

# Machine Learning: Assignment No. 1

## Answer for Question No. 1 (a):

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```
In [1]: # Importing the packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
import warnings as w
```

```
import seaborn as sns
w.filterwarnings("ignore")
```

## Step 1: Reading the dataset from csv file

```
In [2]: mess_dataset = pd.read_csv('MessFoodTimingsDataset.csv', sep=',')
print('Mess timings dataset dimensions (rows,columns):', mess_dataset.shape)
```

Mess timings dataset dimensions (rows,columns): (56, 5)

```
In [3]: mess_dataset.head()
```

```
Out[3]:
```

	Day	Holiday	Time	Category	Time_taken
0	Sunday	Yes	9:30:00 AM	Breakfast	20
1	Sunday	Yes	1:34:00 PM	Lunch	25
2	Sunday	Yes	5:07:00 PM	Tea	15
3	Sunday	Yes	8:12:00 PM	Dinner	30
4	Monday	No	9:40:00 AM	Breakfast	19

## Step 2: Exploratory Data Analysis (EDA):

### (A) Feature Engineering

Converting the 'Time' column into 'Hour' (24 hours format) & 'Minute'

```
In [4]: mess_dataset['Minute'] = (pd.to_datetime(mess_dataset['Time']).dt.hour * 60) + pd.to_c
mess_dataset.drop(['Time'], axis=1, inplace=True)
mess_dataset.head()
```

```
Out[4]:
```

	Day	Holiday	Category	Time_taken	Minute
0	Sunday	Yes	Breakfast	20	570
1	Sunday	Yes	Lunch	25	814
2	Sunday	Yes	Tea	15	1027
3	Sunday	Yes	Dinner	30	1212
4	Monday	No	Breakfast	19	580

### (B) Understanding the datatype of each feature

```
In [5]: mess_dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 56 entries, 0 to 55
Data columns (total 5 columns):
#   Column      Non-Null Count  Dtype
---  -
0   Day         56 non-null    object
1   Holiday     56 non-null    object
2   Category    56 non-null    object
3   Time_taken  56 non-null    int64
4   Minute      56 non-null    int64
dtypes: int64(2), object(3)
memory usage: 2.3+ KB
```

### Observations:

1. Day, Holiday and Category are categorical features. Hence, they need to be converted into nominal features using OneHotEncoding scheme. We will use OneHotEncoding here, because these features are nominal, i.e. there is no order among values. Hence, in 'Feature Engineering' section we will encode them.
2. The features 'Time taken' & 'Minute' is of datatype float.

### (C) Checking for null values

```
In [6]: mess_dataset.isnull().sum()
```

```
Out[6]: Day         0
Holiday      0
Category     0
Time_taken   0
Minute       0
dtype: int64
```

### (D) Printing number of unique values in each categorical feature

```
In [7]: mess_dataset.loc[:,['Day','Holiday','Category']].nunique()
```

```
Out[7]: Day         7
Holiday      2
Category     4
dtype: int64
```

### (E) Descriptive Statistics: Printing feature-wise statistical info of entire dataset

```
In [8]: mess_dataset.describe(include='all').T
```

```
Out[8]:
```

	count	unique	top	freq	mean	std	min	25%	50%	75%	max
<b>Day</b>	56	7	Sunday	8	NaN	NaN	NaN	NaN	NaN	NaN	NaN
<b>Holiday</b>	56	2	No	32	NaN	NaN	NaN	NaN	NaN	NaN	NaN
<b>Category</b>	56	4	Breakfast	14	NaN	NaN	NaN	NaN	NaN	NaN	NaN
<b>Time_taken</b>	56.0	NaN	NaN	NaN	24.875	9.633394	11.0	16.5	22.5	35.0	40.0
<b>Minute</b>	56.0	NaN	NaN	NaN	911.303571	243.822284	560.0	748.75	923.5	1087.5	1235.0

**(F) Data Visualization:****1. Scatter plot for 'Time taken' against different days for each meal type**

```

In [9]: fig, ax = plt.subplots(1, 1, figsize=(12,7))

breakfast_df = mess_dataset[(mess_dataset['Category'] == 'Breakfast')]
lunch_df = mess_dataset[(mess_dataset['Category'] == 'Lunch')]
tea_df = mess_dataset[(mess_dataset['Category'] == 'Tea')]
dinner_df = mess_dataset[(mess_dataset['Category'] == 'Dinner')]

days = breakfast_df['Day'][0:7]

ax.scatter(np.arange(len(days)), breakfast_df[0:7]['Time_taken'], color='mediumspringgreen')
ax.scatter(np.arange(len(days)), breakfast_df[7:14]['Time_taken'], color='mediumspringgreen')

ax.scatter(np.arange(len(days)), lunch_df[0:7]['Time_taken'], color='mediumturquoise')
ax.scatter(np.arange(len(days)), lunch_df[7:14]['Time_taken'], color='mediumturquoise')

ax.scatter(np.arange(len(days)), tea_df[0:7]['Time_taken'], color='chocolate')
ax.scatter(np.arange(len(days)), tea_df[7:14]['Time_taken'], color='chocolate')

