CSCE 633 Homework 2: Urban Traffic Prediction

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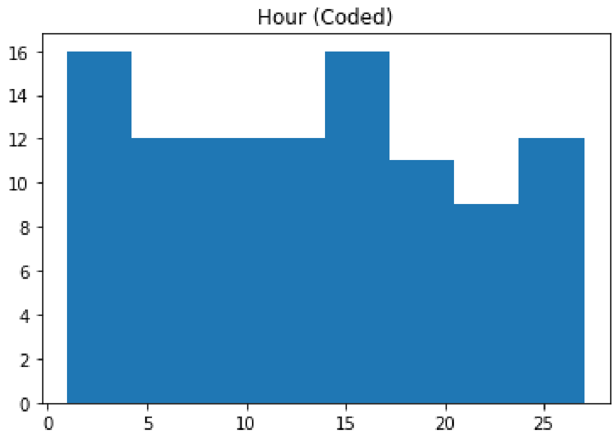
[1]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

from scipy.stats import pearsonr

from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn.model_selection import RepeatedKFold
```

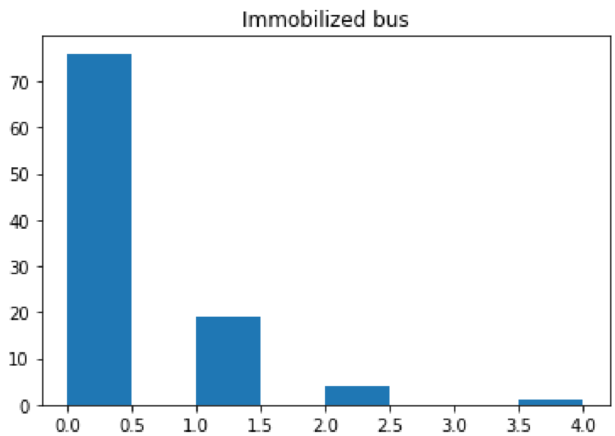
[2]:
```
# Import data into dataframes
df_train = pd.read_csv('hw2__question1_train.csv', sep = ',')
df_test = pd.read_csv('hw2__question1_test.csv', sep = ',')

