime_traffic_violations-motorcycle_violations_count',
            'crime_runaway_count'], axis=1, inplace=True)
```

In [17]:
```
df.head()
```

Out[17]:

	blighted	violation_count	call_count	crime_count
0	1	2.00	0.00	0.00
1	1	1.00	0.00	0.00
2	1	0.00	0.00	0.00
3	1	0.00	0.00	0.00
4	1	0.00	0.00	0.00

In [18]:
```
df.columns
```

Out[18]:
```
Index(['blighted', 'violation_count', 'call_count', 'crime_count'], dtype='objec
t')
```

In [19]:
```
df2 = df[['violation_count', 'call_count', 'crime_count', 'blighted']]
df2
```

Out[19]:

	violation_count	call_count	crime_count	blighted
0	2.00	0.00	0.00	1
1	1.00	0.00	0.00	1
2	0.00	0.00	0.00	1
3	0.00	0.00	0.00	1
4	0.00	0.00	0.00	1
...	...	...	...	...
11071	1.00	0.00	0.00	0
11072	1.00	0.00	0.00	0
11073	0.00	0.00	1.00	0
11074	0.00	0.00	1.00	0
11075	0.00	0.00	8.00	0

11076 rows × 4 columns

In [20]:
```
#df2.to_csv("blight2.csv", index=False)
```