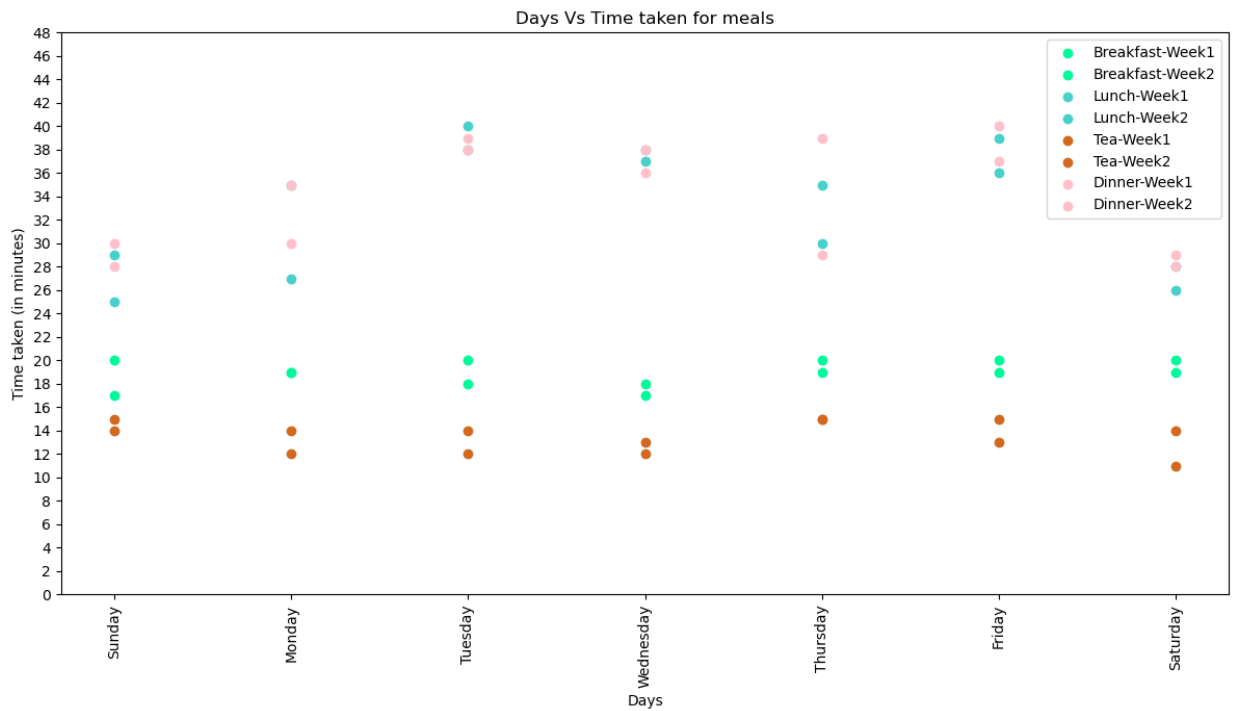
ax.scatter(np.arange(len(days)), dinner_df[0:7]['Time_taken'], color='pink')
ax.scatter(np.arange(len(days)), dinner_df[7:14]['Time_taken'], color='pink')

ax.set_xlabel('Days')
ax.set_ylabel('Time taken (in minutes)')
ax.set_title('Days Vs Time taken for meals')

ax.set_xticklabels(days, rotation=90)
ax.set_xticks(np.arange(len(days)))
ax.set_yticks(np.arange(0, 50, 2))

ax.legend(['Breakfast-Week1', 'Breakfast-Week2', 'Lunch-Week1', 'Lunch-Week2', 'Tea-Week1', 'Tea-Week2', 'Dinner-Week1', 'Dinner-Week2'])
fig.tight_layout()
plt.show()

```



## 2. Combined line graph for 'Time taken' against different days for each meal type

```
In [10]: fig, ax = plt.subplots(1, 1, figsize=(12,8))