# Segregate the outcome column in both train and test data
newX = df_train.iloc[:,:-1]
testX = df_test.iloc[:,:-1]
newY= df_train.iloc[:,-1]
testY = df_test.iloc[:,-1]
```

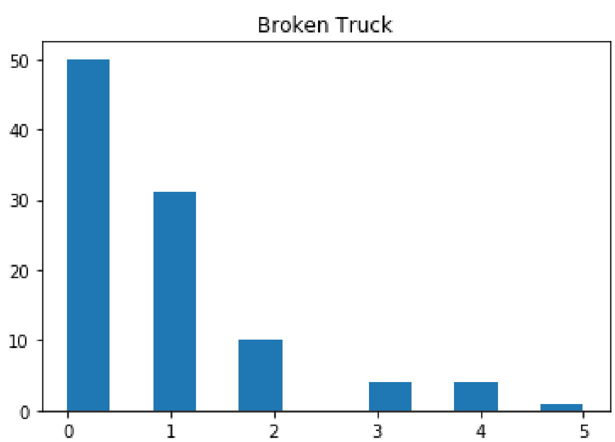
1 (i.) Data Exploration

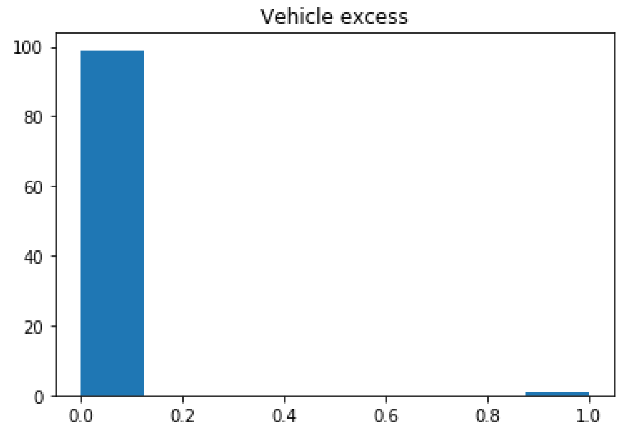
Histogram of Features and Outcome of interest

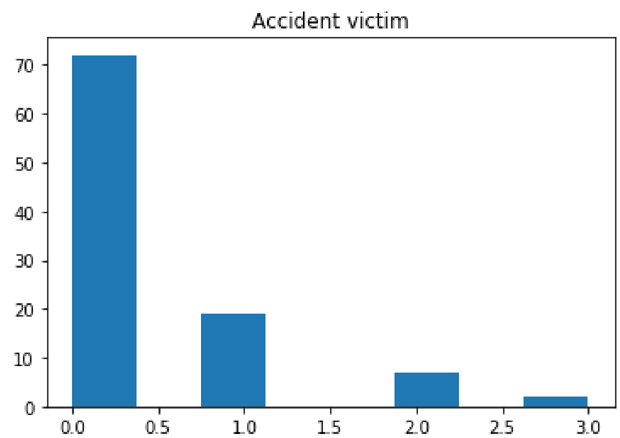
[3]:
```
# Plot histogram of features
for i in range(df_train.shape[1]):
    plt.hist(df_train.iloc[:,i], bins='auto')
    plt.title(df_train.columns[i])
    plt.figure()
```

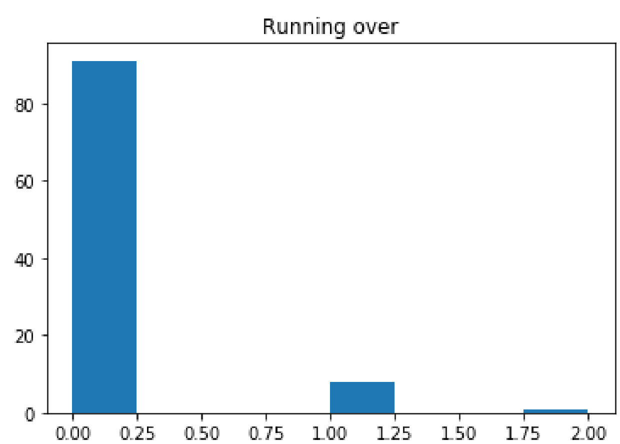

Hour (Coded)
0
2
4
6
8
10
12
14
16
0
5
10
15
20
25

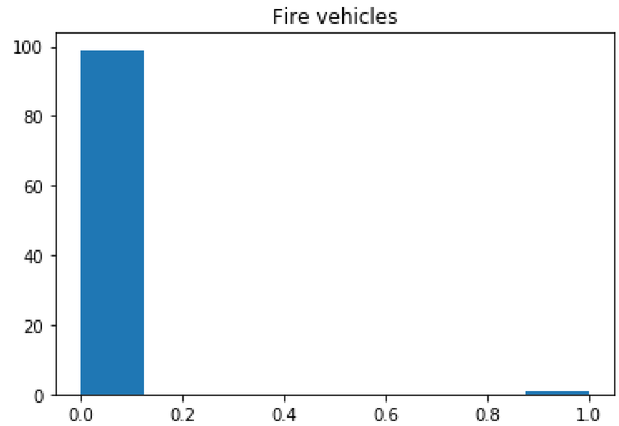

Immobilized bus
0
10