```
========================================================================
```

Exploratory Data Analysis

Exploratory Data Analysis (EDA) is the crucial process of using summary statistics and graphical representations to perform preliminary investigations on data to uncover patterns, detect anomalies, test hypotheses, and verify assumptions.

Sample a smaller dataset

In [21]:
```
df = pd.read_csv("blight2.csv")
```

In [22]:
```
df = df.sample(frac=0.5)
```

In [23]:
```
df
```

Out[23]:

	violation_count	call_count	crime_count	blighted
9509	2.00	0.00	0.00	0
651	0.00	0.00	0.00	1
3443	1.00	0.00	0.00	1
5646	1.00	0.00	0.00	0
8278	0.00	0.00	2.00	0
...	...	...	...	...
6886	0.00	0.00	2.00	0
4012	0.00	0.00	0.00	1
5447	3.00	0.00	0.00	1
241	12.00	0.00	0.00	1
10422	0.00	0.00	3.00	0

5538 rows × 4 columns

In [24]:
```
df.reset_index(drop=True, inplace=True)
```

In [25]:
```
df
```

Out[25]:

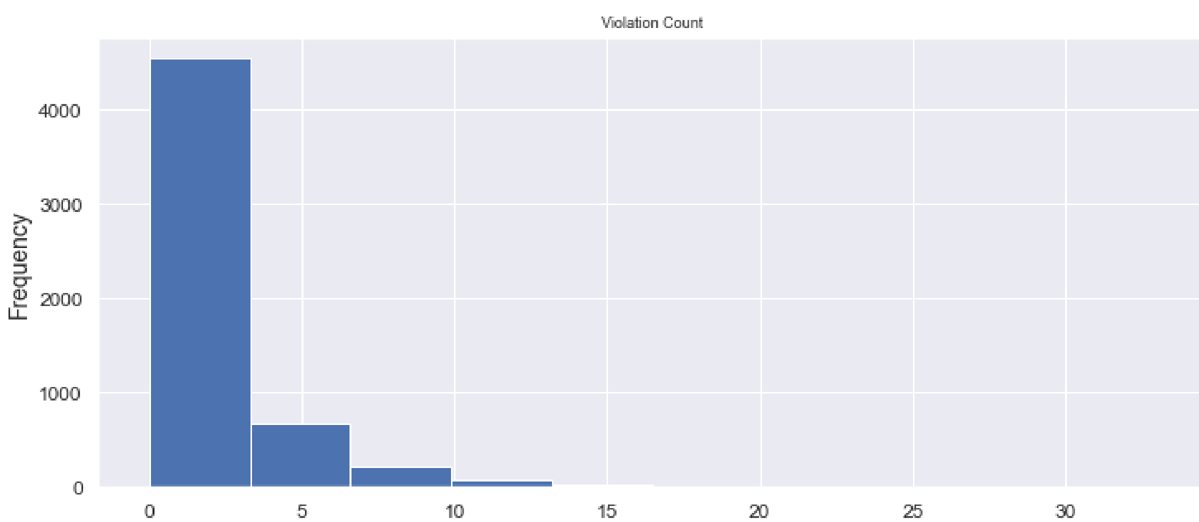
	violation_count	call_count	crime_count	blighted
0	2.00	0.00	0.00	0
1	0.00	0.00	0.00	1
2	1.00	0.00	0.00	1
3	1.00	0.00	0.00	0
4	0.00	0.00	2.00	0
...	...	...	...	...
5533	0.00	0.00	2.00	0
5534	0.00	0.00	0.00	1
5535	3.00	0.00	0.00	1
5536	12.00	0.00	0.00	1
5537	0.00	0.00	3.00	0

5538 rows × 4 columns

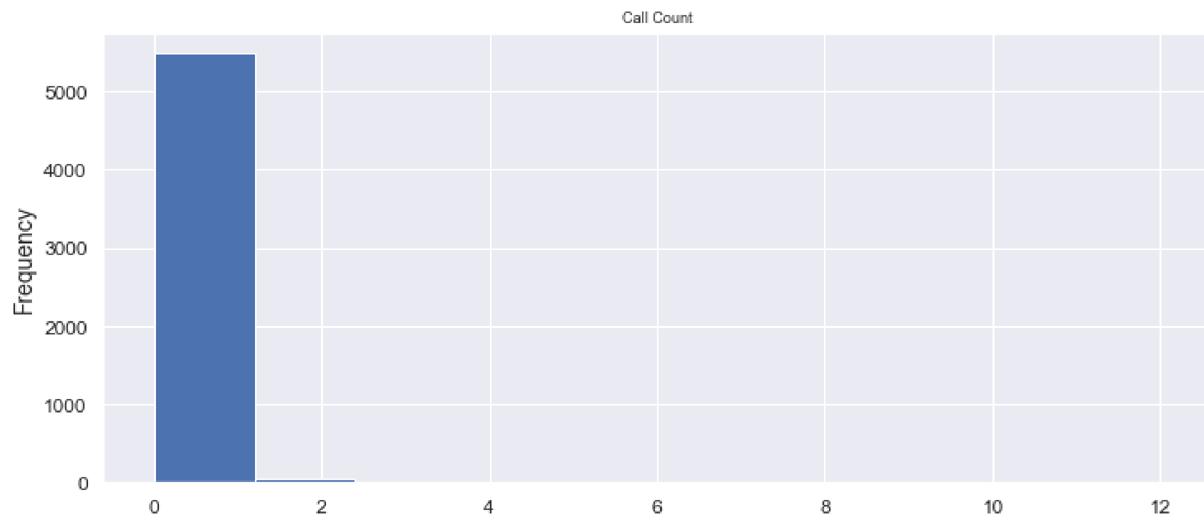
In [26]:
```
df.shape
```

Out[26]: (5538, 4)

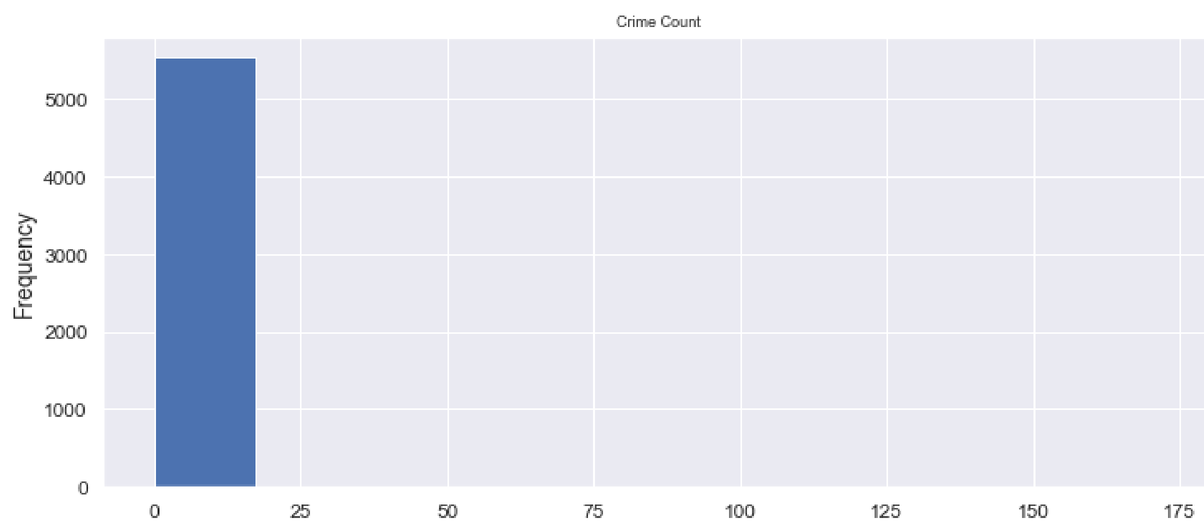
In [27]:
```
df.violation_count.plot(kind = "hist", figsize = (12,5), fontsize = 12, title="Viol
plt.show()
```



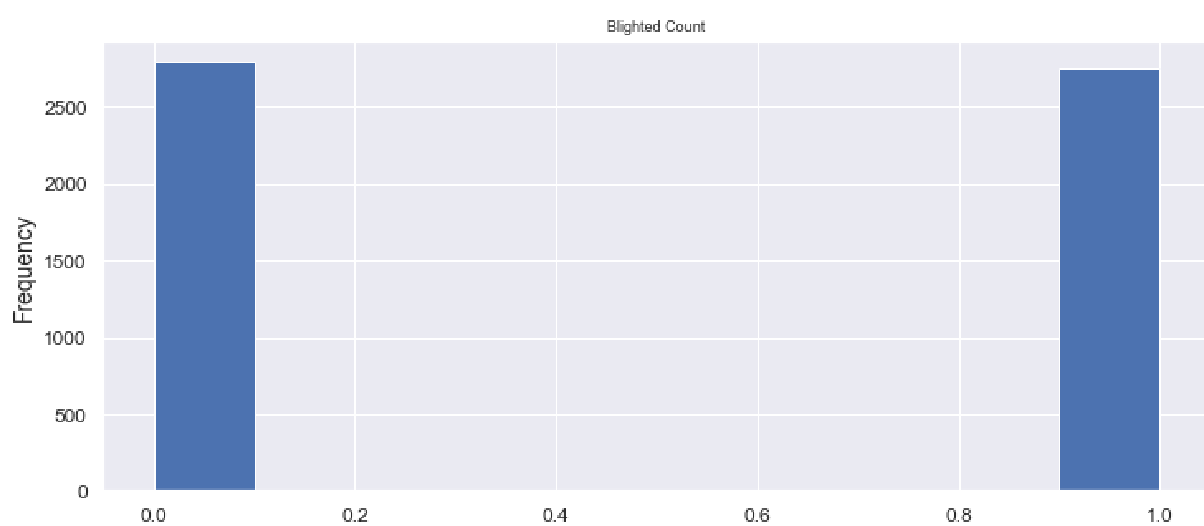
In [28]:
```
df.call_count.plot(kind = "hist", figsize = (12,5), fontsize = 12, title="Call Coun
plt.show()
```



In [29]:
```
df.crime_count.plot(kind = "hist", figsize = (12,5), fontsize = 12, title="Crime Co
plt.show()
```



In [30]:
```
df.blighted.plot(kind = "hist", figsize = (12,5), fontsize = 12, title="Blighted Co
plt.show()
```



===

Groupby

Most commonly, we use `groupby()` to split the data into groups,this will apply some function to each of the groups (e.g. mean, median, min, max, count), then combine the results into a data structure. For example, let's select the 'VALUE' column and calculate the mean of the gasoline prices per year. First, we specify the 'Year" column, following by the 'VALUE' column, and the `mean()` function.

In [31]:
```
df.columns
```

Out[31]:
```
Index(['violation_count', 'call_count', 'crime_count', 'blighted'], dtype='objec
t')
```

In [32]:
```
df.groupby(['blighted'], as_index=True).mean()
```

Out[32]:

	violation_count	call_count	crime_count
blighted			
0	1.96	0.14	0.80
1	1.71	0.02	0.07

