# *Rio de Janeiro*

## Relationship between guns captured by the police in the city of Rio de Janeiro and the amount of thefts, robberies, threats and reports to the police

## Contents

# 1) Introduction/Business Problem

I have decided to deal with the relationship between guns captured by the police in the city of Rio de Janeiro and the amount of thefts, robberies, threats and reports to the police, as Rio de Janeiro is known for being one of the most violent cities in the world.

In my opinion many might be interested in the problem, but most likely people involved with security of citizens in Rio de Janeiro, so police and politicians mostly.

# 2) Data

The data I used was taken from the public security portal. The files I used were the top three, those are monthly statistics for almost all things public security related and then statistics for guns apprehended. All statistics I got went from 2003 all through 2019.

In [17]:
```python
# File with all data public security related
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
dfCisp = pd.read_csv('http://www.ispdados.rj.gov.br/Arquivos/BaseDPEvolucaoMensalCisp.csv', encoding = "ISO-8859-1", delimiter =
';')
dfCisp.head()
```

Here is an extract of the table:

| | CISP | mes | vano | mes_ano | AISP | RISP | munic | mcirc | Regiao | hom_doloso | ... | pessoas_desaparecidas | encontro_cadaver | encontro_ossad |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | 1 | 2003 | 2003m1 | 5 | 1 | Rio de Janeiro | 3304557 | Capital | 0 | ... | 2 | 0 | 0 |
| 1 | 4 | 1 | 2003 | 2003m1 | 5 | 1 | Rio de Janeiro | 3304557 | Capital | 3 | ... | 6 | 0 | 1 |
| 2 | 5 | 1 | 2003 | 2003m1 | 5 | 1 | Rio de Janeiro | 3304557 | Capital | 3 | ... | 2 | 1 | 0 |
| 3 | 6 | 1 | 2003 | 2003m1 | 1 | 1 | Rio de Janeiro | 3304557 | Capital | 6 | ... | 2 | 1 | 0 |
| 4 | 7 | 1 | 2003 | 2003m1 | 1 | 1 | Rio de Janeiro | 3304557 | Capital | 4 | ... | 1 | 3 | 0 |

## a) Data Pre-processing

```python
# Guns from 2000-2006
dfA1 = pd.read_csv('http://www.ispdados.rj.gov.br/Arquivos/ArmasEstado2000_2006.csv', encoding = "ISO-8859-1", delimiter = ';')
dfA1.head()
```

| | vano | mes | armas_apreendidas |
|---|---|---|---|
| 0 | 2000 | 1 | 697 |
| 1 | 2000 | 2 | 751 |
| 2 | 2000 | 3 | 784 |
| 3 | 2000 | 4 | 780 |
| 4 | 2000 | 5 | 761 |

```
# Guns from 2006-2019 (categorized)
dfGuns = pd.read_excel('http://www.ispdados.rj.gov.br/Arquivos/ArmasApreendidasEvolucaoCisp.xlsx', index_col = 0, sheet_name =
"Arma_de_Fogo")
dfGuns.head()
```

| | mes | vano | aisp | risp | arma_fabricacao_caseira | carabina | espingarda | fuzil | garrucha | garruchao | metralhadora | outros | pistola | revolver | sub |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **circ** | | | | | | | | | | | | | | | |
| **1** | 1 | 2007 | 5 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 |
| **1** | 2 | 2007 | 5 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |
| **1** | 3 | 2007 | 5 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **1** | 4 | 2007 | 5 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 4 | 1 | 0 |
| **1** | 5 | 2007 | 5 | 1 | 0 | 0 | 0 | 0 | 6 | 0 | 0 | 0 | 1 | 2 | 0 |

