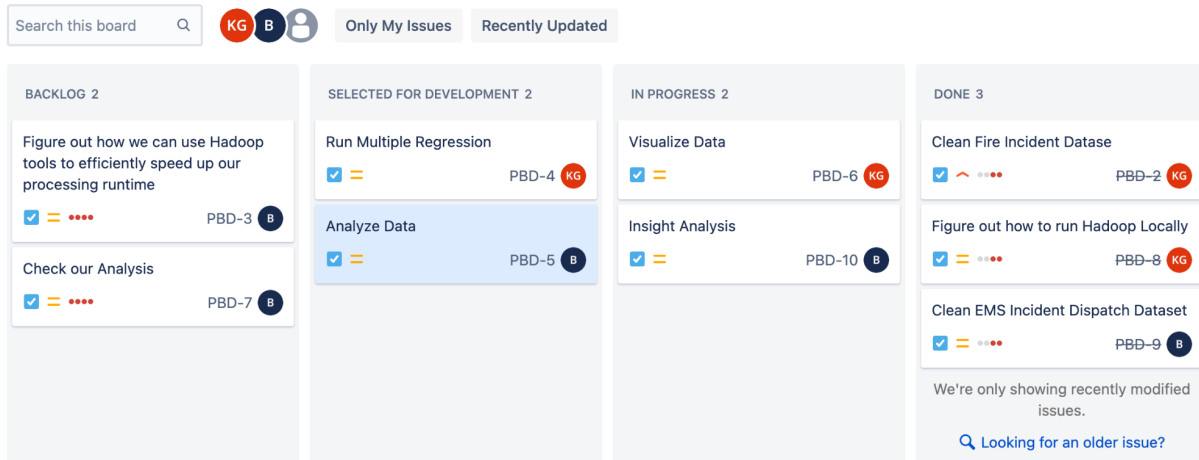


## Jira Board

Projects / Processing Big Data / PBD board

### Kanban board



## Code Drop

Apart from our MapReduce programs (cleaning and counting bad records), we have extended our code for visualizations and analysis.

```
import numpy as np
import pandas as pd
import random

data = pd.read_csv('EMS_Incident_Dispatch_Data.csv')
df = pd.DataFrame(data)

sample_df = df.sample(frac = 0.2)
cleaned =
sample_df[['CAD_INCIDENT_ID','FINAL_CALL_TYPE','FINAL_SEVERITY_LEVEL_CODE','DIS
PATCH_RESPONSE_SECONDS_QY','INCIDENT_RESPONSE_SECONDS_QY','INCIDENT_T
RAVEL_TM_SECONDS_QY','BOROUGH','ZIPCODE','POLICEPRECINCT']]
cleaned = cleaned.dropna()

# Figure 1
import matplotlib.pyplot as plt

f = plt.figure(figsize=(19, 15))
plt.matshow(cleaned.corr(), fignum=f.number)
plt.xticks(range(cleaned.select_dtypes(['number']).shape[1]),
cleaned.select_dtypes(['number']).columns, fontsize=14, rotation=45)
plt.yticks(range(cleaned.select_dtypes(['number']).shape[1]),
cleaned.select_dtypes(['number']).columns, fontsize=14)
cb = plt.colorbar()
```

```

cb.ax.tick_params(labelsize=14)
plt.title('Correlation Matrix', fontsize=16);

response_time =
cleaned.groupby(by=['FINAL_CALL_TYPE','FINAL_SEVERITY_LEVEL_CODE']).mean().reset_index()

# Figure 2
# Scatter plot with day against tip
plt.scatter(cleaned['FINAL_SEVERITY_LEVEL_CODE'],
cleaned['DISPATCH_RESPONSE_SECONDS_QY'])

# Adding Title to the Plot
plt.title("Scatter Plot")

# Setting the X and Y labels
plt.xlabel('Severity Code')
plt.ylabel('Dispatch Response Time')

plt.show()

# Figure 3
plt.scatter(cleaned['FINAL_SEVERITY_LEVEL_CODE'],
cleaned['INCIDENT_RESPONSE_SECONDS_QY'])

# Adding Title to the Plot
plt.title("Scatter Plot")

# Setting the X and Y labels
plt.xlabel('Severity Code')
plt.ylabel('Incident Response Time')

plt.show()

# Figure 4
import seaborn as sns

sns.scatterplot(x='DISPATCH_RESPONSE_SECONDS_QY',
y='INCIDENT_RESPONSE_SECONDS_QY', data=cleaned,
hue='FINAL_SEVERITY_LEVEL_CODE')
plt.show()

# Figure 5