```
==================================================================
```

Data Visualization

Matplotlib: Standard Python Visualization Library

The primary plotting library we will explore in the course is Matplotlib. As mentioned on their website:

> Matplotlib is a Python 2D plotting library which produces publication quality figures in a variety of hardcopy formats and interactive environments across platforms. Matplotlib can be used in Python scripts, the Python and IPython shell, the jupyter notebook, web application servers, and four graphical user interface toolkits.

Matplotlib.Pyplot

One of the core aspects of Matplotlib is `matplotlib.pyplot`. It is Matplotlib's scripting layer which we studied in details in the videos about Matplotlib. Recall that it is a collection of command style functions that make Matplotlib work like MATLAB. Each `pyplot` function makes some change to a figure: e.g., creates a figure, creates a plotting area in a figure, plots some lines in a plotting area, decorates the plot with labels, etc. In this lab, we will work with the scripting layer to learn how to generate line plots. In future labs, we will get to work with the Artist layer as well to experiment first hand how it differs from the scripting layer.

Seaborn Library

1. Numerical Data Ploting

- relplot()
- scatterplot()
- lineplot()

2. Categorical Data Ploting

- catplot()
- boxplot()
- stripplot()
- swarmplot()
- etc...

3. Visualizing Distribution of the Data

- distplot()
- kdeplot()
- jointplot()
- rugplot()

4. Linear Regression and Relationship

- regplot()
- lmplot()

5. Controlling Ploted Figure Aesthetics

- figure styling
- axes styling
- color palettes
- etc..

Subplots

Often times we might want to plot multiple plots within the same figure. For example, we might want to perform a side by side comparison of the box plot with the line plot of China and India's immigration.

To visualize multiple plots together, we can create a `figure` (overall canvas) and divide it into `subplots`, each containing a plot. With **subplots**, we usually work with the **artist layer** instead of the **scripting layer**.

Typical syntax is :