The data was cleaned up and most of the columns left out. I only used total number of guns to have the guns apprehended databases the same. In all stats I removed most of the columns, only keeping the total number of thefts, robberies, threats and reports.

```
# Clean unnecessary columns
dfA2 = dfGuns.drop(['aisp', 'risp', 'arma_fabricacao_caseira', 'carabina',
       'espingarda', 'fuzil', 'garrucha', 'garruchao', 'metralhadora',
       'outros', 'pistola', 'revolver', 'submetralhadora'], axis=1)

# Clean the database and set up total number of guns
dfA1.columns = ['Year', 'Month', 'Guns']
dfA2.columns = ['Month', 'Year', 'Guns']
dfA2 = dfA2.groupby(['Year','Month']).sum()
dfA2.reset_index(inplace = True)

# Join the guns databases
dfA = dfA1.append(dfA2)
dfA.head()
```

| | Year | Month | Guns |
|---|---|---|---|
| **0** | 2000 | 1 | 697 |
| **1** | 2000 | 2 | 751 |
| **2** | 2000 | 3 | 784 |
| **3** | 2000 | 4 | 780 |
| **4** | 2000 | 5 | 761 |

```
# Drop unnecessary columns
dfC = dfCisp.drop(['CISP', 'mes_ano', 'munic', 'AISP', 'RISP', 'mcirc', 'cmp', 'cmba', 'aaapai', 'apf', 'roubo_comercio', 'roubo
_residencia',
       'roubo_veiculo', 'roubo_carga', 'roubo_transeunte', 'roubo_em_coletivo',
       'roubo_banco', 'roubo_cx_eletronico', 'roubo_celular',
       'roubo_conducao_saque', 'roubo_apos_saque', 'roubo_bicicleta',
       'outros_roubos', 'furto_veiculos', 'furto_transeunte',
       'furto_coletivo', 'furto_celular', 'furto_bicicleta', 'outros_furtos',
        'sequestro', 'extorsao', 'sequestro_relampago', 'estelionato', 'apreensao_drogas',
       'posse_drogas', 'trafico_drogas', 'apreensao_drogas_sem_autor',
       'recuperacao_veiculos', 'fase', 'pessoas_desaparecidas',
       'encontro_cadaver', 'encontro_ossada', 'pol_militares_mortos_serv',
       'pol_civis_mortos_serv', 'hom_doloso', 'lesao_corp_morte',
       'latrocinio', 'hom_por_interv_policial', 'tentat_hom',
       'lesao_corp_dolosa', 'estupro', 'hom_culposo', 'lesao_corp_culposa',
        'indicador_letalidade', 'indicador_roubo_rua', 'indicador_roubo_veic', 'Regiao'], axis=1)
```

```
#Rename columns
dfC.columns = ['Month', 'Year', 'Robberies', 'Thefts', 'Threats',
       'Reports']

# Group together stats from different areas
dfC = dfC.groupby(['Year', 'Month']).sum()
dfC.reset_index(inplace = True)

dfC.head()
```

Here is the output table:

| | Year | Month | Robberies | Thefts | Threats | Reports |
|---|---|---|---|---|---|---|
| **0** | 2003 | 1 | 10296 | 10483 | 6127 | 44793 |
| **1** | 2003 | 2 | 10634 | 10335 | 6047 | 45403 |
| **2** | 2003 | 3 | 9976 | 10976 | 5793 | 45417 |
| **3** | 2003 | 4 | 10222 | 10409 | 5626 | 44184 |
| **4** | 2003 | 5 | 10875 | 10414 | 5436 | 45572 |

## b) Final Data frame

```
# Join the databases for final database for analysis
df = pd.merge(dfC, dfA, on=['Year', 'Month'])
df.head()
```

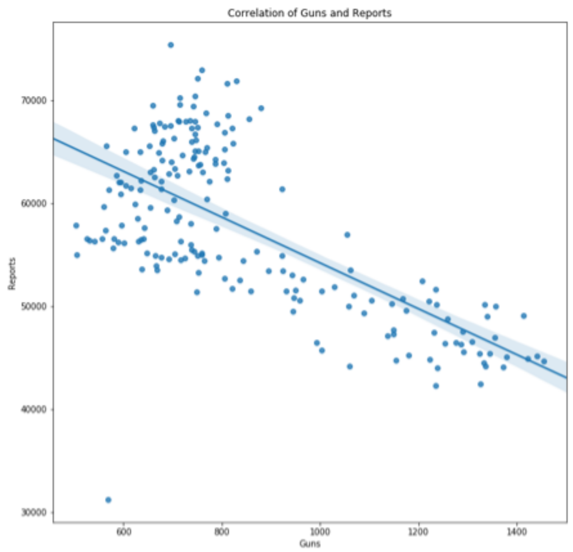
| | Year | Month | Robberies | Thefts | Threats | Reports | Guns |
|---|---|---|---|---|---|---|---|
| 0 | 2003 | 1 | 10296 | 10483 | 6127 | 44793 | 1154 |
| 1 | 2003 | 2 | 10634 | 10335 | 6047 | 45403 | 1324 |
| 2 | 2003 | 3 | 9976 | 10976 | 5793 | 45417 | 1344 |
| 3 | 2003 | 4 | 10222 | 10409 | 5626 | 44184 | 1336 |
| 4 | 2003 | 5 | 10875 | 10414 | 5436 | 45572 | 1292 |