```

```
sns.scatterplot(x='POLICEPRECINCT', y='INCIDENT_RESPONSE_SECONDS_QY',
data=cleaned,
hue='FINAL_SEVERITY_LEVEL_CODE')
plt.show()
```

```
boroughs = cleaned.groupby(by=['BOROUGH']).mean().reset_index()
boroughs_final =
boroughs[['BOROUGH','DISPATCH_RESPONSE_SECONDS_QY','INCIDENT_RESPONSE_S
ECONDS_QY','INCIDENT_TRAVEL_TM_SECONDS_QY']]
```

# Figure 6

```
plt.scatter(cleaned['FINAL_SEVERITY_LEVEL_CODE'],
cleaned['INCIDENT_RESPONSE_SECONDS_QY'], color='red')
plt.title('Severity Code Vs Incident Response Time', fontsize=14)
plt.xlabel('Severity Rate', fontsize=14)
plt.ylabel('Incident Response Time Price', fontsize=14)
plt.grid(True)
plt.show()
```

# Figure 7

```
plt.scatter(cleaned['DISPATCH_RESPONSE_SECONDS_QY'],
cleaned['INCIDENT_RESPONSE_SECONDS_QY'], color='red')
plt.title('Dispatch Response Time Vs Incident Response Time', fontsize=14)
plt.xlabel('Dispatch Response Time', fontsize=14)
plt.ylabel('Incident Response Time Price', fontsize=14)
plt.grid(True)
plt.show()
```

# OLS

```
from sklearn import linear_model
import statsmodels.api as sm
```

```
X = cleaned[['FINAL_SEVERITY_LEVEL_CODE','DISPATCH_RESPONSE_SECONDS_QY']]
y = cleaned['INCIDENT_RESPONSE_SECONDS_QY']
```

```
regr = linear_model.LinearRegression()
regr.fit(X, y)
```

```
print('Intercept: \n', regr.intercept_)
print('Coefficients: \n', regr.coef_)
```