```
fig = plt.figure() # create figure
    ax = fig.add_subplot(nrows, ncols, plot_number) # create subplots
```

Where

- `nrows` and `ncols` are used to notionally split the figure into (`nrows` * `ncols`) sub-axes,
- `plot_number` is used to identify the particular subplot that this function is to create within the notional grid. `plot_number` starts at 1, increments across rows first and has a maximum of `nrows` * `ncols` as shown below.

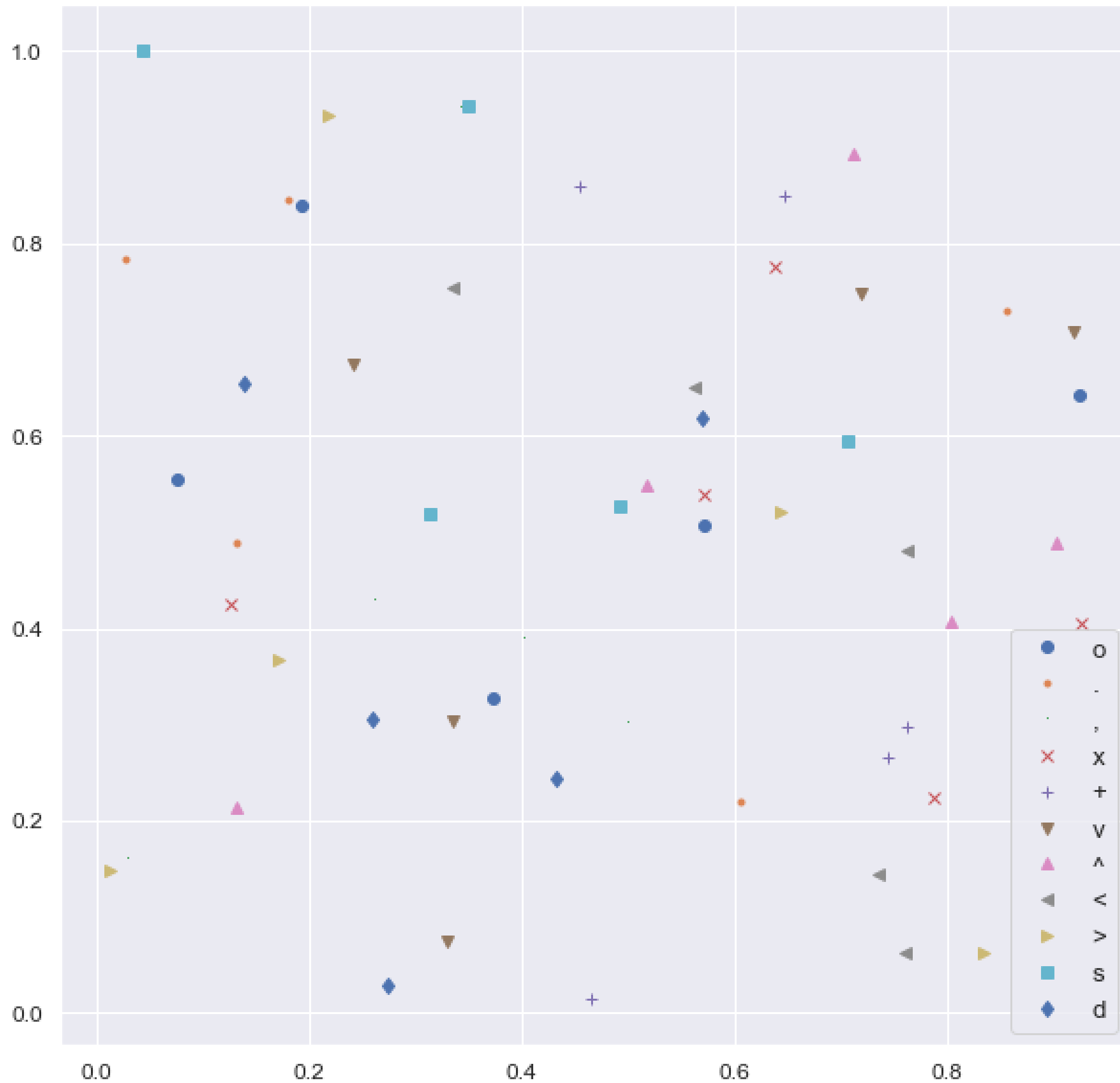
In the case when `nrows`, `ncols`, and `plot_number` are all less than 10, a convenience exists such that a 3-digit number can be given instead, where the hundreds represent `nrows`, the tens represent `ncols` and the units represent `plot_number`. For instance,

