FBI Uniform Crime Reporting Analysis | 2012

Author: Team members name

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Image Source

1- Importing dataset ditectly from kaggle

```
from google.colab import files
file = files.upload()  #upload file into google colab session
```

Choose Files U.S._Offen…y_2012.xlsx

- **U.S._Offense_Type_by_Agency_2012.xlsx**(application/vnd.openxmlformats-officedocument.spreadsheetml.sheet) - 811670 bytes, last modified: 3/26/2023 - 100% done

Saving U.S._Offense_Type_by_Agency_2012.xlsx to U.S._Offense_Type_by_Agency_2012.xlsx

2- Importing libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
from sklearn.decomposition import PCA

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import r2_score
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import RandomForestRegressor

import math
```

3- Importing dataset

```
df = pd.read_excel("U.S._Offense_Type_by_Agency_2012.xlsx", skiprows=3, skipfooter= 4, header
df
```

	State	Agency Type	Agency Name	Population1	Crimes Against Persons	
	Unnamed: 0_level_1	Unnamed: 1_level_1	Unnamed: 2_level_1	Unnamed: 3_level_1	Assault\nOffenses	Aggravated\nAss
0	ALABAMA	Cities	Hoover	82332.0	870.0	
1	ARIZONA	Cities	Apache Junction	36986.0	559.0	
2	NaN	NaN	Gilbert	214264.0	1242.0	
3	NaN	Metropolitan Counties	Yuma2	NaN	555.0	
4	ARKANSAS	Cities	Alma	5439.0	197.0	
...	...	...	...	...	...	
5230	NaN	NaN	Sauk	NaN	80.0	
5231	NaN	NaN	Sawyer	NaN	79.0	
5232	NaN	NaN	Vilas	NaN	42.0	
5233	NaN	Other Agencies - Tribal	Oneida Tribal	NaN	56.0	

4- Basic Text Data Pre-processing

```
df["State"] = df["State"].fillna(method='ffill', axis=0)
df["Agency Type"] = df["Agency Type"].fillna(method='ffill', axis=0)

new_col = []
for col in df.columns:
  if "Unnamed" in col[1]:
    new_col.append(col[0])
  else:
    new_col.append((col[0],col[1]))
new_col

df.columns = new_col
df
```

	State	Agency Type	Agency Name	Population1	(Crimes Against Persons, Assault\nOffenses)	(Crimes Aggravated\n
0	ALABAMA	Cities	Hoover	82332.0	870.0	
1	ARIZONA	Cities	Apache Junction	36986.0	559.0	
2	ARIZONA	Cities	Gilbert	214264.0	1242.0	
3	ARIZONA	Metropolitan Counties	Yuma2	NaN	555.0	
4	ARKANSAS	Cities	Alma	5439.0	197.0	
...	...	...	...	...	...	
5230	WISCONSIN	Nonmetropolitan Counties	Sauk	NaN	80.0	
5231	WISCONSIN	Nonmetropolitan Counties	Sawyer	NaN	79.0	
5232	WISCONSIN	Nonmetropolitan Counties	Vilas	NaN	42.0	
5233	WISCONSIN	Other Agencies - Tribal	Oneida Tribal	NaN	56.0	
5234	WISCONSIN	Other Agencies - Tribal	St. Croix Tribal	NaN	14.0	

5235 rows × 59 columns

```
def col_filter(columns, cat):
  tot_cols = []
  for col in columns:
    if type(col)!=str:
      if col[1].endswith("\nOffenses") and col[0] == cat:
        tot_cols.append(col)
  return tot_cols

def index_cal(columns, cat):
  for index in range(len(columns)):
    if cat in columns[index]:
      return index
```

5- Preparing Data for Exploratory Data Analysis (EDA)

```
df["('Crimes Against Persons', 'Total Offenses')"] = df[col_filter(df.columns, cat="Crimes Ag
df["('Crimes Against Property', 'Total Offenses')"] = df[col_filter(df.columns, cat="Crimes A
df["('Crimes Against Society', 'Total Offenses')"] = df[col_filter(df.columns, cat="Crimes Ag

df.to_excel("Cleaned.xlsx")
```

6- Exploratory data analysis

Que - A

```
assault_offences = df.loc[:,['State','Agency Type',('Crimes Against Persons', 'Assault\nOffen
assault_offences
```

```
/usr/local/lib/python3.9/dist-packages/pandas/core/common.py:241: VisibleDeprecationWarn

Creating an ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-t
```

State	Agency Type	(Crimes Against Persons,	(Crimes Against Persons,	(Crimes Aga Pers