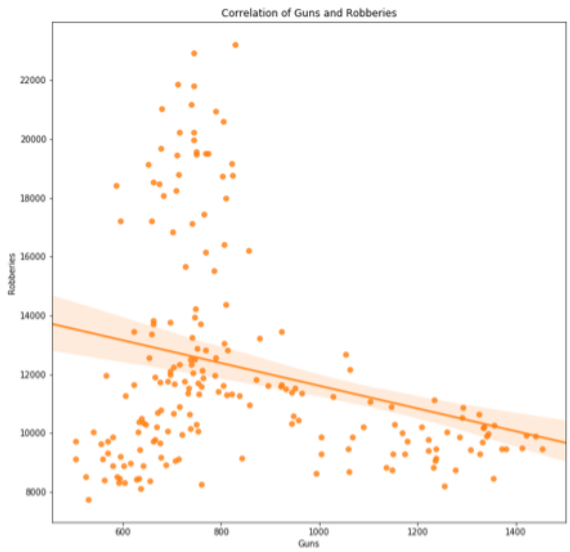
# 3) Methodology

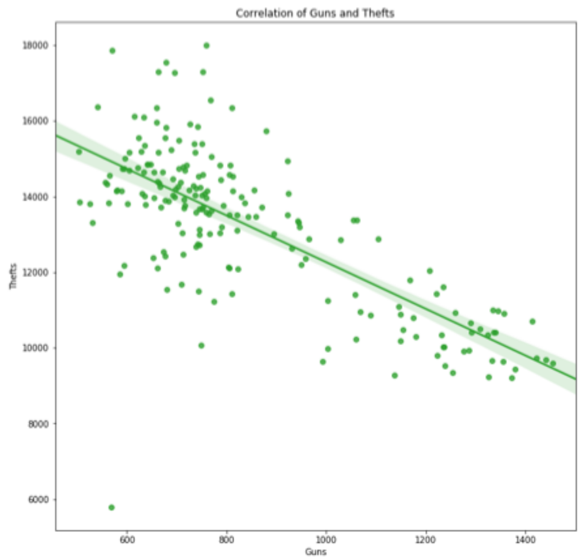
### Use regression to figure out a connection between guns apprehended and crimes.