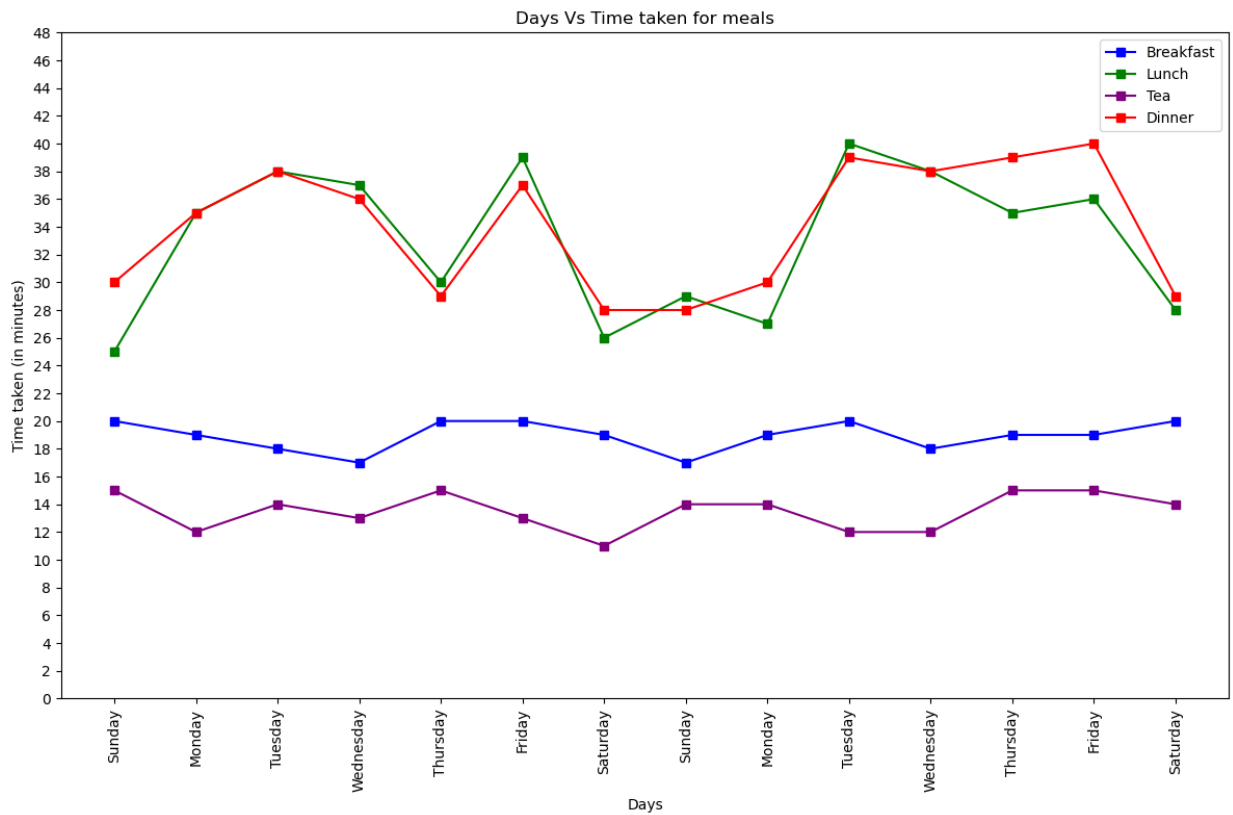
breakfast_df = mess_dataset[(mess_dataset['Category'] == 'Breakfast')]
lunch_df = mess_dataset[(mess_dataset['Category'] == 'Lunch')]
tea_df = mess_dataset[(mess_dataset['Category'] == 'Tea')]
dinner_df = mess_dataset[(mess_dataset['Category'] == 'Dinner')]

ax.plot(np.arange(len(breakfast_df['Day'])), breakfast_df['Time_taken'], marker = 's', color='green')
ax.plot(np.arange(len(lunch_df['Day'])), lunch_df['Time_taken'], marker = 's', color='teal')
ax.plot(np.arange(len(tea_df['Day'])), tea_df['Time_taken'], marker = 's', color='purple')
ax.plot(np.arange(len(dinner_df['Day'])), dinner_df['Time_taken'], marker = 's', color='pink')

ax.set_xlabel('Days')
ax.set_ylabel('Time taken (in minutes)')
ax.set_title('Days Vs Time taken for meals')
ax.set_xticks(np.arange(len(breakfast_df['Day'])))
ax.set_yticks(np.arange(0, 50, 2))

ax.set_xticklabels(breakfast_df['Day'], rotation=90)
ax.legend(['Breakfast', 'Lunch', 'Tea', 'Dinner'])

fig.tight_layout()
plt.show()
```



### 3. Scatter plot of 'Category' Vs 'Time taken'

```
In [11]: fig, ax = plt.subplots(1, 1, figsize=(7,7))
categories = ['Breakfast', 'Lunch', 'Tea', 'Dinner']

breakfast_xtick_locations = [0]*14
lunch_xtick_locations = [1]*14
tea_xtick_locations = [2]*14
dinner_xtick_locations = [3]*14