```
subplot(211) == subplot(2, 1, 1)
```

produces a subaxes in a figure which represents the top plot (i.e. the first) in a 2 rows by 1 column notional grid (no grid actually exists, but conceptually this is how the returned subplot has been positioned).

In [33]:
```
# Check plot styles
#plt.style.available
```

In [34]:
```
markers = ['o','.',',','x','+','v','^','<','>','s','d']

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

for m in markers:
    plt.plot(np.random.rand(5),np.random.rand(5),m,label=m)

plt.legend()
plt.show()
```



FacetGrid (Building structured multi-plot grids)

The FacetGrid class is useful when you want to visualize the distribution of a variable or the relationship between multiple variables separately within subsets of your dataset. A FacetGrid can be drawn with up to three dimensions: row, col, and hue. The first two have obvious correspondence with the resulting array of axes; think of the hue variable as a third dimension along a depth axis, where different levels are plotted with different colors.

Each of relplot(), displot(), catplot(), and lmplot() use this object internally, and they return the object when they are finished so that it can be used for further tweaking.

Seaborn Version

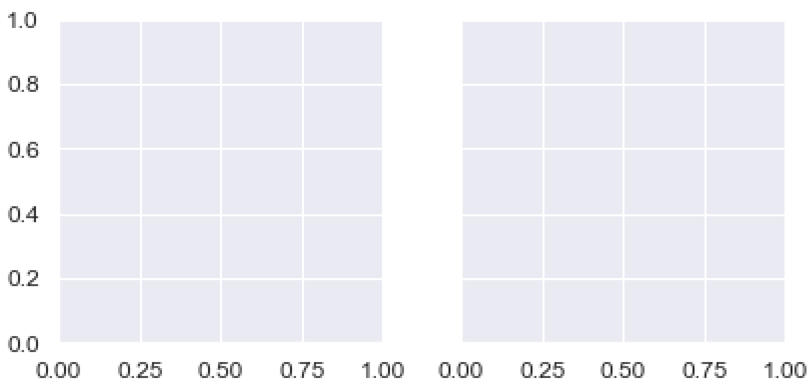
In [35]:
```
df.columns
```

Out[35]:
```
Index(['violation_count', 'call_count', 'crime_count', 'blighted'], dtype='objec
t')
```

