

```

import pandas as pd
import numpy as np
from statsmodels.formula.api import ols
from scipy import stats
import statsmodels.api as sm
from datetime import datetime
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import StratifiedKFold
from sklearn.preprocessing import StandardScaler, OneHotEncoder, StandardScaler,
MinMaxScaler, LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestRegressor, RandomForestClassifier

from sklearn.metrics import accuracy_score, recall_score, precision_score, f1_score,
confusion_matrix, classification_report, roc_auc_score, roc_curve

df = pd.read_csv('MCI.csv', encoding='utf-8-sig')

#remove rows with null values.. there are 100 of null values as we saw in exploratory
analysis
df = df.dropna()
print("Viewing all columns")
print(df.info()) #to confirm its deleted for null values
print('\n')
#remove rows with null values.. there are 100 of null values as we saw in exploratory
analysis
df = df.dropna()
#remove trailing spaces & delete columns not needed
df.columns = df.columns.str.strip() #For column names
df.columns = [col.strip() for col in df.columns] #For data in each column
print('\n')
del df["X"]
del df["Y"]
del df["Index_"]
del df["event_unique_id"]
del df["Division"]
del df["occurrencedate"]
del df["reporteddate"]
del df["ucr_code"]
del df["ucr_ext"]
del df["reporteddayofyear"]
del df["occurrencedayofyear"]
del df["Hood_ID"]
del df["Longitude"]
del df["Latitude"]
del df["ObjectId"]

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del df["Neighbourhood"]
del df["location_type"]

#####LOGISTIC REGRESSION MCI
CATEGORY#####
#logistics regression
print('\n')
# one hot encoding
print("creating a df_dummy")
#remove mci from df_dummy since its now encoded
df_lr = pd.get_dummies(df, drop_first=False) #logistic regression
df_dummy=pd.get_dummies(df['mci_category'])

#changing each mci type to INT for one hot encoding
df_dummy['Assault']=df_dummy['Assault'].astype(int)
df_dummy['Auto Theft']=df_dummy['Auto Theft'].astype(int)
df_dummy['Break and Enter']=df_dummy['Break and Enter'].astype(int)
df_dummy['Robbery']=df_dummy['Robbery'].astype(int)
df_dummy['Theft Over']=df_dummy['Theft Over'].astype(int)
print("printing to see df1 with INT encoding")
print(df_dummy.info())
print("_____Now lets view the contents of df_dummy")
df_dummy=pd.concat([df, df_dummy], axis=1) #adding the df_dummy to df_premise
print(df_dummy.head())
print('\n')

#compare regression of each mci category with occurrencehour

print('\n')
print("Regression Analysis of Assault mci-category with Occurrence Hour")
reg0 = sm.OLS(df_dummy["Assault"],
sm.add_constant(df_dummy[["occurrencehour"]])).fit()
print(reg0.summary())

print('\n')
print("Regression Analysis of Auto Theft mci-category with Occurrence Hour")
reg1 = sm.OLS(df_dummy["Auto Theft"],
sm.add_constant(df_dummy[["occurrencehour"]])).fit()
print(reg1.summary())

print('\n')
print("Regression Analysis of Break and Enter mci-category with Occurrence Hour")
reg2 = sm.OLS(df_dummy["Break and Enter"],
sm.add_constant(df_dummy[["occurrencehour"]])).fit()
print(reg2.summary())

```

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print('\n')
print("Regression Analysis of Robbery mci-category with Occurrence Hour")
reg3= sm.OLS(df_dummy["Robbery"], sm.add_constant(df_dummy[["occurrencehour"]])).fit()
print(reg3.summary())

print('\n')
print("Regression Analysis of Theft Over mci-category with Occurrence Hour")
reg4= sm.OLS(df_dummy["Theft Over"],
sm.add_constant(df_dummy[["occurrencehour"]])).fit()
print(reg4.summary())

```

The default interactive shell is now zsh.

To update your account to use zsh, please run `chsh -s /bin/zsh`.

For more details, please visit <https://support.apple.com/kb/HT208050>.