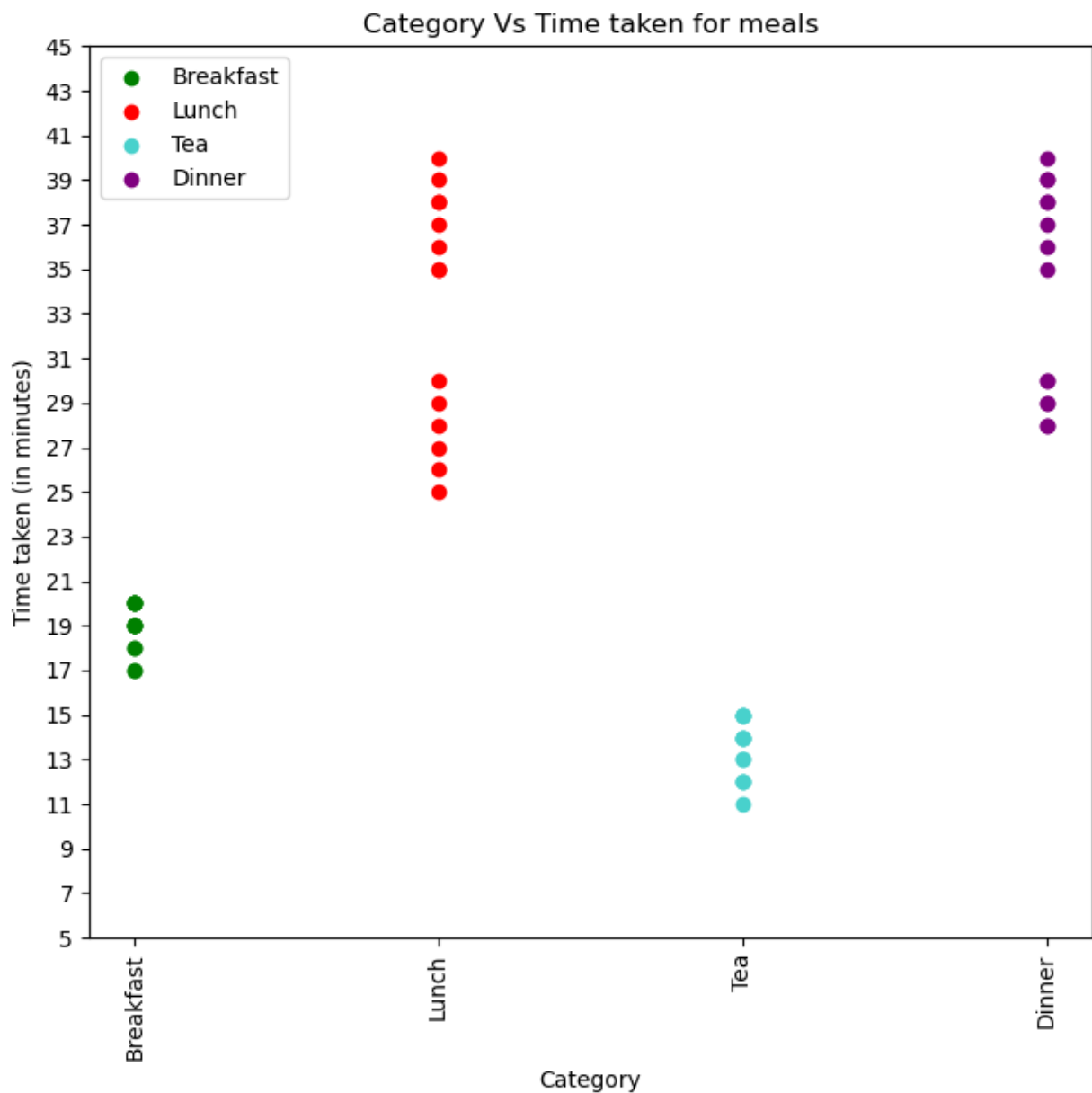
breakfast_df = mess_dataset[(mess_dataset['Category'] == 'Breakfast')]
lunch_df = mess_dataset[(mess_dataset['Category'] == 'Lunch')]
tea_df = mess_dataset[(mess_dataset['Category'] == 'Tea')]
dinner_df = mess_dataset[(mess_dataset['Category'] == 'Dinner')]

ax.scatter(breakfast_xtick_locations, breakfast_df['Time_taken'], color='g')
ax.scatter(lunch_xtick_locations, lunch_df['Time_taken'], color='r')
ax.scatter(tea_xtick_locations, tea_df['Time_taken'], color='mediumturquoise')
ax.scatter(dinner_xtick_locations, dinner_df['Time_taken'], color='purple')

ax.set_xlabel('Category')
ax.set_ylabel('Time taken (in minutes)')
ax.set_title('Category Vs Time taken for meals')