20
30
40
50
60
70
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0

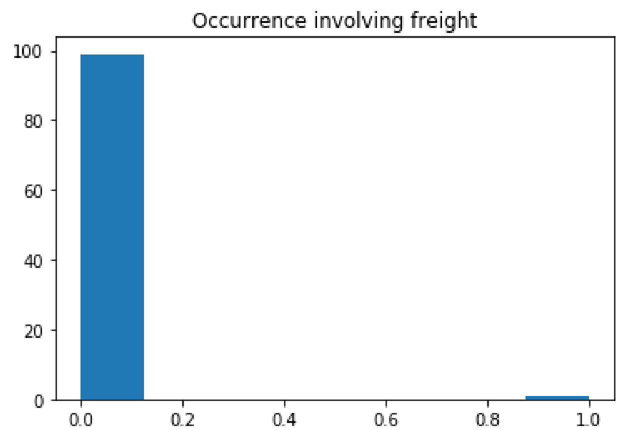

Broken Truck
0
10
20
30
40
50
0
1
2
3
4
5

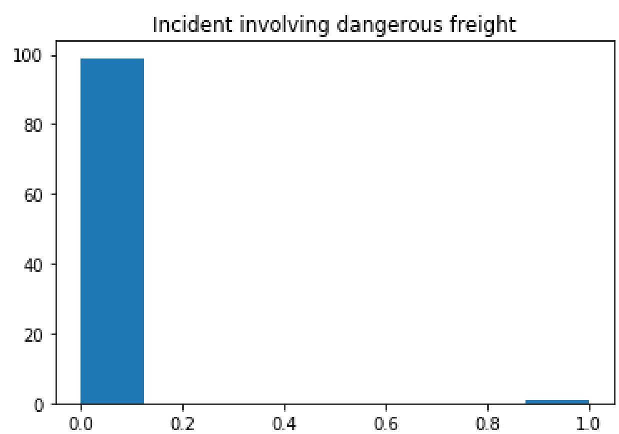

Vehicle excess
100
80
60
40
20
0
0.0
0.2
0.4
0.6
0.8
1.0

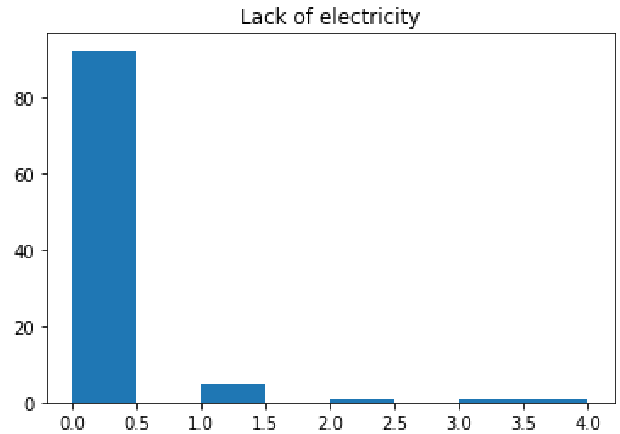

Accident victim
70
60
50
40
30
20
10
0
0.0
0.5
1.0
1.5
2.0
2.5
3.0

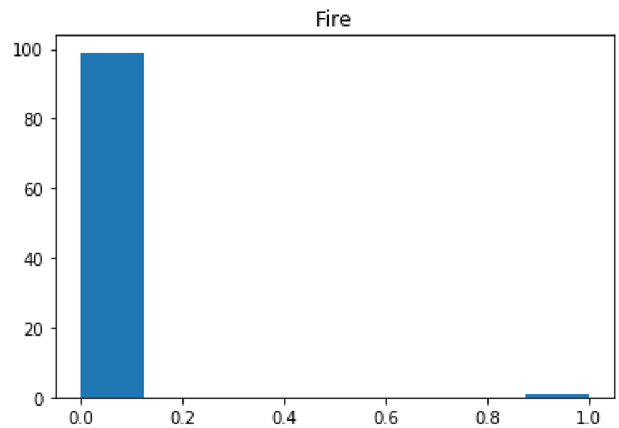

Running over
80
60
40
20
0
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00

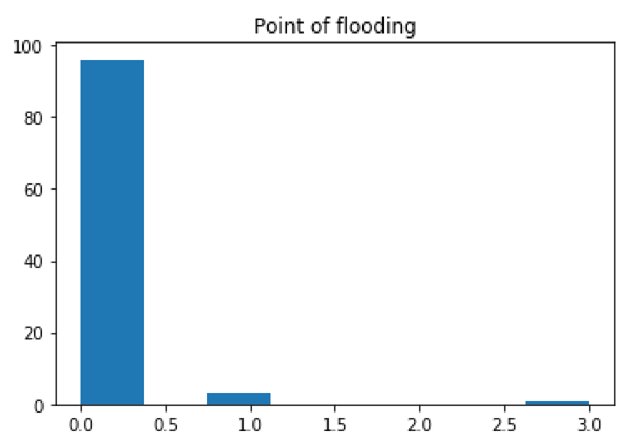

Fire vehicles
100
80
60
40
20
0
0.0
0.2
0.4
0.6
0.8
1.0

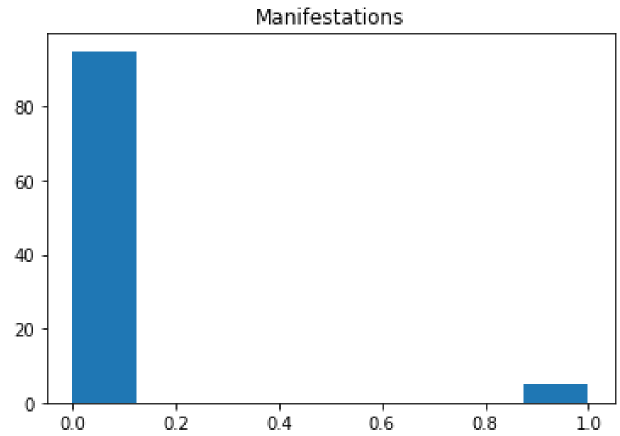

Occurrence involving freight
100
80
60
40
20
0
0.0
0.2
0.4
0.6