```
df11=pd.pivot_table(assault_offences[assault_offences['Agency Type']!='Cities'],index = ['Sta
df11
```

State	(Crimes Against Persons, Aggravated\nAssault)	(Crimes Against Persons, Assault\nOffenses)	(Crimes Against Persons, Intimidation)	(Crimes F Simple\nA
ARIZONA	94.0	555.0	85.0	
ARKANSAS	2028.0	10144.0	2970.0	
COLORADO	1770.0	7651.0	561.0	
CONNECTICUT	215.0	3750.0	1043.0	
DELAWARE	1865.0	12735.0	2795.0	
DISTRICT OF	109.0	726.0	55.0	

```
assault_offences = df11.sort_values(('Crimes Against Persons', 'Assault\nOffenses'),ascending
assault_offences.drop(('Crimes Against Persons', 'Assault\nOffenses'),axis=1, inplace=True)
```

IOWA	844.0	3357.0	450.0

```
assault_offences.head()
```

State	(Crimes Against Persons, Aggravated\nAssault)	(Crimes Against Persons, Intimidation)	(Crimes Against Persons, Simple\nAssault)
SOUTH CAROLINA	10787.0	8418.0	33657.0
VIRGINIA	3709.0	4031.0	39389.0
TENNESSEE	6700.0	7035.0	19922.0
MICHIGAN	4218.0	5418.0	22784.0
NEW HAMPSHIRE	29.0	179.0	57.0

Que - B

OKLAHOMA	636.0	2582.0	781.0

```
df_B = df.loc[:,['Agency Type', 'Agency Name']]
df_B.head()
```

Agency Type	Agency Name			
VERMONT		.0	1190.0	129.0

```
df_B["('Crimes Against Persons', 'Total Offenses')"] = df["('Crimes Against Persons', 'Total
df_B["('Crimes Against Property', 'Total Offenses')"] = df["('Crimes Against Property', 'Tota
df_B["('Crimes Against Society', 'Total Offenses')"] = df["('Crimes Against Society', 'Total
df_B.head()
```

	Agency Type	Agency Name	('Crimes Against Persons', 'Total Offenses')	('Crimes Against Property', 'Total Offenses')	('Crimes Against Society', 'Total Offenses')
0	Cities	Hoover	897.0	1920.0	495.0
1	Cities	Apache Junction	595.0	887.0	308.0
2	Cities	Gilbert	1326.0	3035.0	2069.0
3	Metropolitan				

```
df_clean = df_B
df_BB = df_clean.query('`Agency Type` == "Universities and Colleges"')
df_BB.head()
```

	Agency Type	Agency Name	('Crimes Against Persons', 'Total Offenses')	('Crimes Against Property', 'Total Offenses')	('Crimes Against Society', 'Total Offenses')
149	Universities and Colleges	Arkansas State University, Jonesboro	30.0	135.0	12.0
150	Universities and Colleges	Arkansas Tech University	11.0	103.0	8.0

```
df_BBB = df_BB.groupby("Agency Type").agg({"('Crimes Against Persons', 'Total Offenses')" : "
df_BBB
```

Agency Type	('Crimes Against Persons', 'Total Offenses')	('Crimes Against Property', 'Total Offenses')	('Crimes Against Society', 'Total Offenses')

Que- C

```
df_C = df.loc[:,['Agency Type', 'Agency Name']]
df_C.head()
```

	Agency Type	Agency Name
0	Cities	Hoover
1	Cities	Apache Junction
2	Cities	Gilbert
3	Metropolitan Counties	Yuma2
4	Cities	Alma

```
df_C["('Crimes Against Persons', 'Total Offenses')"] = df["('Crimes Against Persons', 'Total
df_C["('Crimes Against Property', 'Total Offenses')"] = df["('Crimes Against Property', 'Tota
df_C["('Crimes Against Society', 'Total Offenses')"] = df["('Crimes Against Society', 'Total
df_C.head()
```

	Agency Type	Agency Name	('Crimes Against Persons', 'Total Offenses')	('Crimes Against Property', 'Total Offenses')	('Crimes Against Society', 'Total Offenses')
0	Cities	Hoover	897.0	1920.0	495.0
1	Cities	Apache Junction	595.0	887.0	308.0
2	Cities	Gilbert	1326.0	3035.0	2069.0
3	Metropolitan				

```
df_clean = df_C
df_CC = df_clean.query('`Agency Name` == "Michigan State University"')
df_CC.head()
```

	Agency Type	Agency Name	('Crimes Against Persons', 'Total Offenses')	('Crimes Against Property', 'Total Offenses')	('Crimes Against Society', 'Total Offenses')

Que - D

```
digital_offences = df.loc[:,['State',('Crimes Against Property', 'Credit Card/\nAutomated\nTe
#df11=pd.pivot_table(assault_offences[assault_offences['Agency Type']!='Cities'],index = ['St
digital_offences
```

```
/usr/local/lib/python3.9/dist-packages/pandas/core/common.py:241: VisibleDeprecationWarn