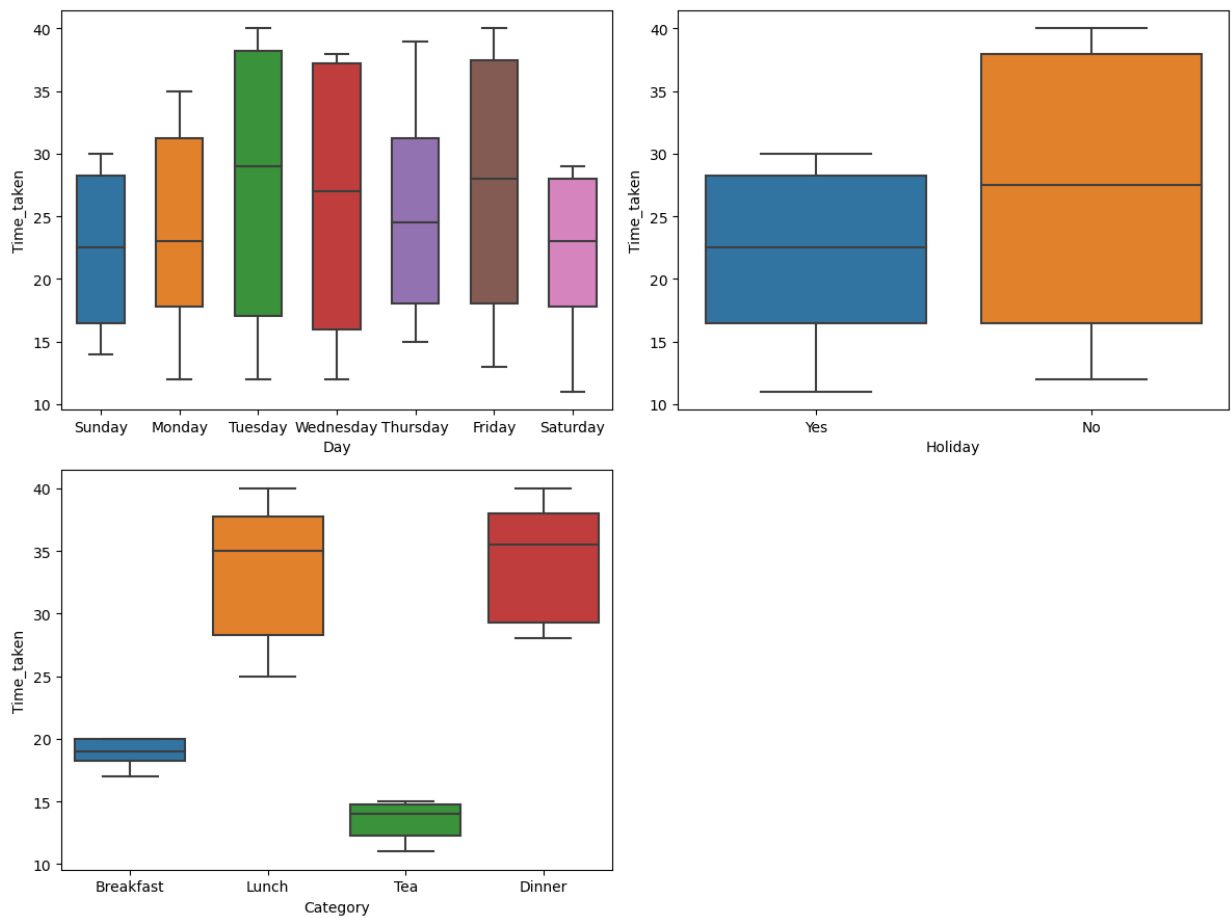
ax.set_xticklabels(categories, rotation=90)
ax.set_xticks(np.arange(len(categories)))
ax.set_yticks(np.arange(5, 46, 2))

ax.legend(categories)
fig.tight_layout()
plt.show()
```



#### 4. Analyzing boxplots for 'Time taken' Vs Each categorical feature

```
In [12]: fig, ((axis1, axis2), (axis3, axis4)) = plt.subplots(2,2,figsize=(12,9))
sns.boxplot(x='Day', y='Time_taken', data=mess_dataset, ax=axis1, width=0.6)
sns.boxplot(x='Holiday', y='Time_taken', data=mess_dataset, ax=axis2)
sns.boxplot(x='Category', y='Time_taken', data=mess_dataset, ax=axis3)
fig.delaxes(axis4)
plt.tight_layout()
plt.show()
```



### Observations:

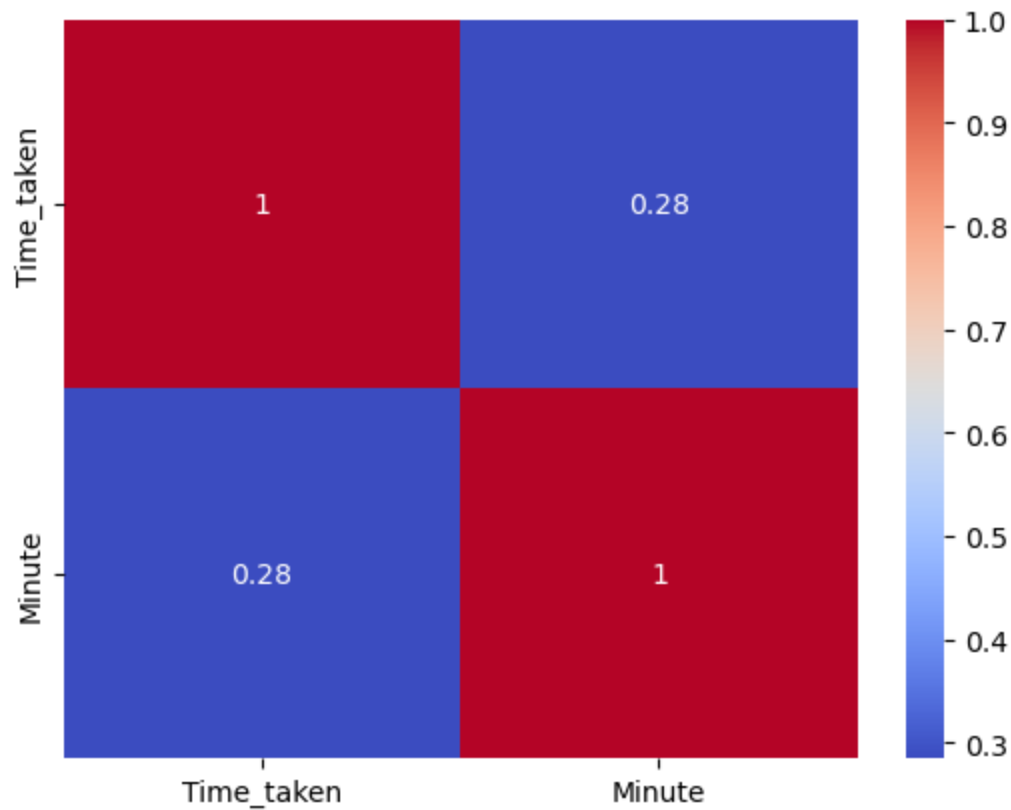
From above boxplots, we can observe that there are noteworthy variations in 'Time taken' against 'Category' feature.

### 5. Analyzing the correlation between 'Time taken' and 'Minute' feature