```
sns.FacetGrid(data,  row=None,  col=None,  hue=None,  col_wrap=None,
sharex=True, sharey=True,  height=3,  aspect=1,  palette=None,
row_order=None,  col_order=None,     hue_order=None,  hue_kws=None,
dropna=False, legend_out=True,  despine=True,     margin_titles=False,
xlim=None,  ylim=None,  subplot_kws=None,  gridspec_kws=None, size=None)
```

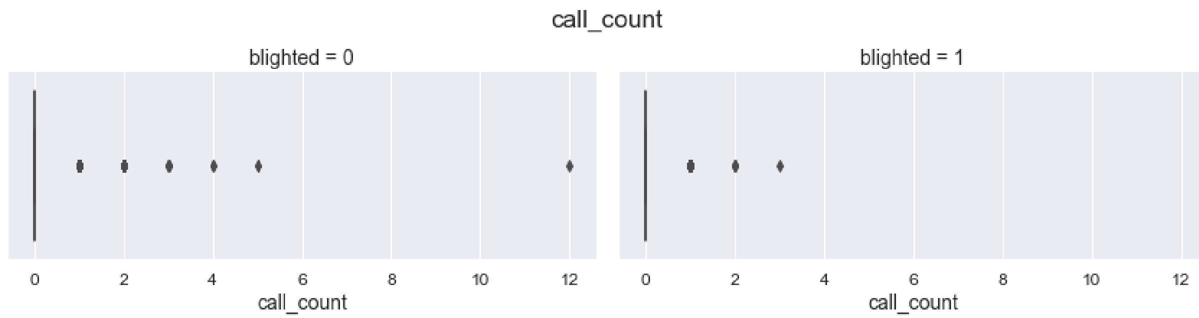
In [36]:
```python
sns.FacetGrid(data=df, col="blighted")
```

Out[36]: <seaborn.axisgrid.FacetGrid at 0x23f80898400>

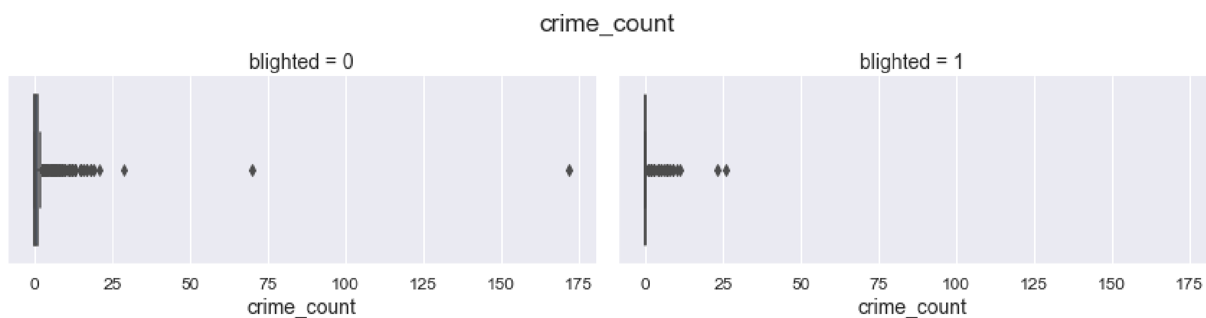


In [37]:
```python
g = sns.FacetGrid(data=df, col="blighted", height=3, aspect=2)

g.map(sns.boxplot, "violation_count")

g.fig.suptitle("violation_count", y=1.05)


plt.show()
```

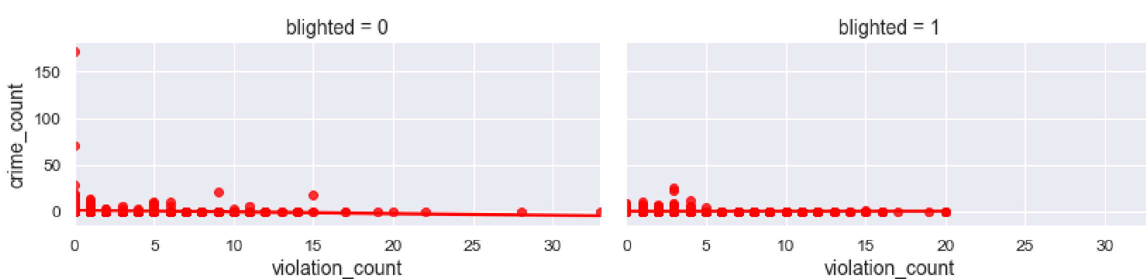
In [38]:
```python
g = sns.FacetGrid(data=df, col="blighted", height=3, aspect=2)