0.8
1.0

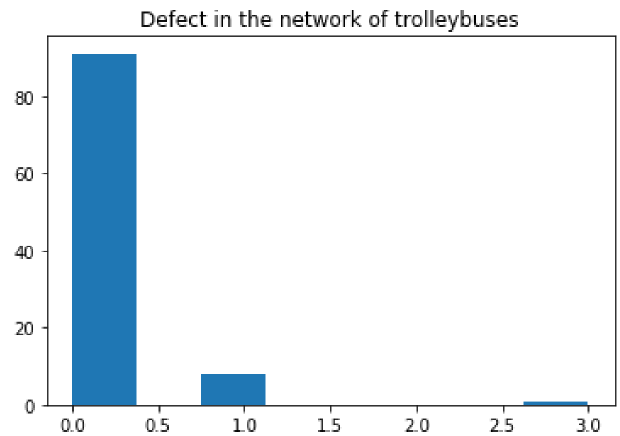

Incident involving dangerous freight
100
80
60
40
20
0
0.0
0.2
0.4
0.6
0.8
1.0

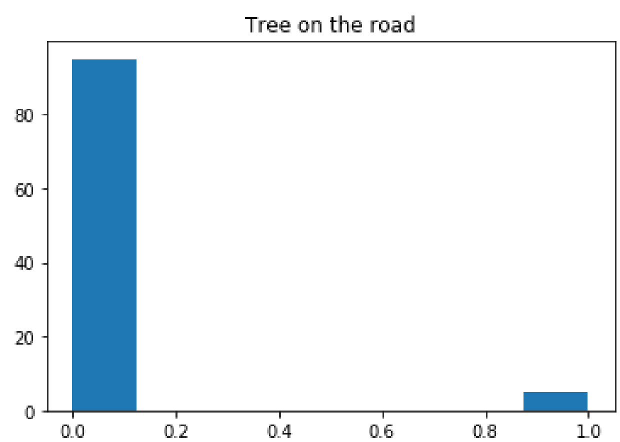

Lack of electricity
80
60
40
20
0
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0

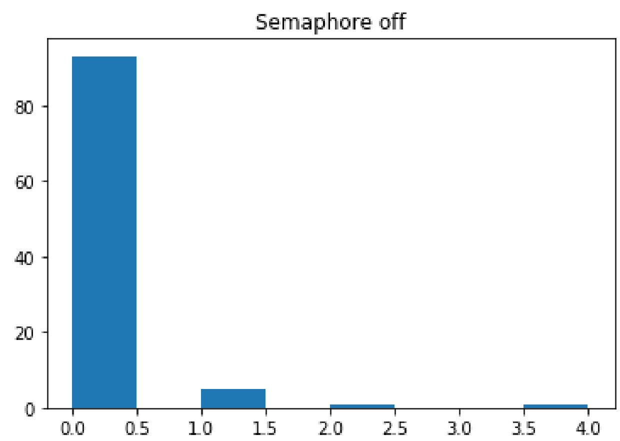

Fire
100
80
60
40
20
0
0.0
0.2
0.4
0.6
0.8
1.0

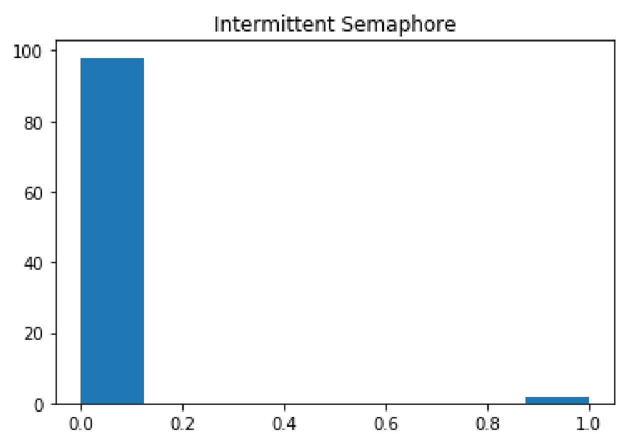

Point of flooding
100
80
60
40
20
0
0.0
0.5
1.0
1.5
2.0
2.5
3.0

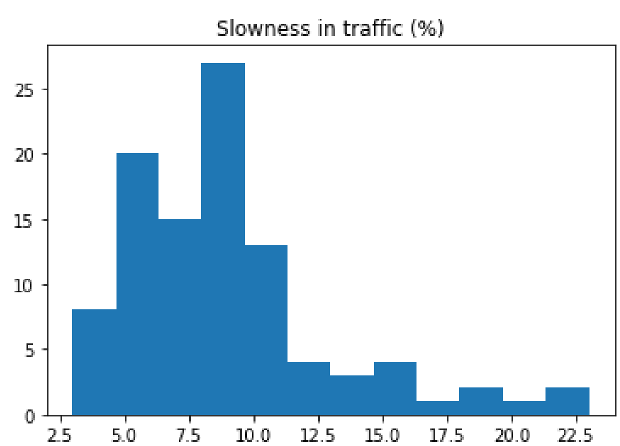

Manifestations
80
60
40
20
0
0.0
0.2
0.4
0.6
0.8
1.0


Defect in the network of trolleybuses
80
60
40
20
0
0.0
0.5
1.0
1.5
2.0
2.5
3.0


Tree on the road
80
60
40
20
0
0.0
0.2
0.4
0.6
0.8
1.0