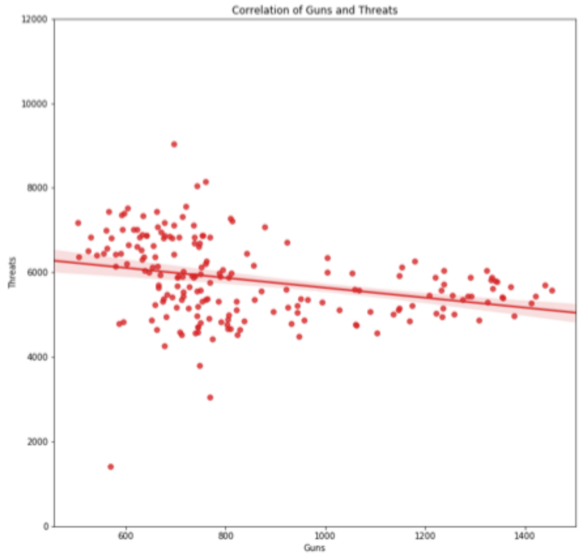
```
# import the visualization package: seaborn
import seaborn as sns
%matplotlib inline

# Plot the regression plot for Guns and Thefts
# Plot the variables each on its own plot

fig = plt.figure(figsize = (24,24)) # create figure

ax0 = fig.add_subplot(2, 2, 1) # add subplot 1
ax1 = fig.add_subplot(2, 2, 2) # add subplot 2
ax2 = fig.add_subplot(2, 2, 3) # add subplot 3
ax3 = fig.add_subplot(2, 2, 4) # add subplot 4
```

```
# Subplot 1: Guns apprehended
sns.regplot(x="Guns", y="Reports", data=df, ax=ax0)
plt.ylim(0,)
ax0.set_title('Correlation of Guns and Reports')
ax0.set_xlabel('Guns')
ax0.set_ylabel('Reports')

# Subplot 2: Robberies reported
sns.regplot(x="Guns", y="Robberies", data=df, ax=ax1)
plt.ylim(0,)
ax1.set_title('Correlation of Guns and Robberies')
ax1.set_xlabel('Guns')
ax1.set_ylabel('Robberies')

# Subplot 3: Thefts reported
sns.regplot(x="Guns", y="Thefts", data=df, ax=ax2)
plt.ylim(0,)
ax2.set_title('Correlation of Guns and Thefts')
ax2.set_xlabel('Guns')
ax2.set_ylabel('Thefts')

# Subplot 4: Threats reported
sns.regplot(x="Guns", y="Threats", data=df, ax=ax3)
plt.ylim(0,12000)
ax3.set_title('Correlation of Guns and Threats')
ax3.set_xlabel('Guns')
ax3.set_ylabel('Threats')

plt.show()
```



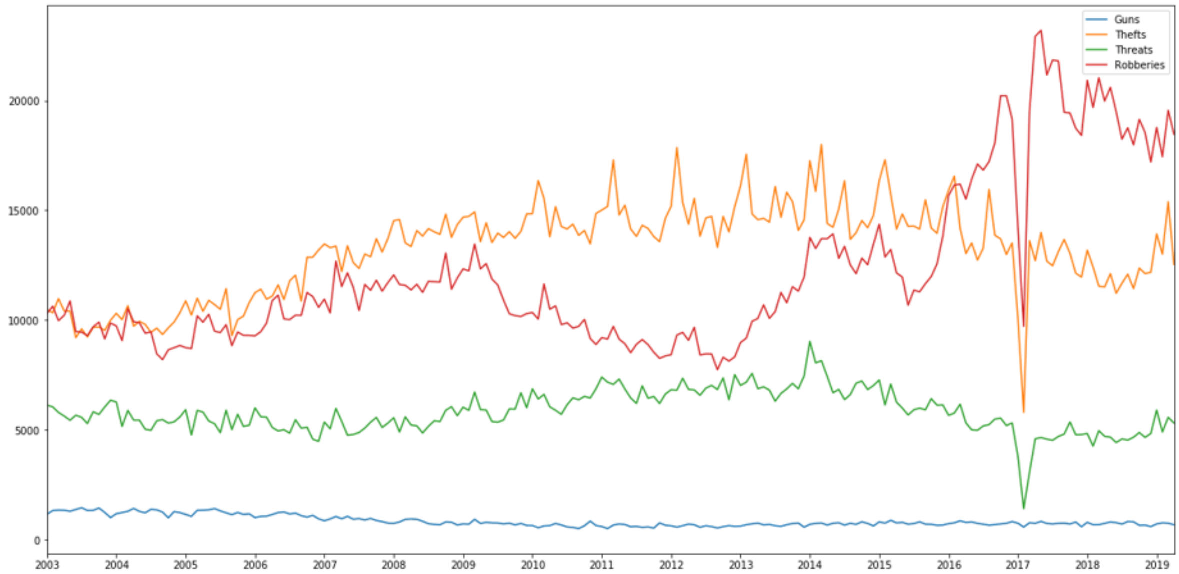

As we can see, there is an obvious correlation between the apprehension of guns and crimes committed. There is a negative line which means that the more guns are apprehended the fewer crimes are committed, which was to be expected. To be sure we will check out the correlation between all variables.

```
df[['Robberies', 'Thefts', 'Threats','Reports','Guns']].corr()
```