```
In [13]: corr = mess_dataset[['Time_taken', 'Minute']].corr()
sns.heatmap(corr, annot=True, cmap='coolwarm')
```

```
Out[13]: <Axes: >
```

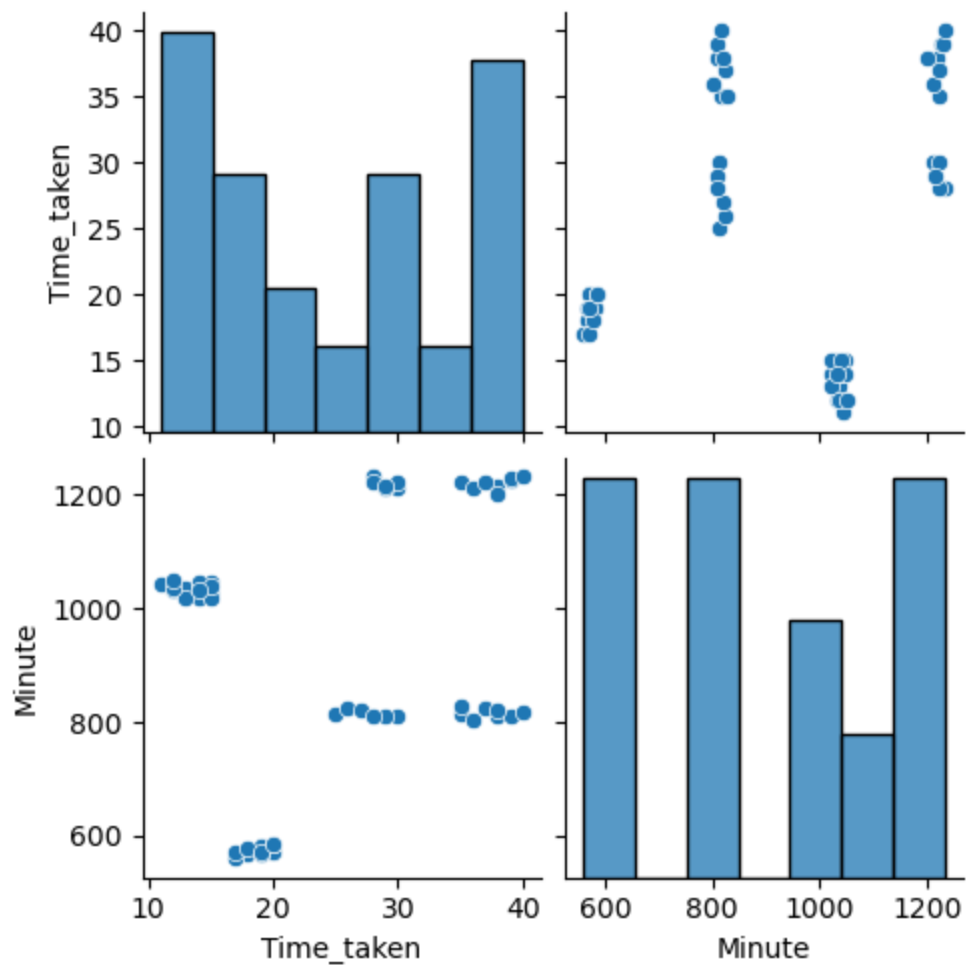




There is pretty small but positive correlation between 'Time\_taken' and 'Minute' features. Lets also see scatter plot of these features to take final decision about inclusion of this feature in X.

## 6. Plotting pair plot for 'Time taken' against all non-categorical features

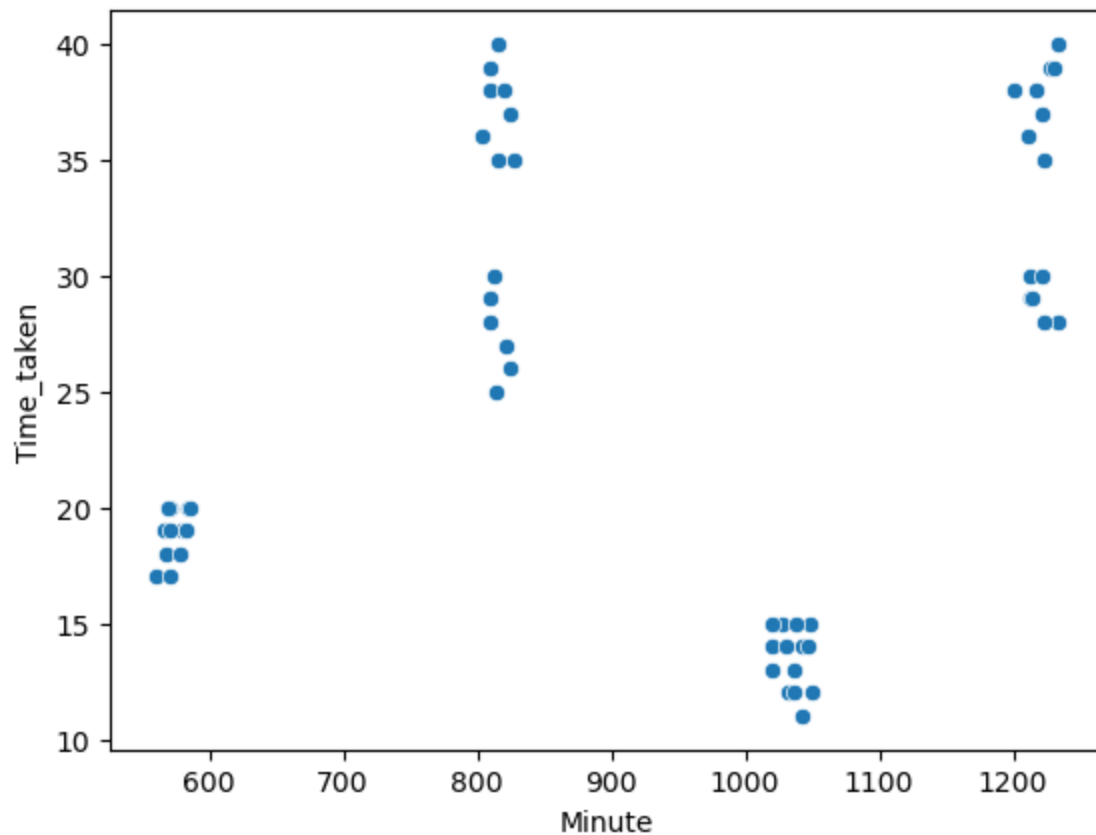
```
In [14]: sns.pairplot(mess_dataset[['Time_taken', 'Minute']])  
plt.show()
```



### 7. Scatter plot of 'Time taken' Vs 'Minute' (Same plot can be seen from pairplot)