```
<Figure size 432x288 with 0 Axes>
```

2 (ii.) Data Exploration

Pearson Coefficient between each feature and the outcome of interest

[4]:
```
# Computer pearson's correlation coefficient between all features and the␣
↪outcome of interest
print("Computation of Pearson's correlation coefficient"
      " between features and the outcome of interest (% slowness in traffic):␣
↪\n")
print("Correlation  \t Feature ")
for i in range(df_train.shape[1]-1):
    corr, p = pearsonr(df_train.iloc[:,i], newY)
    print("%0.3f\t\t" % corr, df_train.columns[i] )
```

```
Computation of Pearson's correlation coefficient between features and the
outcome of interest (% slowness in traffic):

Correlation      Feature
0.671            Hour (Coded)
0.155            Immobilized bus
0.147            Broken Truck
-0.146           Vehicle excess
0.127            Accident victim
-0.012           Running over
0.184            Fire vehicles
0.057            Occurrence involving freight
0.032            Incident involving dangerous freight
0.574            Lack of electricity
-0.045           Fire
0.456            Point of flooding
-0.056           Manifestations
-0.168           Defect in the network of trolleybuses
-0.079           Tree on the road
0.429            Semaphore off
-0.136           Intermittent Semaphore
```

3 (iii.) Implementation of Linear Regression

[5]:
```
# Implementaion of Linear Regression

# Add the ones column in the input matrix in the train data
intercept = np.ones((newX.shape[0],1))
X = np.concatenate((intercept,newX.values),1)
```

```
# Add the ones column in the input matrix in the test data
intercept_test = np.ones((df_test.shape[0],1))
X_test = np.concatenate((intercept_test,testX.values),1)

# Compute the optimal weight vector w* using the OLS solution
term1 = X.T.dot(X)
term1_inv = np.linalg.inv(term1)
term2 = X.T.dot(newY.values)
w = term1_inv.dot(term2)
```

4 (iv.) Testing of model

[6]:
```
# Predict Y (outcome of interest) on test data
Y_pred = np.matmul(X_test,np.transpose(w))

# Using the Pearson's Correlation Coefficient
# Compute the correlation between predicted and actual output
test_score, test_score_p = pearsonr(Y_pred,testY.values)
print("Pearson's Correlation Coefficient Metrics: ")
print("r=" + format(test_score, '.2f') + ", p=" + format(test_score_p, '.2f'))

# Using the RSS
# Compute the RSS between predicted and actual output
rss = np.sum(np.square(Y_pred - testY.values))
print("Residual Sum of Squares Metrics: ")
print("rss_err=" + format(rss, '.2f'))
```

```
Pearson's Correlation Coefficient Metrics:
r=0.82, p=0.00
Residual Sum of Squares Metrics:
rss_err=501.86
```

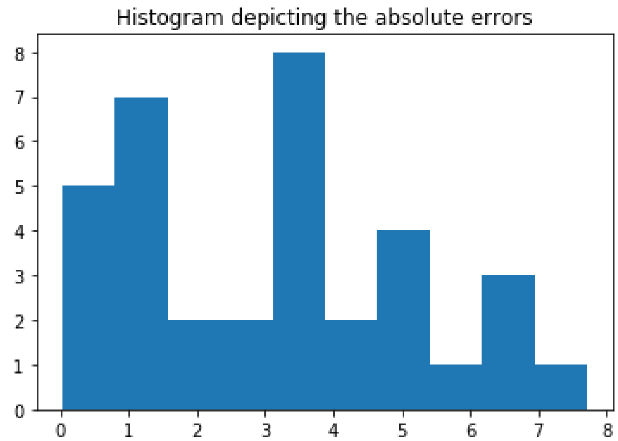
5 (v.) Different Feature Combinations

[7]:
```
# Helper Modular Function

def test_linreg(newX_drop, testX_drop):

    # Implementaion of Linear Regression
    # Add the ones column in the input matrix in the train data
    intercept = np.ones((newX_drop.shape[0],1))
    X = np.concatenate((intercept,newX_drop.values),1)
    # Add the ones column in the input matrix in the test data
    intercept_test = np.ones((testX_drop.shape[0],1))
    X_test = np.concatenate((intercept_test,testX_drop.values),1)
```

```
    # Compute the optimal weight vector w* using the OLS solution
    term1 = X.T.dot(X)
    term1_inv = np.linalg.inv(term1)
    term2 = X.T.dot(newY.values)
    w = term1_inv.dot(term2)