# with statsmodels

```
X = sm.add_constant(X) # adding a constant
```

```
model = sm.OLS(y, X).fit()
predictions = model.predict(X)

print_model = model.summary()
print(print_model)

from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error

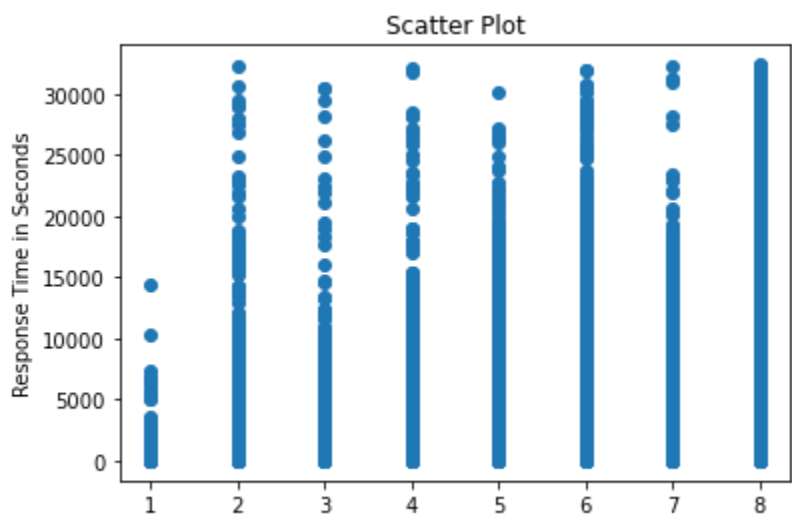
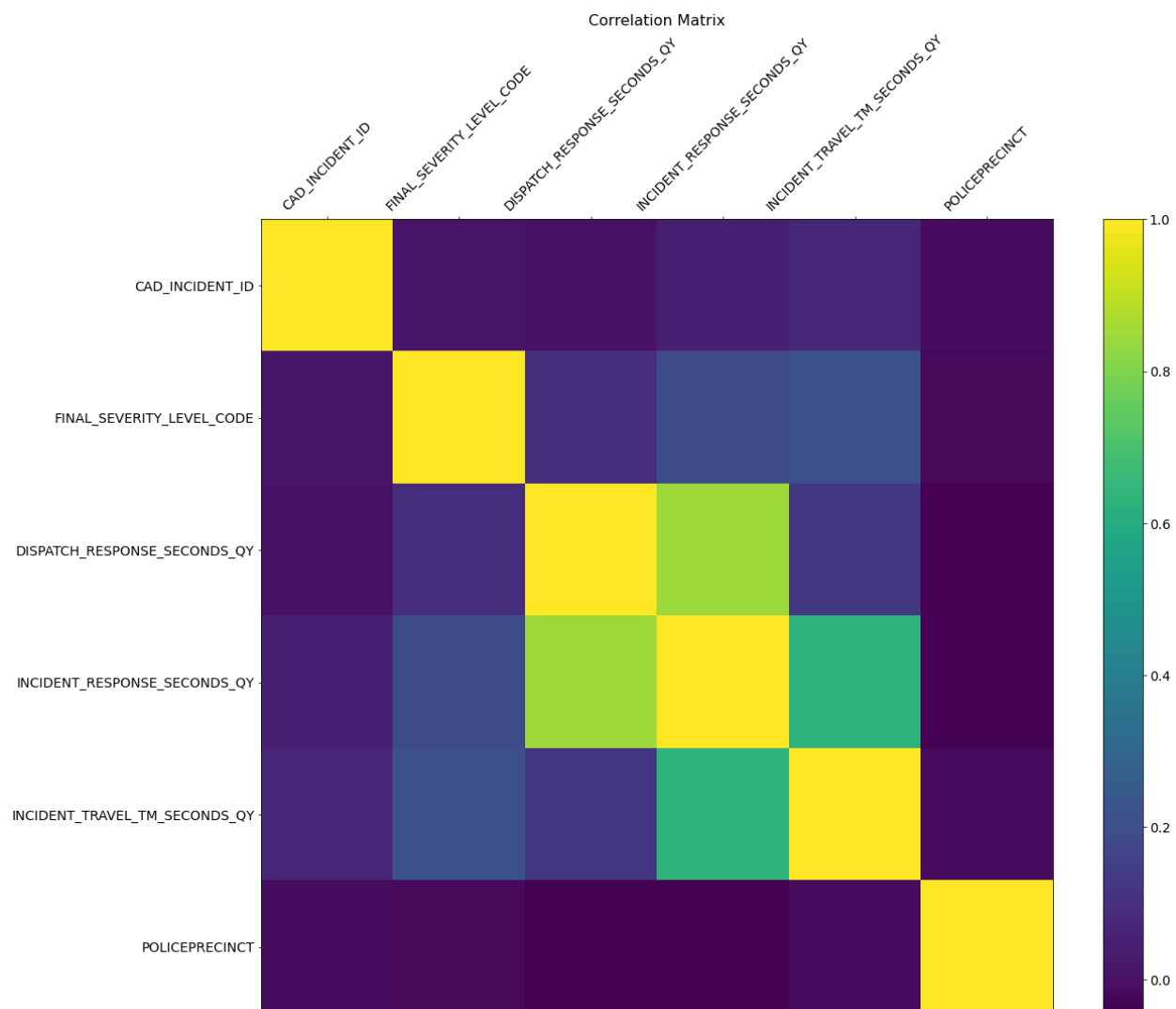
X = cleaned[['FINAL_SEVERITY_LEVEL_CODE','DISPATCH_RESPONSE_SECONDS_QY']]
y = cleaned['INCIDENT_RESPONSE_SECONDS_QY']

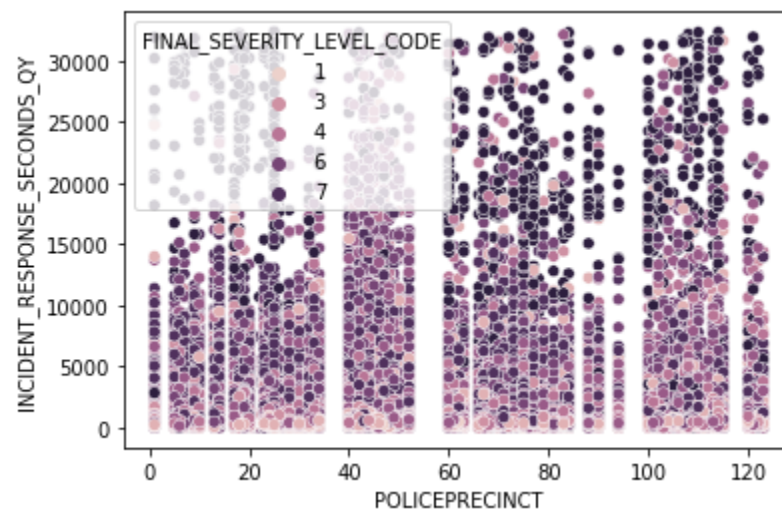