Creating an ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-t
```

	State	(Crimes Against Property, Credit Card/\nAutomated\nTeller\nMachine Fraud)	(Crimes Against Property, Wire\nFraud)
0	ALABAMA	109.0	NaN
1	ARIZONA	62.0	NaN
2	ARIZONA	150.0	NaN
3	ARIZONA	48.0	NaN
4	ARKANSAS	10.0	NaN
...	...	...	...
5230	WISCONSIN	20.0	2.0
5231	WISCONSIN	12.0	1.0

```
df12 = pd.pivot_table(digital_offences,index='State',aggfunc='sum')
df12["Total digital_offences"] = df12[('Crimes Against Property', 'Credit Card/\nAutomated\nT
df12
```

State	(Crimes Against Property, Credit Card/\nAutomated\nTeller\nMachine Fraud)	(Crimes Against Property, Wire\nFraud)	Total digital_offences
ALABAMA	109.0	0.0	109.0
ARIZONA	260.0	0.0	260.0
ARKANSAS	4082.0	45.0	4127.0
COLORADO	3684.0	494.0	4178.0
CONNECTICUT	2226.0	279.0	2505.0
DELAWARE	1279.0	3.0	1282.0
DISTRICT OF COLUMBIA	0.0	0.0	0.0
IDAHO	1425.0	124.0	1549.0
ILLINOIS	209.0	0.0	209.0
IOWA	1843.0	238.0	2081.0
KANSAS	4183.0	0.0	4183.0
KENTUCKY	3196.0	0.0	3196.0
MAINE	245.0	12.0	257.0
MASSACHUSETTS	3609.0	144.0	3753.0
MICHIGAN	6678.0	738.0	7416.0
MISSISSIPPI	85.0	4.0	89.0
MISSOURI	712.0	267.0	979.0

```
digital_offences = df12.sort_values("Total digital_offences",ascending=True)
digital_offences.drop([('Crimes Against Property', 'Credit Card/\nAutomated\nTeller\nMachine
```

```
digital_offences.head()
```

	Total digital_offences		
TENNESSEE	7940.0	662.0	8602.0

Que E

MISSISSIPPI	89.0		

```
df_EE = df.loc[:,['State','Agency Type', 'Agency Name','Population1']]
df_EE.head()
```

	State	Agency Type	Agency Name	Population1
0	ALABAMA	Cities	Hoover	82332.0
1	ARIZONA	Cities	Apache Junction	36986.0
2	ARIZONA	Cities	Gilbert	214264.0
3	ARIZONA	Metropolitan Counties	Yuma2	NaN
4	ARKANSAS	Cities	Alma	5439.0

```
df_EE["Total offence"] = df["('Crimes Against Persons', 'Total Offenses')"]+df["('Crimes Agai
df_EE.head()
```

	State	Agency Type	Agency Name	Population1	Total offence
0	ALABAMA	Cities	Hoover	82332.0	3312.0
1	ARIZONA	Cities	Apache Junction	36986.0	1790.0
2	ARIZONA	Cities	Gilbert	214264.0	6430.0
3	ARIZONA	Metropolitan Counties	Yuma2	NaN	1895.0
4	ARKANSAS	Cities	Alma	5439.0	545.0

```
df_EE['offence/million'] = df_EE['Total offence']/df_EE['Population1']
df_EE.head()
```

	State	Agency Type	Agency Name	Population1	Total offence	offence/million
0	ALABAMA	Cities	Hoover	82332.0	3312.0	0.040227
1	ARIZONA	Cities	Apache Junction	36986.0	1790.0	0.048397
2	ARIZONA	Cities	Gilbert	214264.0	6430.0	0.030010
3	ARIZONA	Metropolitan Counties	Yuma2	NaN	1895.0	NaN

```
df_EEE = pd.pivot_table(df_EE[["Agency Type", "Agency Name", "State", "offence/million"]],ind
df_EEE.sort_values("offence/million",inplace=True,ascending=False)
df_EEE
```

Agency Type	Agency Name	State	offence/million
Cities	**Lakeside**	COLORADO	4.500000
	Black Hawk	COLORADO	2.591667
	Fruitport	MICHIGAN	0.868566
	Linndale	OHIO	0.724719
	Mackinac Island	MICHIGAN	0.599182
...	...	...	...
Universities and Colleges	**University of Michigan:**	MICHIGAN	NaN
	University of South Carolina:	SOUTH CAROLINA	NaN
	University of Tennessee:	TENNESSEE	NaN
	Vancouver3	WASHINGTON	NaN
	Washington State University:	WASHINGTON	NaN

4378 rows × 2 columns

QUE F

```
df["('Crimes Against Persons', 'Total Offenses')"] = df[col_filter(df.columns, cat="Crimes Ag
df["('Crimes Against Property', 'Total Offenses')"] = df[col_filter(df.columns, cat="Crimes A
df["('Crimes Against Society', 'Total Offenses')"] = df[col_filter(df.columns, cat="Crimes Ag

df_Total_offences = pd.DataFrame(df["('Crimes Against Persons', 'Total Offenses')"]+df["('Cri
#print(df['State'].count())
#print(df_Total_offences.count())
df_Total_offences.head()
```