g.map(sns.boxplot, "call_count")

g.fig.suptitle("call_count", y=1.05)


plt.show()
```



In [39]:
```
g = sns.FacetGrid(data=df, col="blighted", height=3, aspect=2)

g.map(sns.boxplot, "crime_count")

g.fig.suptitle("crime_count", y=1.05)


plt.show()
```



In [40]:
```
g = sns.FacetGrid(data=df, col="blighted", hue=None, col_wrap=None, height=3, aspec
g.map(sns.regplot, "violation_count", "crime_count", color="red", fit_reg=True, x_j
g.add_legend()
plt.show()
```

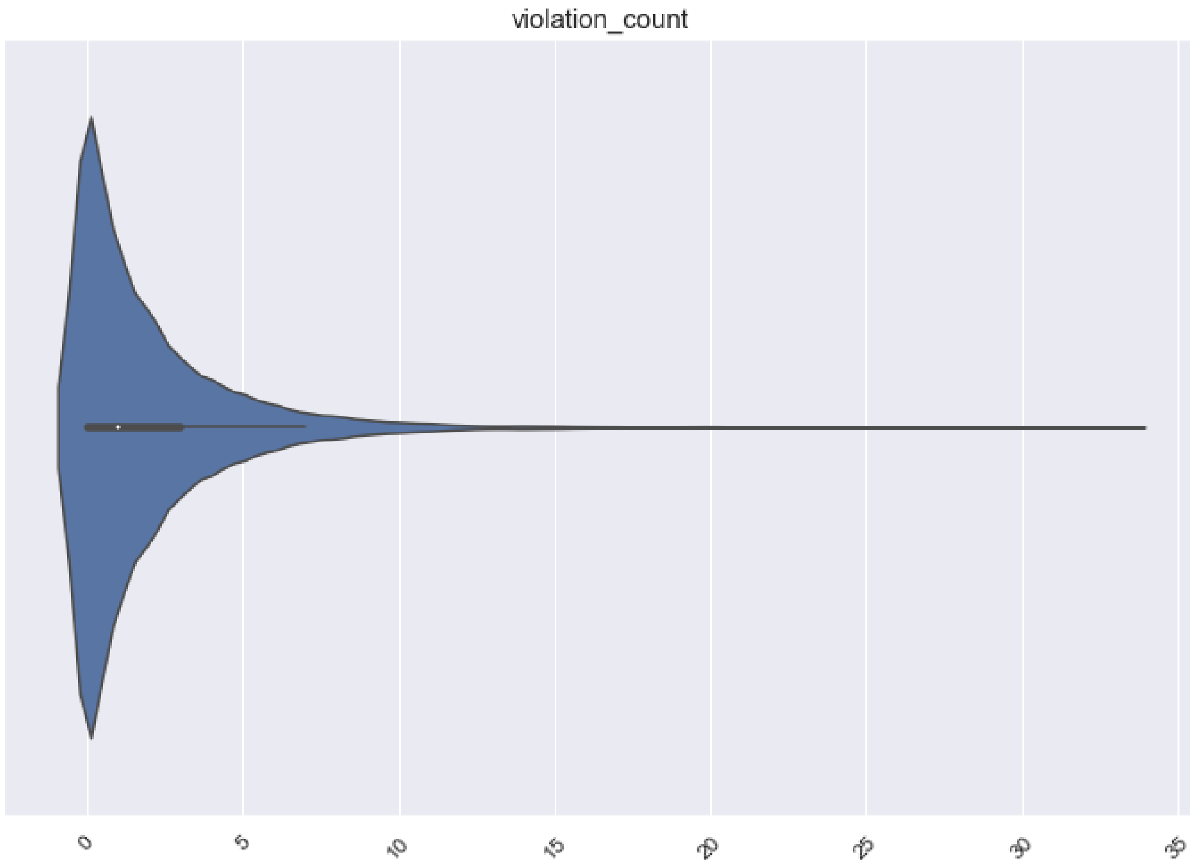