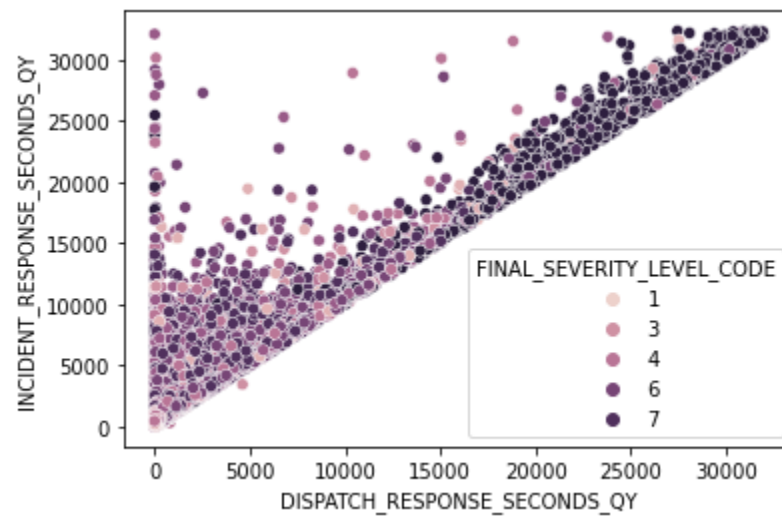
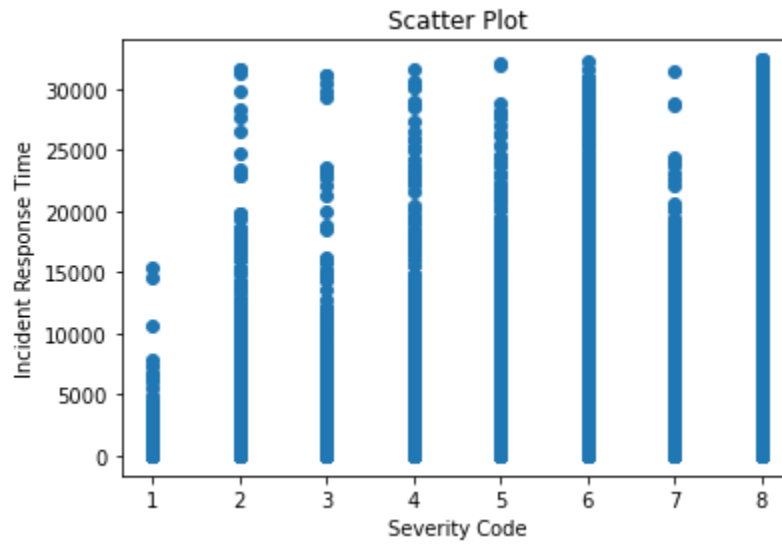
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state = 42)

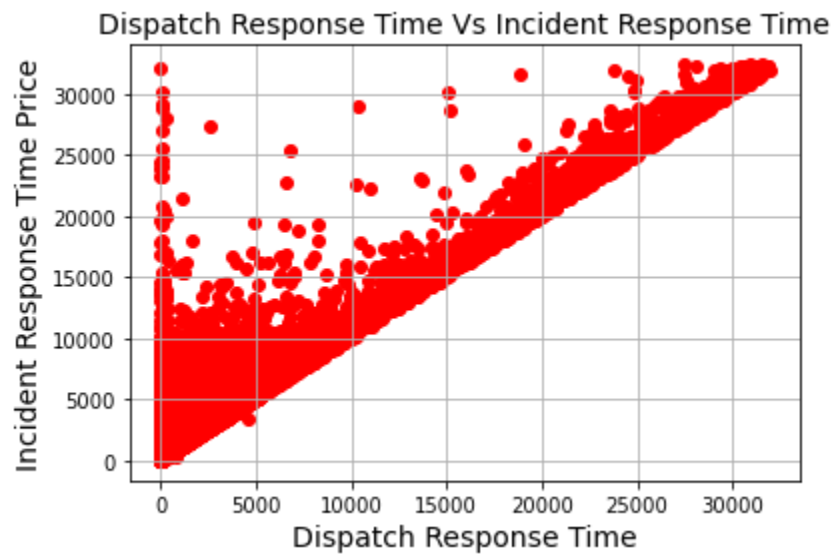
regr = linear_model.LinearRegression()
regr.fit(X, y)

y_prediction = regr.predict(X_test)

score=r2_score(y_test,y_prediction)
print('R^2 score: ',score)
print('MSE: ', mean_squared_error(y_test,y_prediction))
print('RMSE: ', np.sqrt(mean_squared_error(y_test,y_prediction)))
```