```

ndasprojectok:pandasproject royasalehzai$ cd /Users/royasalehzai/studysession/pa
/usr/local/bin/python3 /Users/royasalehzai/studysession/pandasproject/LogisticsRegression.py

```

```

Royas-MacBook:pandasproject royasalehzai$ /usr/local/bin/python3

```

```

/Users/royasalehzai/studysession/pandasproject/LogisticsRegression.py

```

Viewing all columns

```

<class 'pandas.core.frame.DataFrame'>

```

```

Int64Index: 299828 entries, 0 to 299827

```

Data columns (total 30 columns):

#	Column	Non-Null Count	Dtype
0	X	299828 non-null	float64
1	Y	299828 non-null	float64
2	Index_	299828 non-null	int64
3	event_unique_id	299828 non-null	object
4	Division	299828 non-null	object
5	occurrencedate	299828 non-null	object
6	reporteddate	299828 non-null	object
7	location_type	299828 non-null	object
8	premises_type	299828 non-null	object
9	ucr_code	299828 non-null	int64
10	ucr_ext	299828 non-null	int64
11	offence	299828 non-null	object
12	reportedyear	299828 non-null	int64
13	reportedmonth	299828 non-null	object
14	reportedday	299828 non-null	int64
15	reporteddayofyear	299828 non-null	int64
16	reporteddayofweek	299828 non-null	object

```

17 reportedhour      299828 non-null int64
18 occurrenceyear    299828 non-null float64
19 occurrencemonth    299828 non-null object
20 occurredday       299828 non-null float64
21 occurreddayofyear  299828 non-null float64
22 occurreddayofweek  299828 non-null object
23 occurrencehour     299828 non-null int64
24 mci_category       299828 non-null object
25 Hood_ID           299828 non-null object
26 Neighbourhood      299828 non-null object
27 Longitude          299828 non-null float64
28 Latitude           299828 non-null float64
29 Objectid           299828 non-null int64
dtypes: float64(7), int64(9), object(14)
memory usage: 70.9+ MB
None

```

```

creating a df_dummy
printing to see df1 with INT encoding
<class 'pandas.core.frame.DataFrame'>
Int64Index: 299828 entries, 0 to 299827
Data columns (total 5 columns):
#  Column      Non-Null Count  Dtype
---  ---
0  Assault      299828 non-null  int64
1  Auto Theft   299828 non-null  int64
2  Break and Enter  299828 non-null  int64
3  Robbery      299828 non-null  int64
4  Theft Over   299828 non-null  int64
dtypes: int64(5)
memory usage: 13.7 MB
None

```

Now lets view the contents of df_dummy

	premises_type	offence	reportedyear	reportedmonth	reportedday	...	Assault	Auto Theft	Break and Enter	Robbery	Theft Over
0	Apartment	Assault	2014	January	3 ...	1	0	0	0	0	0
1	House	B&E	2014	January	3 ...	0	0	1	0	0	0
2	Outside	Assault	2014	January	3 ...	1	0	0	0	0	0

3	Commercial	Theft Over	2014	January	3 ...	0	0	0	0
1									
4	Commercial	Robbery - Business	2014	January	3 ...	0	0	0	0
1	0								

[5 rows x 18 columns]

Regression Analysis of Assault mci-category with Occurrence Hour

OLS Regression Results

```

=====
Dep. Variable:      Assault  R-squared:      0.000
Model:             OLS  Adj. R-squared:     0.000
Method:            Least Squares  F-statistic:    139.1
Date:              Wed, 12 Apr 2023  Prob (F-statistic):  4.24e-32
Time:              02:28:27  Log-Likelihood:   -2.1676e+05
No. Observations:   299828  AIC:              4.335e+05
Df Residuals:       299826  BIC:              4.335e+05
Df Model:           1
Covariance Type:    nonrobust
=====
=====
              coef  std err      t  P>|t|  [0.025  0.975]
-----
const          0.5174   0.002  282.491   0.000   0.514   0.521
occurrencehour  0.0015   0.000   11.794   0.000   0.001   0.002
=====
Omnibus:         1035622.654  Durbin-Watson:      1.522
Prob(Omnibus):    0.000  Jarque-Bera (JB):    49884.582
Skew:             -0.145  Prob(JB):           0.00
Kurtosis:         1.023  Cond. No.           29.4
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression Analysis of Auto Theft mci-category with Occurrence Hour