```
df15 = pd.concat([df["State"], df_Total_offences["Total Offences"]], axis=1)
df15.rename(columns = {0:"Total offence"},inplace=True)
df15
#df.rename(columns={"A": "a", "B": "c"})
```

	State	Total Offences
0	ALABAMA	3312.0
1	ARIZONA	1790.0
2	ARIZONA	6430.0
3	ARIZONA	1895.0
4	ARKANSAS	545.0
...	...	...
5230	WISCONSIN	793.0
5231	WISCONSIN	348.0
5232	WISCONSIN	223.0
5233	WISCONSIN	226.0
5234	WISCONSIN	81.0

5235 rows × 2 columns

```
df15.dtypes
```

```
State              object
Total Offences    float64
dtype: object
```

```
df15 = pd.pivot_table(df15,index='State',aggfunc="sum")
df15.reset_index(inplace = True)
#print(df15)
df15.sort_values("Total Offences",inplace=True,ascending=False)
df15.head()
```

```
"District of Columbia".title()
```

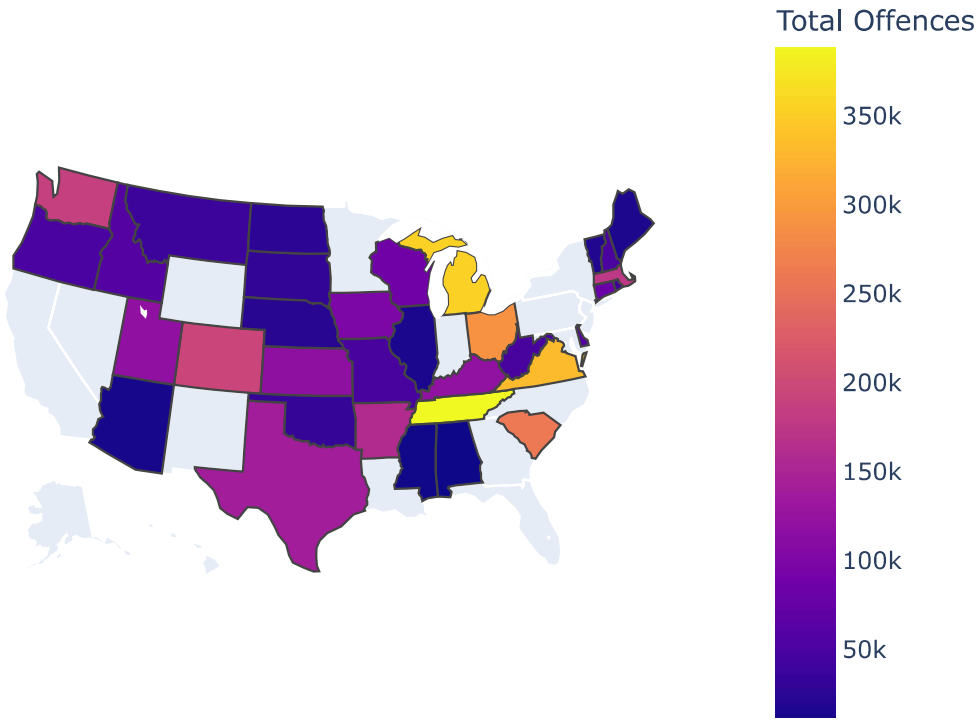
```
'District Of Columbia'
```

```
state_codes = {
    'District Of Columbia' : 'dc','Mississippi': 'MS', 'Oklahoma': 'OK',
    'Delaware': 'DE', 'Minnesota': 'MN', 'Illinois': 'IL', 'Arkansas': 'AR',
    'New Mexico': 'NM', 'Indiana': 'IN', 'Maryland': 'MD', 'Louisiana': 'LA',
    'Idaho': 'ID', 'Wyoming': 'WY', 'Tennessee': 'TN', 'Arizona': 'AZ',
    'Iowa': 'IA', 'Michigan': 'MI', 'Kansas': 'KS', 'Utah': 'UT',
    'Virginia': 'VA', 'Oregon': 'OR', 'Connecticut': 'CT', 'Montana': 'MT',
    'California': 'CA', 'Massachusetts': 'MA', 'West Virginia': 'WV',
    'South Carolina': 'SC', 'New Hampshire': 'NH', 'Wisconsin': 'WI',
    'Vermont': 'VT', 'Georgia': 'GA', 'North Dakota': 'ND',
    'Pennsylvania': 'PA', 'Florida': 'FL', 'Alaska': 'AK', 'Kentucky': 'KY',
    'Hawaii': 'HI', 'Nebraska': 'NE', 'Missouri': 'MO', 'Ohio': 'OH',
    'Alabama': 'AL', 'Rhode Island': 'RI', 'South Dakota': 'SD',
    'Colorado': 'CO', 'New Jersey': 'NJ', 'Washington': 'WA',
    'North Carolina': 'NC', 'New York': 'NY', 'Texas': 'TX',
    'Nevada': 'NV', 'Maine': 'ME'}