```
In [15]: sns.scatterplot(x='Minute', y='Time_taken', data=mess_dataset)
```

```
Out[15]: <Axes: xlabel='Minute', ylabel='Time_taken'>
```

**Observation:**

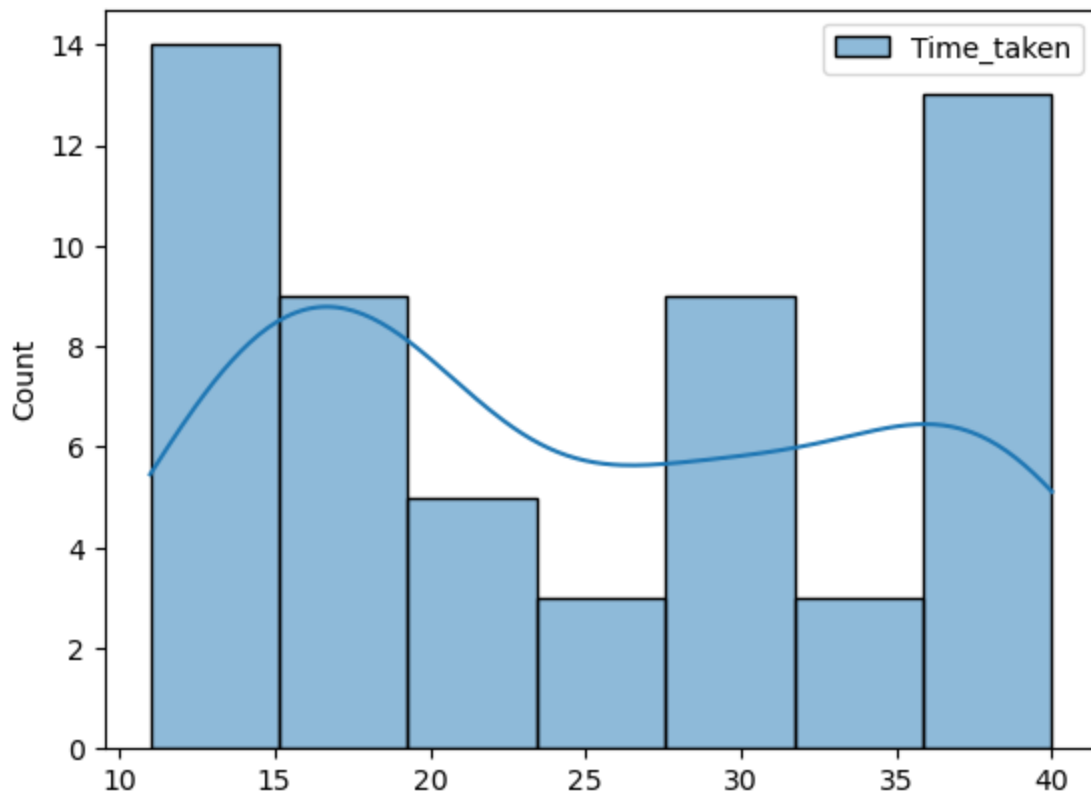
We can observe that there is very little correlation between 'Time taken' and 'Minute' columns.

**Hence excluding 'Minute' column from X**

**8. Visualizing histogram of 'Time taken' column to see its distribution pattern**