| | Robberies | Thefts | Threats | Reports | Guns |
|---|---|---|---|---|---|
| **Robberies** | 1.000000 | 0.081872 | -0.403189 | 0.631975 | -0.255823 |
| **Thefts** | 0.081872 | 1.000000 | 0.604089 | 0.718246 | -0.731101 |
| **Threats** | -0.403189 | 0.604089 | 1.000000 | 0.339211 | -0.301067 |
| **Reports** | 0.631975 | 0.718246 | 0.339211 | 1.000000 | -0.671801 |
| **Guns** | -0.255823 | -0.731101 | -0.301067 | -0.671801 | 1.000000 |

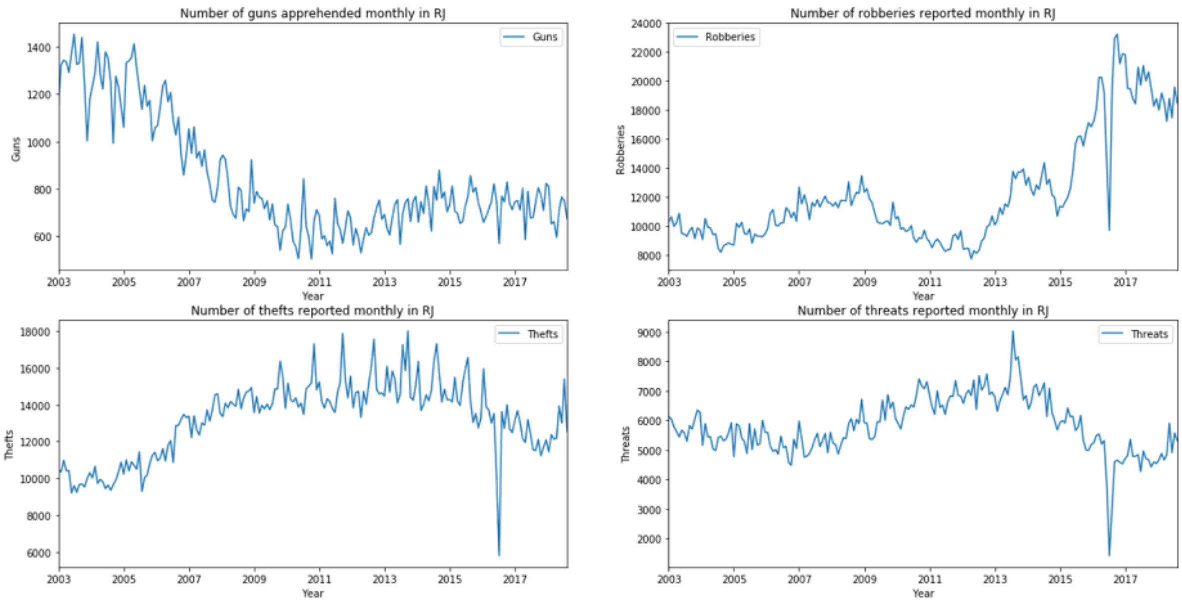
We plot up the variables to see if there is an obvious visual correlation:

```python
# Plot all variables on the same plot
df[['Guns','Thefts', 'Threats', 'Robberies']].plot(figsize=(20, 10))
unique_years, ind = np.unique(df["Year"].values,return_index=True)
plt.xticks(df.index[ind], unique_years)
plt.show()
```




```python
# Plot the variables each on its own plot

fig = plt.figure() # create figure

ax0 = fig.add_subplot(2, 2, 1) # add subplot 1
ax1 = fig.add_subplot(2, 2, 2) # add subplot 2
ax2 = fig.add_subplot(2, 2, 3) # add subplot 3
ax3 = fig.add_subplot(2, 2, 4) # add subplot 4
years = [2003,2005,2007,2009,2011,2013,2015,2017,2019]
```

```python
# Subplot 1: Guns apprehended
df[['Guns']].plot(figsize=(20, 10), ax=ax0)
ax0.set_title('Number of guns apprehended monthly in RJ')
ax0.set_xlabel('Year')
ax0.set_ylabel('Guns')

# Subplot 2: Robberies reported
df[['Robberies']].plot(figsize=(20, 10), ax=ax1)
ax1.set_title('Number of robberies reported monthly in RJ')
ax1.set_xlabel('Year')
ax1.set_ylabel('Robberies')

# Subplot 3: Thefts reported
df[['Thefts']].plot(figsize=(20, 10), ax=ax2)
ax2.set_title('Number of thefts reported monthly in RJ')
ax2.set_xlabel('Year')
ax2.set_ylabel('Thefts')

# Subplot 4: Threats reported
df[['Threats']].plot(figsize=(20, 10), ax=ax3)
ax3.set_title('Number of threats reported monthly in RJ')
ax3.set_xlabel('Year')
ax3.set_ylabel('Threats')


ax0.set_xticklabels(years)
ax1.set_xticklabels(years)
ax2.set_xticklabels(years)
ax3.set_xticklabels(years)



plt.show()
```