df15['state_code'] = df15['State'].apply(lambda x : state_codes[x.title()])
df15
```

	State	Total Offences	state_code
27	TENNESSEE	388773.0	TN
14	MICHIGAN	352358.0	MI
31	VIRGINIA	331093.0	VA
21	OHIO	288750.0	OH
25	SOUTH CAROLINA	258833.0	SC
3	COLORADO	192890.0	CO
32	WASHINGTON	185625.0	WA
13	MASSACHUSETTS	176188.0	MA
2	ARKANSAS	158314.0	AR
28	TEXAS	138698.0	TX
11	KENTUCKY	119404.0	KY
29	UTAH	118013.0	UT
10	KANSAS	116898.0	KS
9	IOWA	98615.0	IA
34	WISCONSIN	85254.0	WI
4	CONNECTICUT	79196.0	CT
5	DELAWARE	60801.0	DE
7	IDAHO	58735.0	ID
19	NEW HAMPSHIRE	50184.0	NH
23	OREGON	49154.0	OR

```
fig = px.choropleth(df15, locations="state_code",
                    color="Total Offences",
                    hover_name="Total Offences",
                    color_continuous_scale=px.colors.sequential.Plasma,
                    locationmode="USA-states",scope= 'usa')
fig.update_layout(
    title_text='highest number of offences'
)
fig.show()
```

highest number of offences



8. Data Modelling

```
df.columns[index_cal(df.columns, cat = "Drug/\nNarcotic\nOffenses")]
```

```
('Crimes Against Society', 'Drug/\nNarcotic\nOffenses')
```

Data modelling: 40 Points

a. Data: X: Population, Drug/Narcotic Offenses, Drug/Narcotic Violations, Drug Equipment Violations, Theft from Building, Theft from Coin-operated Machine, Theft from Motor Vehicle, Theft of Motor Vehicle Parts or Accessories. Y: Total number of offenses

Task: Build a linear regression model that fits best to the above data. You can use feature engineering to derive new features from columns in X.

Output: Can linear regression model fit the above data well? What type of linear regression model performs best? Justify your findings.

b. Build a statistical model of your choice from data available predicting total number of offenses.

Evaluate performance of the model. Show and explain the findings.