Intercept:  
271.1995982854357  
Coefficients:  
[43.49949337 1.07161985]

#### OLS Regression Results

```
=====
Dep. Variable:    INCIDENT_RESPONSE_SECONDS_QY    R-squared:    0.720
Model:            OLS                            Adj. R-squared: 0.720
Method:          Least Squares                    F-statistic:   5.615e+06
Date:            Wed, 16 Nov 2022                  Prob (F-statistic): 0.00
Time:            18:23:39                          Log-Likelihood: -3.1562e+07
No. Observations: 4376996                          AIC:           6.312e+07
Df Residuals:    4376993                          BIC:           6.312e+07
Df Model:        2
Covariance Type: nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
const	271.1996	0.417	650.328	0.000	270.382	272.017
FINAL_SEVERITY_LEVEL_CODE	43.4995	0.094	462.990	0.000	43.315	43.684
DISPATCH_RESPONSE_SECONDS_QY	1.0716	0.000	3260.675	0.000	1.071	1.072

```
=====
Omnibus:            5937314.162    Durbin-Watson:    1.999
Prob(Omnibus):      0.000          Jarque-Bera (JB): 10585682659.985
Skew:               7.057          Prob(JB):         0.00
Kurtosis:           243.509        Cond. No.         1.32e+03
=====
```

#### Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.  
[2] The condition number is large, 1.32e+03. This might indicate that there are strong multicollinearity or other numerical problems.

**R<sup>2</sup> score: 0.7203704041380895**

**MSE: 108600.12941593894**

**RMSE: 329.5453374210276**