Now we can see the visual correlation that when gun apprehension was very high in the early 2000's crime rate was lower. When gun apprehension went down, crime rate went up. We'll explore it a bit further:

```
In [36]: from scipy import stats

         pearson_coef, p_value = stats.pearsonr(df['Guns'], df['Thefts'])
         print("The Pearson Correlation Coefficient for Theft is", pearson_coef, " with a P-value of P = ", p_value)
         pearson_coef, p_value = stats.pearsonr(df['Guns'], df['Threats'])
         print("The Pearson Correlation Coefficient for Threats is", pearson_coef, " with a P-value of P = ", p_value)
         pearson_coef, p_value = stats.pearsonr(df['Guns'], df['Robberies'])
         print("The Pearson Correlation Coefficient for Robberies is", pearson_coef, " with a P-value of P = ", p_value)
         pearson_coef, p_value = stats.pearsonr(df['Guns'], df['Reports'])
         print("The Pearson Correlation Coefficient for Reports is", pearson_coef, " with a P-value of P = ", p_value)

         The Pearson Correlation Coefficient is -0.7311007989079222  with a P-value of P =  4.775783191642987e-34
         The Pearson Correlation Coefficient is -0.3010673224077392  with a P-value of P =  1.8037693207423l2e-05
         The Pearson Correlation Coefficient is -0.25582274994672677  with a P-value of P =  0.0002957215346176379
         The Pearson Correlation Coefficient is -0.6718014009591574  with a P-value of P =  4.382898870449731e-27
```

→ The P-Value is very good for Thefts and for Reports but not very good for Threats and Robberies. We'll next try to use the Single Linear Regression Machine Learning Technique

## 4) Results

```
# Split data into test and train set, fit the data and plot regression plots.
from sklearn import linear_model
from sklearn.metrics import r2_score


msk = np.random.rand(len(df)) < 0.8
train = df[msk]
test = df[~msk]

fig = plt.figure(figsize=(20,20)) # create figure

ax0 = fig.add_subplot(2, 2, 1) # add subplot 1
ax1 = fig.add_subplot(2, 2, 2) # add subplot 2
ax2 = fig.add_subplot(2, 2, 3) # add subplot 3
ax3 = fig.add_subplot(2, 2, 4) # add subplot 4
regr = linear_model.LinearRegression()
```

```
# Subplot 1: Guns and Thefts
train_x = np.asanyarray(train[['Guns']])
train_y = np.asanyarray(train[['Thefts']])
regr.fit (train_x, train_y)

test_x = np.asanyarray(test[['Guns']])
test_y = np.asanyarray(test[['Thefts']])
test_y_hat = regr.predict(test_x)

print("Theft Mean absolute error: %.2f" % np.mean(np.absolute(test_y_hat - test_y)))
print("Theft Residual sum of squares (MSE): %.2f" % np.mean((test_y_hat - test_y) ** 2))
print("Theft R2-score: %.2f" % r2_score(test_y_hat , test_y) )

ax0.scatter(train.Guns, train.Thefts,  color='blue')
ax0.plot(train_x, regr.coef_[0][0]*train_x + regr.intercept_[0], '-r')
ax0.set_xlabel("Guns")
ax0.set_ylabel("Thefts")
```