    # Predict Y (outcome of interest) on test data
    Y_pred = np.matmul(X_test,np.transpose(w))

    # Compute the correlation between predicted and actual output
    test_score, test_score_p = pearsonr(Y_pred,testY.values)
    # Compute the RSS between predicted and actual output
    rss = np.sum(np.square(Y_pred - testY.values))

    plt.hist(abs(Y_pred - testY.values))
    plt.title("Histogram depicting the absolute errors")
    plt.figure()

    return test_score, test_score_p, rss
```

[8]:
```
# Feature Edit 1
# Remove three features with correlation < 0.5

drop_col1 = ['Fire','Incident involving dangerous freight','Running over']
newX_drop1 = newX.drop(columns=drop_col1)
testX_drop1 = testX.drop(columns=drop_col1)
test_score, test_score_p, rss = test_linreg(newX_drop1, testX_drop1)
print("Pearson's Correlation Coefficient Metrics: ")
print("r=" + format(test_score, '.2f') + ", p=" + format(test_score_p, '.2f'))
print("Residual Sum of Squares Metrics: ")
print("rss_err=" + format(rss, '.2f'))
```

```
Pearson's Correlation Coefficient Metrics:
r=0.82, p=0.00
Residual Sum of Squares Metrics:
rss_err=498.86
```




```
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```
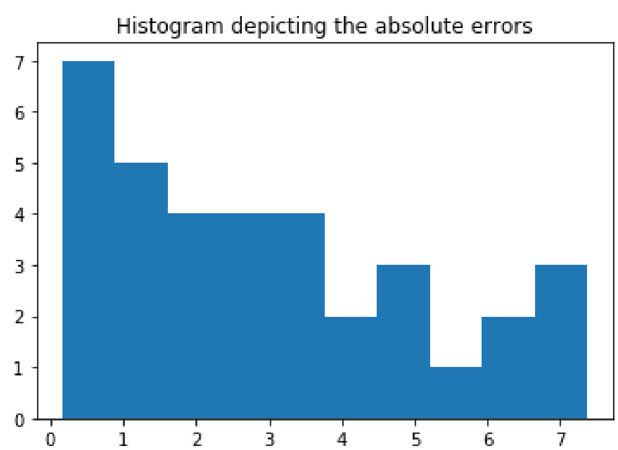

[9]:
```
# Feature Edit 2
# Use only three features with maximum |correlation|

drop_col2 = columns=['Point of flooding','Lack of electricity','Hour (Coded)']
newX_drop2 = newX[drop_col2]
testX_drop2 = testX[drop_col2]
test_score, test_score_p, rss = test_linreg(newX_drop2, testX_drop2)
print("Pearson's Correlation Coefficient Metrics: ")
print("r=" + format(test_score, '.2f') + ", p=" + format(test_score_p, '.2f'))
print("Residual Sum of Squares Metrics: ")
print("rss_err=" + format(rss, '.2f'))
```

```
Pearson's Correlation Coefficient Metrics:
r=0.80, p=0.00
Residual Sum of Squares Metrics:
rss_err=447.93
```



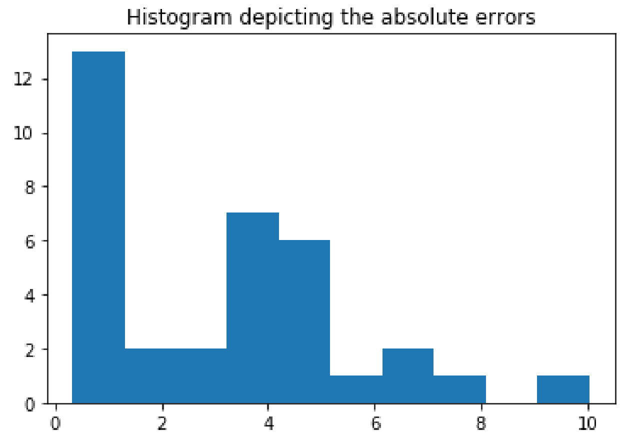
```
<Figure size 432x288 with 0 Axes>
```

[10]:
```python
# Feature Edit 3
# Check the correlation between features
# if two features are highly correlated, one can be removed to reduce redundancy and dimension of feature space

# Pearson's correlation between pairs of features
numFeatures = df_train.shape[1]-1

print("Feature Columns with absolute correlation greater than 0.5: ")
for i in range(numFeatures):
    for j in range(numFeatures):
        corr, p = pearsonr(newX.iloc[:,i], newX.iloc[:,j])
        # print(format(corr, '.2f'), end = ', ')
        if (abs(corr) > 0.5) and (i != j):
            print(i, j)
    # print()
```

```
Feature Columns with absolute correlation greater than 0.5:
9 11
9 15
11 9
15 9
```