```
X = df[[
    "Population1",
```

```
    df.columns[index_cal(df.columns, cat = "Drug/\nNarcotic\nOffenses")],
    df.columns[index_cal(df.columns, cat = "Drug/\nNarcotic\nViolations")],
    df.columns[index_cal(df.columns, cat = "Drug\nEquipment\nViolations")],
    df.columns[index_cal(df.columns, cat = "Theft\nFrom\nBuilding")],
    df.columns[index_cal(df.columns, cat = "Theft\nFrom\nCoin-\noperated\nMachine")],
    df.columns[index_cal(df.columns, cat = "Theft\nFrom\nMotor\nVehicle")],
    df.columns[index_cal(df.columns, cat = "Theft of\nMotor\nVehicle\nParts or\nAccessories")
    df.columns[index_cal(df.columns, cat = "Drug/\nNarcotic\nOffenses")]
        ]]
y = df["('Crimes Against Persons', 'Total Offenses')"] + df["('Crimes Against Property', 'Tot
```

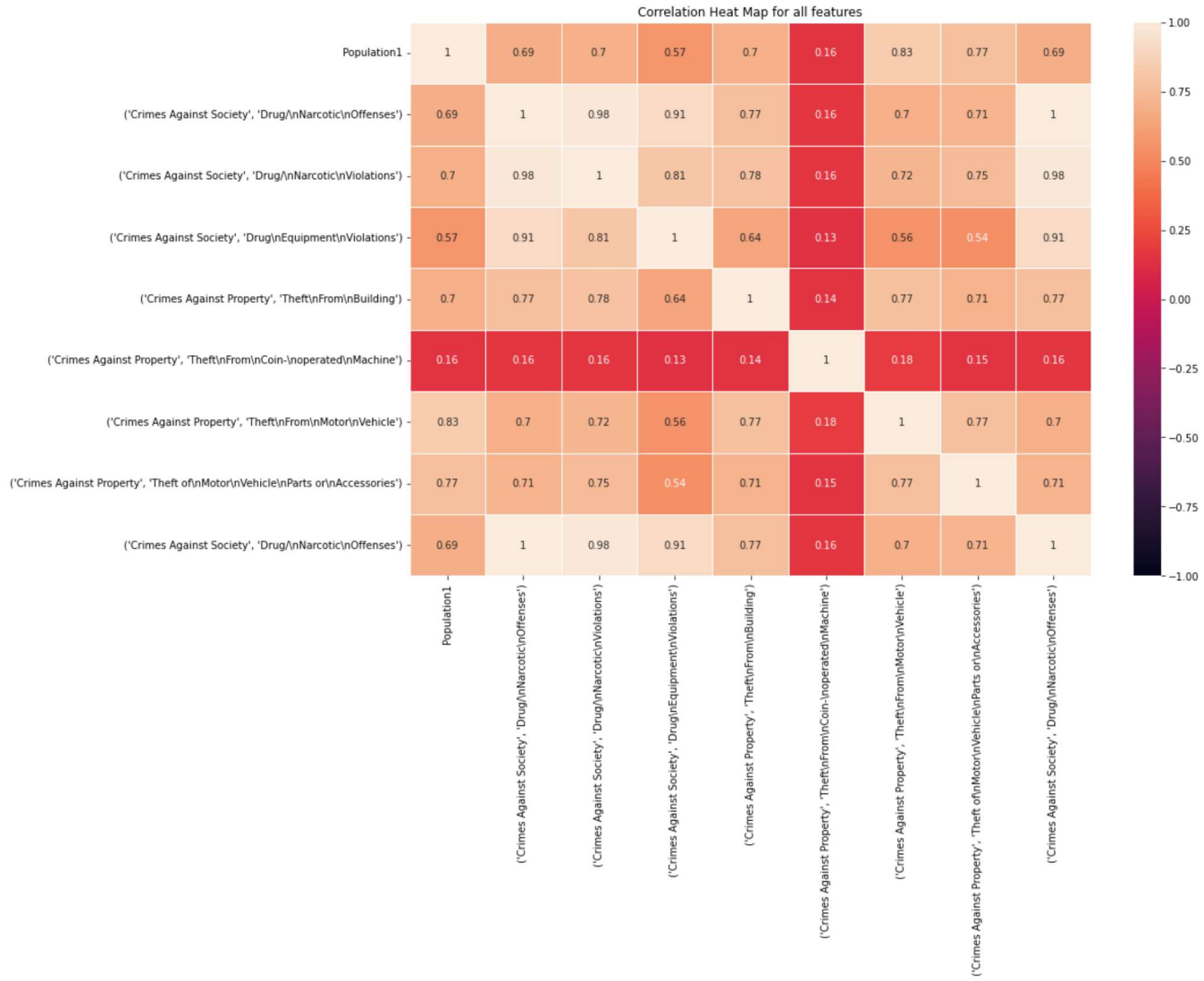
```
/usr/local/lib/python3.9/dist-packages/pandas/core/common.py:241: VisibleDeprecationWarr

Creating an ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-t
```

```
X = X.fillna(0)
```

7. Feature Selection

```
plt.figure(figsize = (15,10))
sns.heatmap(X.corr(), annot=True,linewidth=.5, vmin=-1, vmax=1)
plt.title("Correlation Heat Map for all features")
```

```
Text(0.5, 1.0, 'Correlation Heat Map for all features')
```



Using PCA as the co-relation is very good among the variables which causes the standard linear regression to fail

- There are some obvious relations such as As the Drug Narcotic Offenses is addition of Drug Narcotic Violations and Drug Equipment Violations according to metadata we can confidently only consider Drug Narcotic Offenses
- But we choose to let the theft features be even though there is an abvious dependency as the total encompases alot more variables than the 3 we have taken

```
X = X.drop(columns = [df.columns[index_cal(df.columns, cat = "Drug/\nNarcotic\nViolations")],
X
```

	Population1	(Crimes Against Society, Drug/\nNarcotic\nOffenses)	(Crimes Against Property, Theft\nFrom\nBuilding)	(Crimes Aga Prope Theft\nFrom\nC \noperated\nMach
0	82332.0	495.0	410.0	
1	36986.0	308.0	12.0	
2	214264.0	2069.0	96.0	
3	0.0	437.0	0.0	
4	5439.0	66.0	39.0	
...	...	...	...	
5230	0.0	196.0	110.0	
5231	0.0	55.0	29.0	
5232	0.0	49.0	0.0	

```
data_pca = (X - X.mean())/X.std()
data_pca = data_pca.T.reset_index(drop=True).T
```

5235 rows × 7 columns