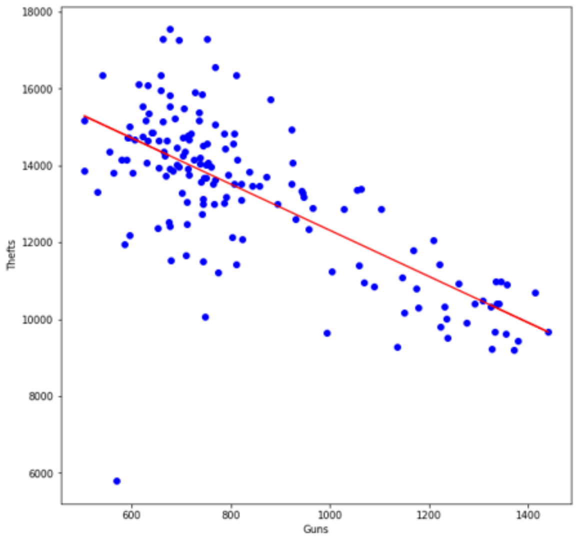
```
# Subplot 2: Guns and Reports
train_x = np.asanyarray(train[['Guns']])
train_y = np.asanyarray(train[['Reports']])
regr.fit (train_x, train_y)

test_x = np.asanyarray(test[['Guns']])
test_y = np.asanyarray(test[['Reports']])
test_y_hat = regr.predict(test_x)

print("Reports Mean absolute error: %.2f" % np.mean(np.absolute(test_y_hat - test_y)))
print("Reports Residual sum of squares (MSE): %.2f" % np.mean((test_y_hat - test_y) ** 2))
print("Reports R2-score: %.2f" % r2_score(test_y_hat , test_y) )

ax1.scatter(train.Guns, train.Reports,  color='blue')
ax1.plot(train_x, regr.coef_[0][0]*train_x + regr.intercept_[0], '-r')
ax1.set_xlabel("Guns")
ax1.set_ylabel("Reports")
```

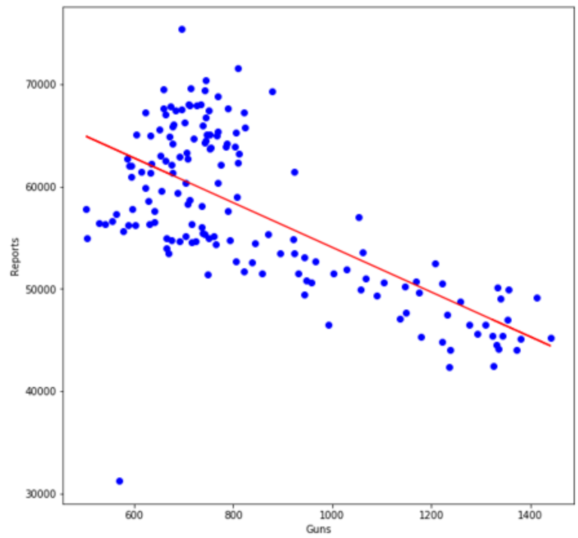
```
# Subplot 3: Guns and Robberies
train_x = np.asanyarray(train[['Guns']])
train_y = np.asanyarray(train[['Robberies']])
regr.fit (train_x, train_y)

test_x = np.asanyarray(test[['Guns']])
test_y = np.asanyarray(test[['Robberies']])
test_y_hat = regr.predict(test_x)

print("Robbery Mean absolute error: %.2f" % np.mean(np.absolute(test_y_hat - test_y)))
print("Robbery Residual sum of squares (MSE): %.2f" % np.mean((test_y_hat - test_y) ** 2))
print("Robbery R2-score: %.2f" % r2_score(test_y_hat , test_y) )

ax2.scatter(train.Guns, train.Robberies,  color='blue')
ax2.plot(train_x, regr.coef_[0][0]*train_x + regr.intercept_[0], '-r')
ax2.set_xlabel("Guns")
ax2.set_ylabel("Robberies")
```