[11]:
```python
# We observe that following pair of features are highly correlated:
    # 'Lack of electricity' (9) and 'Point of flooding' (11)
    # 'Lack of electricity' (9) and'Semaphore off' (15)

# Hence we may drop the 'Lack of electricity' feature and test.

drop_col3 = ['Lack of electricity']
newX_drop3 = newX.drop(columns=drop_col3)
testX_drop3 = testX.drop(columns=drop_col3)
test_score, test_score_p, rss = test_linreg(newX_drop3, testX_drop3)
print("Pearson's Correlation Coefficient Metrics: ")
print("r=" + format(test_score, '.2f') + ", p=" + format(test_score_p, '.2f'))
print("Residual Sum of Squares Metrics: ")
print("rss_err=" + format(rss, '.2f'))
```

```
Pearson's Correlation Coefficient Metrics:
r=0.80, p=0.00
Residual Sum of Squares Metrics:
rss_err=514.16
```




```
<Figure size 432x288 with 0 Axes>
```

Three observations were made: 1. Upon dropping the three features that had minimum correlation with the outcome of interest, RSS got reduced with no reduction in correlation metrics. 2. Upon using only three features, the ones with maximum correlation with the outcome of interest, RSS got further reduced with a slight decrease in correlation metrics. 3. By dropping a feature with a decent correlation with the outcome of interest but redundant, there was only a slight decrease in correlation metrics. Although some increase in RSS could be observed.

6 (vi.) Implementation of Logistic Regression

[12]:
```
# Binarise the output (Slowness in traffic (%))
mean_thres = np.mean(newY)
newY_bin = (newY > mean_thres).astype(np.int_)
testY_bin = (testY > mean_thres).astype(np.int_)
```

[13]:
```
# Logistic Regression using scikit.learn

# Train the model
logreg = LogisticRegression(penalty='none', solver='lbfgs', max_iter = 10000)
logreg.fit(newX,newY_bin)

# Predict on test data
y_pred=logreg.predict(testX)

print('Coefficient of each feature: \n', logreg.coef_)
print("Accuracy:",metrics.accuracy_score(testY_bin, y_pred))
print("Precision:",metrics.precision_score(testY_bin, y_pred))
print("Recall:",metrics.recall_score(testY_bin, y_pred))
```

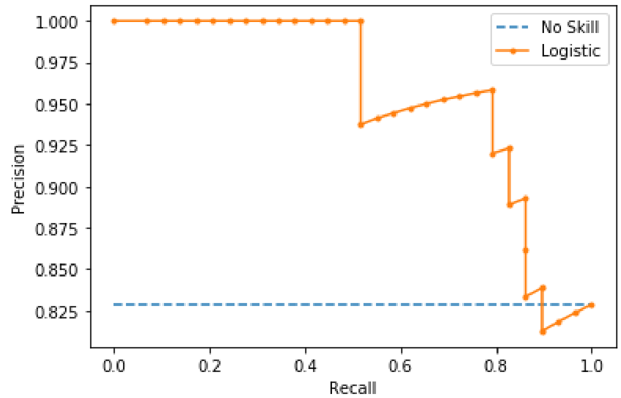
```
Coefficient of each feature:
```

```
 [[ 1.89257219e-01  4.50414910e-01  1.26057504e-01 -8.71892960e+00
   5.75540431e-02 -1.25063014e+00  2.52578729e+01  3.79245872e+01
   5.12618523e+01  3.04937299e-01 -3.61385696e+01  8.28954991e+01
  -2.46284455e+01 -7.75676030e-01  1.32735399e+00  6.13680124e-01
  -1.69957370e+01]]
Accuracy: 0.5714285714285714
Precision: 1.0
Recall: 0.4827586206896552
```

[14]:

```
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import roc_auc_score
from sklearn.metrics import f1_score
from sklearn.metrics import roc_curve
from sklearn.metrics import auc
from matplotlib import pyplot
# predict probabilities
lr_probs = logreg.predict_proba(testX)
# keep probabilities for the positive outcome only
lr_probs = lr_probs[:, 1]
# predict class values
yhat = logreg.predict(testX)
lr_precision, lr_recall, _ = precision_recall_curve(testY_bin, lr_probs)
lr_f1, lr_auc = f1_score(testY_bin, yhat), auc(lr_recall, lr_precision)
# summarize scores
print('Logistic: f1=%.3f auc=%.3f' % (lr_f1, lr_auc))
# plot the precision-recall curves
no_skill = len(testY_bin[testY_bin==1]) / len(testY_bin)
pyplot.plot([0, 1], [no_skill, no_skill], linestyle='--', label='No Skill')
pyplot.plot(lr_recall, lr_precision, marker='.', label='Logistic')
# axis labels
pyplot.xlabel('Recall')
pyplot.ylabel('Precision')
# show the legend
pyplot.legend()
# show the plot
pyplot.show()
```