OLS Regression Results

```

=====
Dep. Variable:      Auto Theft  R-squared:      0.007
Model:             OLS  Adj. R-squared:     0.007

```

Method: Least Squares F-statistic: 1980.
Date: Wed, 12 Apr 2023 Prob (F-statistic): 0.00
Time: 02:28:27 Log-Likelihood: -1.0332e+05
No. Observations: 299828 AIC: 2.066e+05
Df Residuals: 299826 BIC: 2.067e+05
Df Model: 1
Covariance Type: nonrobust

```
=====
=====
=====
              coef  std err      t  P>|t|   [0.025   0.975]
-----
const          0.0874    0.001  69.687   0.000    0.085    0.090
occurrencehour  0.0038  8.62e-05  44.497   0.000    0.004    0.004
=====
Omnibus:          111083.844 Durbin-Watson:          0.511
Prob(Omnibus):          0.000 Jarque-Bera (JB):      298697.413
Skew:              2.105 Prob(JB):          0.00
Kurtosis:          5.487 Cond. No.          29.4
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression Analysis of Break and Enter mci-category with Occurrence Hour

OLS Regression Results

```
=====
Dep. Variable:      Break and Enter R-squared:          0.017
Model:              OLS Adj. R-squared:          0.017
Method:             Least Squares F-statistic:        5104.
Date:               Wed, 12 Apr 2023 Prob (F-statistic): 0.00
Time:               02:28:27 Log-Likelihood: -1.4701e+05
No. Observations:   299828 AIC: 2.940e+05
Df Residuals:       299826 BIC: 2.940e+05
Df Model:           1
Covariance Type:    nonrobust
=====
=====
=====
              coef  std err      t  P>|t|   [0.025   0.975]
-----
const          0.2879    0.001  198.360   0.000    0.285    0.291
occurrencehour -0.0071  9.97e-05 -71.439   0.000   -0.007   -0.007
=====
Omnibus:          61969.760 Durbin-Watson:          1.757
```

Prob(Omnibus): 0.000 Jarque-Bera (JB): 110102.548
Skew: 1.477 Prob(JB): 0.00
Kurtosis: 3.290 Cond. No. 29.4

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression Analysis of Robbery mci-category with Occurrence Hour
OLS Regression Results

Dep. Variable: Robbery R-squared: 0.002
Model: OLS Adj. R-squared: 0.002
Method: Least Squares F-statistic: 671.0
Date: Wed, 12 Apr 2023 Prob (F-statistic): 8.63e-148
Time: 02:28:28 Log-Likelihood: -60513.
No. Observations: 299828 AIC: 1.210e+05
Df Residuals: 299826 BIC: 1.211e+05
Df Model: 1
Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]
const	0.0729	0.001	67.012	0.000	0.071	0.075
occurrencehour	0.0019	7.48e-05	25.904	0.000	0.002	0.002

Omnibus: 156646.412 Durbin-Watson: 1.622
Prob(Omnibus): 0.000 Jarque-Bera (JB): 725078.786
Skew: 2.708 Prob(JB): 0.00
Kurtosis: 8.358 Cond. No. 29.4

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Regression Analysis of Theft Over mci-category with Occurrence Hour
OLS Regression Results

Dep. Variable: Theft Over R-squared: 0.000
Model: OLS Adj. R-squared: 0.000
Method: Least Squares F-statistic: 8.611

Date: Wed, 12 Apr 2023 Prob (F-statistic): 0.00334
Time: 02:28:28 Log-Likelihood: 92260.
No. Observations: 299828 AIC: -1.845e+05
Df Residuals: 299826 BIC: -1.845e+05
Df Model: 1
Covariance Type: nonrobust

=====

	coef	std err	t	P> t	[0.025	0.975]
const	0.0344	0.001	52.606	0.000	0.033	0.036
occurrencehour	-0.0001	4.49e-05	-2.935	0.003	-0.000	-4.38e-05

=====

Omnibus: 298552.524 Durbin-Watson: 1.870
Prob(Omnibus): 0.000 Jarque-Bera (JB): 9567890.777
Skew: 5.254 Prob(JB): 0.00
Kurtosis: 28.602 Cond. No. 29.4

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Royas-MacBook:pandasproject royasalehzai\$