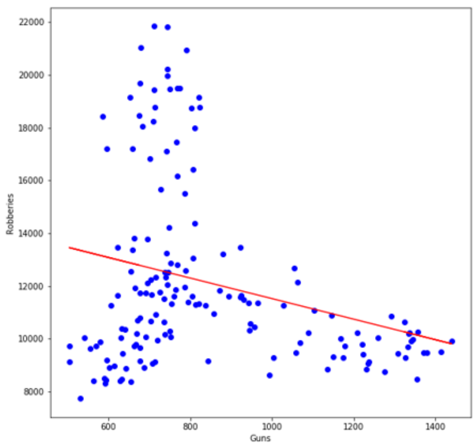
```
# Subplot 4: Guns and Threats
train_x = np.asanyarray(train[['Guns']])
train_y = np.asanyarray(train[['Threats']])
regr.fit (train_x, train_y)

test_x = np.asanyarray(test[['Guns']])
test_y = np.asanyarray(test[['Threats']])
test_y_hat = regr.predict(test_x)

print("Threat Mean absolute error: %.2f" % np.mean(np.absolute(test_y_hat - test_y)))
print("Threat Residual sum of squares (MSE): %.2f" % np.mean((test_y_hat - test_y) ** 2))
print("Threat R2-score: %.2f" % r2_score(test_y_hat , test_y) )

ax3.scatter(train.Guns, train.Threats,  color='blue')
ax3.plot(train_x, regr.coef_[0][0]*train_x + regr.intercept_[0], '-r')
ax3.set_xlabel("Guns")
ax3.set_ylabel("Threats")



plt.show()
```

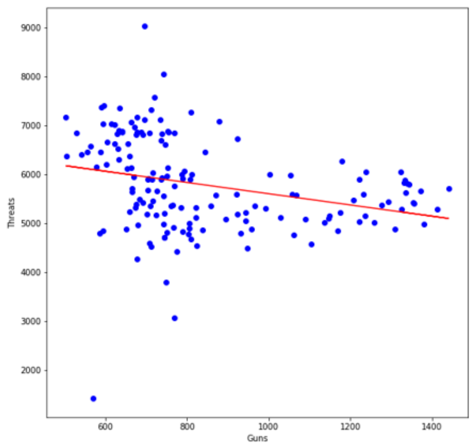
Here are the results of MAE, MSE and R2 scores:

```
Theft Mean absolute error: 897.21
Theft Residual sum of squares (MSE): 1560877.39
Theft R2-score: 0.37
Reports Mean absolute error: 5616.36
Reports Residual sum of squares (MSE): 45685358.54
Reports R2-score: -0.39
Robbery Mean absolute error: 3141.24
Robbery Residual sum of squares (MSE): 18707405.69
Robbery R2-score: -16.96
Threat Mean absolute error: 686.88
Threat Residual sum of squares (MSE): 728326.47
Threat R2-score: -7.00
```




→ We can easily see that there is a good correlation for Thefts and Reports. But not as good for robberies and threats.
The results show a correlation and do give a decent estimation with the learned formula from the single linear regression.

## 5) Discussion

There was a correlation with guns apprehended and crimes committed in Rio de Janeiro, but the results did still not confirm my suspicion in all areas as I had initially expected. There is definitely room for improvement, possibilities to check the data with other ML techniques as well as getting data from other times as well as looking at other crimes committed. The dataset seemed mostly good except a fall in the beginning of 2017 of crimes committed which may have affected the learning a bit. I think this is definitely a problem worth looking into but it does seem like an obvious answer, that if police is working harder on cleaning the street of guns (instead of politicians pushing guns into everyone's hands), crime rate will go down.

It would also be interesting to compare the data with other states/cities and also it would be interesting to include police mortality in the numbers as gun apprehension can be a dangerous feat.

## 6) Conclusion

In this study, I analyzed the correlation between guns captured by police in Rio de Janeiro and the effect on crimes committed in the city. I have setting up the dataset with total number of crimes and guns captured and analyzed it. I also built both regression models and classification models to predict whether gun apprehension had any effect on crime rate.
These models can be useful in helping police force focus their attention.