```
data_pca
```

	0	1	2	3	4	5	6
0	2.003261	1.044830	2.221255	0.212311	1.122167	0.839891	1.044830
1	0.742010	0.538969	-0.176648	-0.002158	-0.048220	0.267934	0.538969
2	5.672812	5.302717	0.329442	0.140821	2.087897	0.138291	5.302717
3	-0.286717	0.887932	-0.248947	-0.073647	-0.188923	-0.098118	0.887932
4	-0.135437	-0.115674	-0.013976	-0.073647	-0.089791	-0.128622	-0.115674
...	...	...	...	...	...	...	...
5230	-0.286717	0.235993	0.413790	-0.073647	-0.099385	-0.067614	0.235993
5231	-0.286717	-0.145431	-0.074225	-0.073647	-0.124967	-0.067614	-0.145431
5232	-0.286717	-0.161662	-0.248947	-0.073647	-0.204911	-0.120996	-0.161662
5233	-0.286717	-0.045341	-0.176648	-0.073647	-0.176131	-0.120996	-0.045341
5234	-0.286717	-0.210354	-0.188698	-0.073647	-0.208109	-0.120996	-0.210354

5235 rows × 7 columns

```
pca = PCA(n_components=6)
pca.fit(data_pca)
```

```
explained_variance = pca.explained_variance_ratio_
cum_explained_variance = np.cumsum(explained_variance)
print("Explained captured variance by each component = ", explained_variance)
print("Explained cumulative captured variance by components = ", cum_explained_variance)

print("Explained captured variance with 2 components = ", sum(explained_variance))
```

```
Explained captured variance by each component =  [0.68703114 0.13732232 0.07878435 0.041
Explained cumulative captured variance by components =  [0.68703114 0.82435346 0.903137
Explained captured variance with 2 components =  0.9999999999999999
```

We take 4/5 components

im taking 5 components

Modelling methods

```
pca = PCA(n_components=5)
data_lr = pca.fit_transform(data_pca)
```

```
data_lr
```

```
array([[ 3.37145905, -0.14222539, -0.39798482, -0.85465846, -0.25194109],
       [ 0.75929004, -0.08308684,  0.16884026,  0.59174968, -0.414052  ],
       [ 7.72178686, -0.64225736,  2.15197877,  2.03300198, -4.8014694 ],
       ...,
       [-0.48764128, -0.0250543 ,  0.06414512,  0.07550701,  0.07219197],
       [-0.35003697, -0.04168038,  0.17760192,  0.04926607,  0.05838249],
       [-0.50524947, -0.02356717,  0.01681966,  0.01444081,  0.10766571]])
```

```
X_train, X_test, y_train, y_test = train_test_split(data_lr, y,test_size=0.25,random_state=42
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((3926, 5), (1309, 5), (3926,), (1309,))
```

```
model1 = LinearRegression()
model1.fit(X_train, y_train)
print("intercept_ = ", model1.intercept_,"\n", "coef_ = ", model1.coef_,"\n", "R2 score = ",
```

```
intercept_ =  692.3721688066646
 coef_ =  [1178.63158576  -82.23693486 -126.07015406  -50.44457413  409.14854668]
 R2 score =  0.9509895956778004
```

Models evaluation

```
def RMSE_MAE(model, X_test, y_test):
  RMSE = mean_squared_error(y_test, model.predict(X_test), squared= False)
  MAE = mean_absolute_error(y_test, model.predict(X_test))
  MSE = mean_squared_error(y_test, model.predict(X_test))
  print(type(model).__name__,"\n")
  print("RMSE = ", RMSE, "\n", "MAE = ", MAE, "\n", "MSE = ", MSE)


RMSE_MAE(model1, X_test, y_test)
```

```
LinearRegression

RMSE =  865.4399382453512
 MAE =  220.61999294246908
 MSE =  748986.2867101174
```

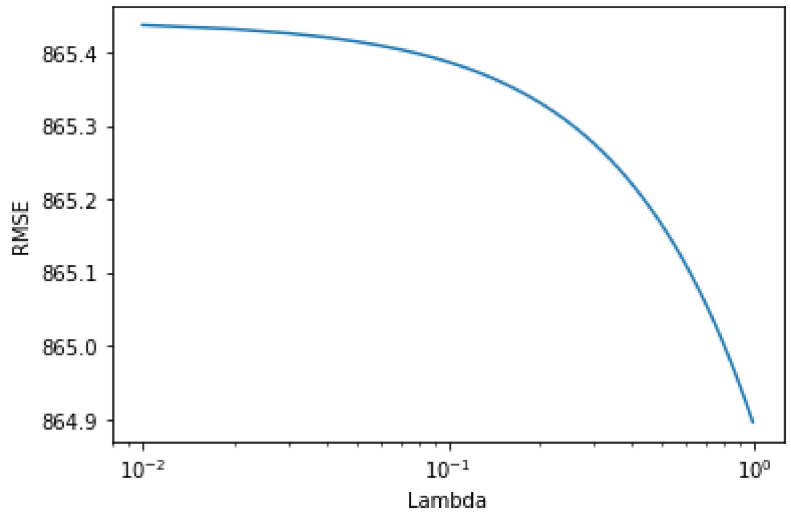
```
scores = cross_val_score(model1, X_test, y_test, cv=5)
scores
```