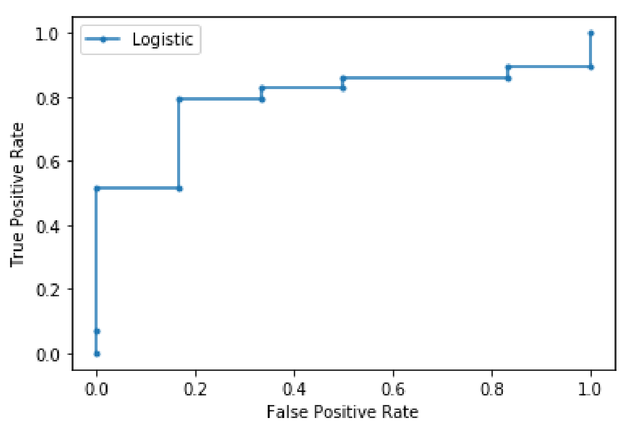
```
Logistic: f1=0.651 auc=0.955
```



[15]:
```
# calculate scores
lr_auc = roc_auc_score(testY_bin, lr_probs)
# summarize scores
print('Logistic: ROC AUC=%.3f' % (lr_auc))
# calculate roc curves
lr_fpr, lr_tpr, _ = roc_curve(testY_bin, lr_probs)
# plot the roc curve for the model
pyplot.plot(lr_fpr, lr_tpr, marker='.', label='Logistic')
# axis labels
pyplot.xlabel('False Positive Rate')
pyplot.ylabel('True Positive Rate')
# show the legend
pyplot.legend()
# show the plot
```

```
Logistic: ROC AUC=0.793
```

[15]: <matplotlib.legend.Legend at 0x1e79a292088>



7 (vii.) Regularisation

[16]:
```
# Split the trainX and trainY into numSplits parts.
# Use 4 for fitting the model, 1 for validation
numSplits = 1
random_state = 12883823

rkf = RepeatedKFold(n_splits=10, n_repeats=1, random_state=random_state)

split = 0
L = [0.001, 0.005, 0.01, 0.1, 0.5, 1, 5, 10, 50, 100, 500, 1000, 5000]
cross_val = [0 for _ in L]

for train, test in rkf.split(newX):
    trainX = newX.values[train,:]
    trainY = newY.values[train]

    devX = newX.values[test,:]
    devY = newY.values[test]

    mean_thres = np.mean(trainY)
    trainY_bin = (trainY > mean_thres).astype(np.int_)
    devY_bin = (devY > mean_thres).astype(np.int_)

    for index in range(len(L)):
        # Train the model
        logreg = LogisticRegression(penalty='l2', C=L[index], solver='lbfgs',␣
 ↪max_iter = 1000)
        logreg.fit(trainX,trainY_bin)

        # Predict on devset
        y_pred=logreg.predict(devX)

        acc_l = metrics.accuracy_score(devY_bin, y_pred)
        cross_val[index] += acc_l
        # print("\tsplit = ",split,"  Accuracy : ", acc_l,"  L = ",L[index],)

    split += 1
```

[17]:
```
bestL_idx = cross_val.index(max(cross_val))
print("Best L value of regularisation: ", L[bestL_idx], "\nAccuracy on Training␣
 ↪Set: ", cross_val[bestL_idx]/10)
```

```
Best L value of regularisation:  0.5
Accuracy on Training Set:  0.8400000000000001
```

[18]:
```
# Train the model
logreg = LogisticRegression(penalty='l2',C=L[bestL_idx], solver='lbfgs',␣
 ↪max_iter = 10000)
logreg.fit(newX,newY_bin)

# Predict on test data
y_pred=logreg.predict(testX)

print('Coefficient of each feature: \n', logreg.coef_)
print("Accuracy on Test Set:",metrics.accuracy_score(testY_bin, y_pred))
```

```
Coefficient of each feature:
 [[ 0.20100647  0.38275589  0.09387355 -0.01645758  0.04317223 -0.38743665
   0.05833577  0.16306789  0.19422704  0.25648591 -0.08685401  0.29662941
   0.22899601 -0.28210608  0.12692961  0.32642708 -0.05365081]]
Accuracy on Test Set: 0.7142857142857143
```

We find that the best model on training data had regularisation value = 0.5 with which the highest accuracy was obtained. Using it on the test set, the accuracy improved from 0.57 (without regularisation) to 0.71 (with regularisation.)