```
=================================================================
```

Violin Plot

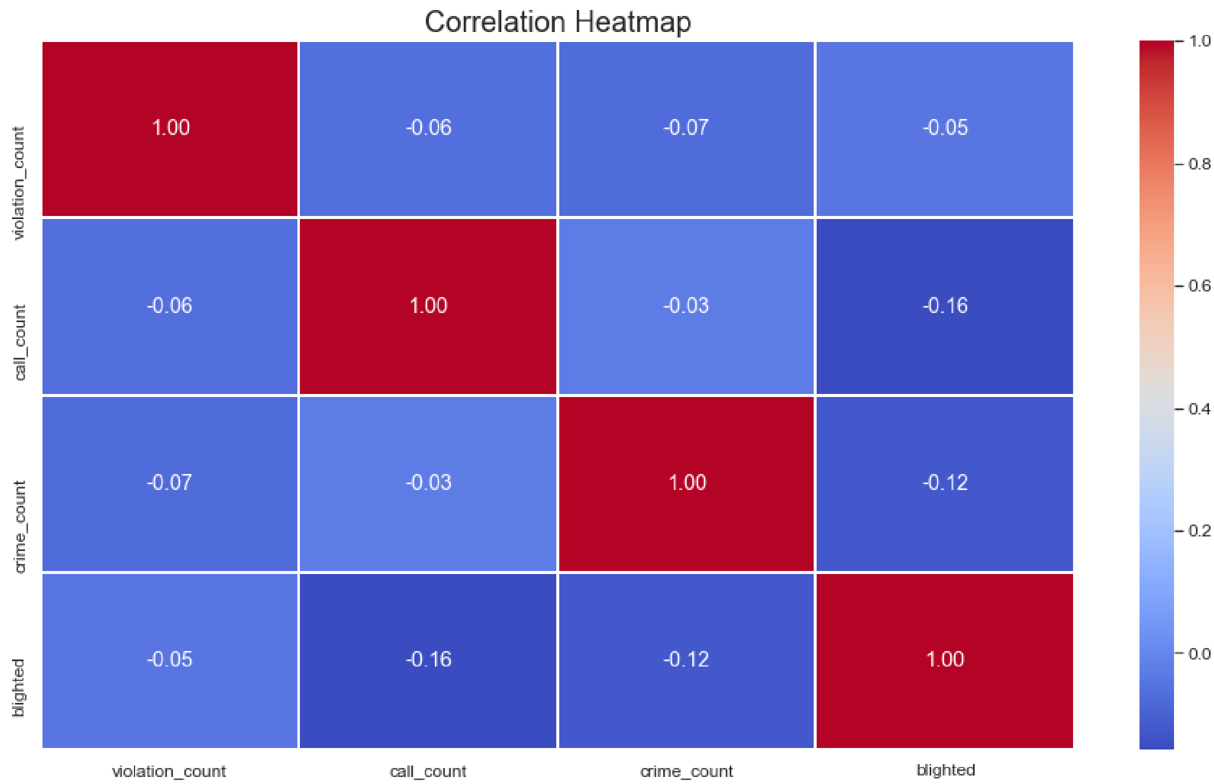
In [41]:
```
fig, ax = plt.subplots(figsize=(12,8))

sns.violinplot(x="violation_count", y=None, hue="blighted", data=df)

ax.set_title('violation_count', size=15)
ax.tick_params('x', labelrotation=45)
```

```
ax.set_xlabel("")
ax.set_ylabel("")
#ax.legend()

plt.show()
```



Heatmap

In [42]:
```
plt.figure(figsize=(16,9))
sns.heatmap(data=df.corr(), cmap="coolwarm", annot=True, fmt='.2f', linewidths=2)
plt.title("Correlation Heatmap", fontsize=20)
plt.show()
```


Correlation Heatmap
violation_count
call_count
crime_count
blighted
1.00
-0.06
-0.07
-0.05
-0.06
1.00
-0.03
-0.16
-0.07
-0.03
1.00
-0.12
-0.05
-0.16
-0.12
1.00
violation_count
call_count
crime_count
blighted
1.0
0.8
0.6
0.4
0.2
0.0