```
array([ 0.95804947,  0.83148883,  0.90461405,  0.84242363, -1.32228496])
```

```
res = []
for lambda_par in np.arange(0.01, 1.0, 0.01):
  clf = Lasso(alpha=lambda_par)
  clf.fit(X_train, y_train)
  res.append([clf, lambda_par, mean_squared_error(y_test, clf.predict(X_test), squared= False

res_df = pd.DataFrame(res , columns = ["Model", "Lambda", "RMSE"])
res_df = res_df.sort_values(by = "RMSE")
res_df
```

	Model	Lambda	RMSE
98	Lasso(alpha=0.99)	0.99	864.897178

```
sns.lineplot(data = res_df, x= 'Lambda', y = 'RMSE')
plt.xscale('log')
```




```
model2 = res_df["Model"].iloc[0]
model2
```

```
Lasso
Lasso(alpha=0.99)
```

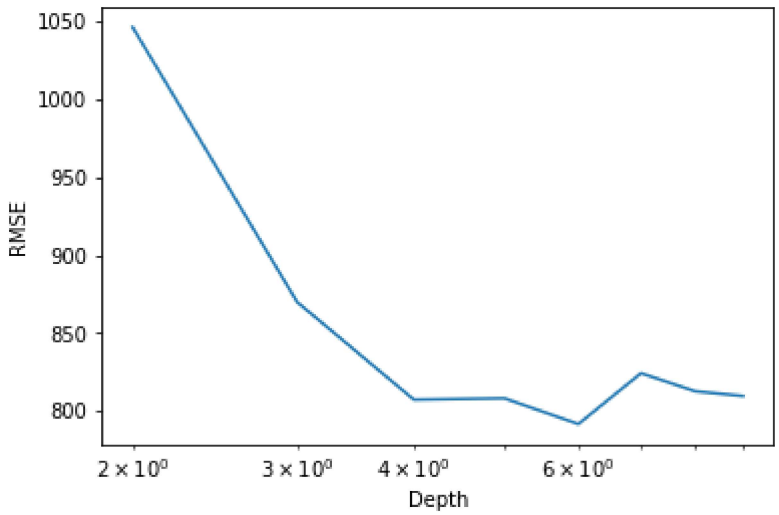
```
RMSE_MAE(model2, X_test, y_test)
print("intercept_ = ", model2.intercept_,"\n", "coef_ = ", model2.coef_,"\n", "R2 score = ",
```

```
Lasso

RMSE =  864.8971784773719
 MAE =  220.278221861578
 MSE =  748047.129338119
intercept_ =  692.3381005040925
 coef_ =  [1178.42167425  -81.15794483 -123.81841888  -46.74507836  404.87993822]
 R2 score =  0.9509877794246799
```

```
res_rf = []
for depth in range(2,10):
  model3 = RandomForestRegressor(max_depth=depth, random_state=0)
  model3.fit(X_train, y_train)
  res_rf.append([model3, depth, mean_squared_error(y_test, model3.predict(X_test), squared= F

res_rf_df = pd.DataFrame(res_rf, columns = ["Model", "Depth", "RMSE"])
res_rf_df = res_rf_df.sort_values(by = "RMSE")
res_rf_df
```

	Model	Depth	RMSE
4	(DecisionTreeRegressor(max_depth=6, max_featur...	6	791.919150
2	(DecisionTreeRegressor(max_depth=4, max_featur...	4	807.510257
3	(DecisionTreeRegressor(max_depth=5, max_featur...	5	808.376613
7	(DecisionTreeRegressor(max_depth=9, max_featur...	9	809.892814
6	(DecisionTreeRegressor(max_depth=8, max_featur...	8	812.903451
5	(DecisionTreeRegressor(max_depth=7, max_featur...	7	824.452582
1	(DecisionTreeRegressor(max_depth=3, max_featur...	3	869.903566
0	(DecisionTreeRegressor(max_depth=2, max_featur...	2	1045.663444

```
sns.lineplot(data = res_rf_df, x= 'Depth', y = 'RMSE')
plt.xscale('log')
```




```
model4 = res_rf_df["Model"].iloc[0]
model4
```

```
RandomForestRegressor
```

```
RMSE_MAE(model4, X_test, y_test)
print("R2 score = ", model4.score(X_train, y_train))
```

```
RandomForestRegressor

RMSE =  791.9191498546378
 MAE =  209.78792131997113
 MSE =  627135.9399064922
R2 score =  0.9731733902638245
```

```
scores2 = cross_val_score(model4, X_test, y_test, cv=5)
scores2
```

```
array([0.54145963, 0.87951444, 0.89131112, 0.92805543, 0.87020669])
```

9- Conclusion

- We can see from the above that Randam foresst regressor is better than Linear regression and lasso Lasso regression with different lambda values
- As we are considering part of the features that is to be expected and random foreast is trying more to capture that inadequecy.

10- Reference

Double-click (or enter) to edit