```
In [16]: #'Kernel Distribution Estimation' plots are used to visualize distribution of data  
sns.histplot(mess_dataset[['Time_taken']], kde=True)
```

```
Out[16]: <Axes: ylabel='Count'>
```

**Observation:**

We can see that the dependant variable Y (Time\_taken) have all integer positive values. Therefore, assuming that the 'Time\_taken' columns follows a poisson distribution.

**Step 3: Feature engineering:**

Based on above EDA, following observations are drawn:

1. We can see that the dependant variable Y (Time\_taken) have all integer positive values. Therefore, assuming that the 'Time\_taken' columns follows a "Poisson distribution".
2. We can observe that there is very little correlation between 'Time\_taken' and 'Minute' columns.  
Hence excluding 'Minute' column from X.
3. 'Day', 'Holiday' and 'Category' are categorical features. Hence, they need to be converted into nominal features using OneHotEncoding scheme.  
We will use OneHotEncoding here, because these features are nominal, i.e. there is no order among values.  
Hence, in 'Feature Engineering' section we will encode them.

**A. Feature Selection: Deleting 'Holiday' and 'Day' features from X**

```
In [17]: selected_mess_dataset = mess_dataset.drop(['Minute'], axis=1)
selected_mess_dataset.columns
```

```
Out[17]: Index(['Day', 'Holiday', 'Category', 'Time_taken'], dtype='object')
```

## B. Feature Transformation: Applying One Hot Encoding on categorical features

```
In [18]: categorical_column_names = selected_mess_dataset.select_dtypes(include='object').columns
categorical_column_names
```

```
Out[18]: Index(['Day', 'Holiday', 'Category'], dtype='object')
```

```
In [19]: # Applying OneHotEncoding on categorical columns
# While encoding, we are one dummy column per category to avoid dummy variable trap, i.e.
encoded_mess_dataset = pd.get_dummies(selected_mess_dataset, columns = categorical_column_names)
encoded_mess_dataset.head()
```

```
Out[19]:
```

	Time_taken	Day_Friday	Day_Monday	Day_Saturday	Day_Sunday	Day_Thursday	Day_Tuesday	Day_Wednesday
0	20	0	0	0	1	0	0	0
1	25	0	0	0	1	0	0	0
2	15	0	0	0	1	0	0	0
3	30	0	0	0	1	0	0	0
4	19	0	1	0	0	0	0	0

```
In [20]: encoded_mess_dataset.shape
```

```
Out[20]: (56, 14)
```

## Step 4: Segregating the dataset into Train and Test set

```
In [21]: X = encoded_mess_dataset.drop('Time_taken', axis=1)
print('Printing X:')
X.head()
```

Printing X:

```
Out[21]:
```

	Day_Friday	Day_Monday	Day_Saturday	Day_Sunday	Day_Thursday	Day_Tuesday	Day_Wednesday
0	0	0	0	1	0	0	0
1	0	0	0	1	0	0	0
2	0	0	0	1	0	0	0
3	0	0	0	1	0	0	0
4	0	1	0	0	0	0	0

```
In [22]: Y = encoded_mess_dataset['Time_taken']
print('Printing Y:')
Y.head()
```

Printing Y:

```
Out[22]: 0    20
         1    25
         2    15
         3    30
         4    19
         Name: Time_taken, dtype: int64
```

### Segregating the dataset into 80 % Train set and 20 % Test set

```
In [23]: X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=
print('----- Train Set -----')
print('Dimensions of X_train (rows,columns):', X_train.shape)
print('Dimensions of Y_train (rows,columns):', Y_train.shape)
print('----- Test Set -----')
print('Dimensions of X_test (rows,columns):', X_test.shape)
print('Dimensions of Y_test (rows,columns):', Y_test.shape)

----- Train Set -----
Dimensions of X_train (rows,columns): (44, 13)
Dimensions of Y_train (rows,columns): (44,)
----- Test Set -----
Dimensions of X_test (rows,columns): (12, 13)
Dimensions of Y_test (rows,columns): (12,)
```

```
In [24]: def calculate_r_square(Y_test, Y_pred):
         Y_mean = np.mean(Y_test)
         ss_total = np.sum((Y_test - Y_mean) ** 2)
         ss_residual = np.sum((Y_test - Y_pred) ** 2)
         r_squared = 1 - (ss_residual / ss_total)
         return r_squared
```

### Step 5: Fitting the Linear Regression model

```
In [25]: from sklearn.linear_model import LinearRegression
linear_reg_model = LinearRegression()
linear_reg_model.fit(X_train, Y_train)
```

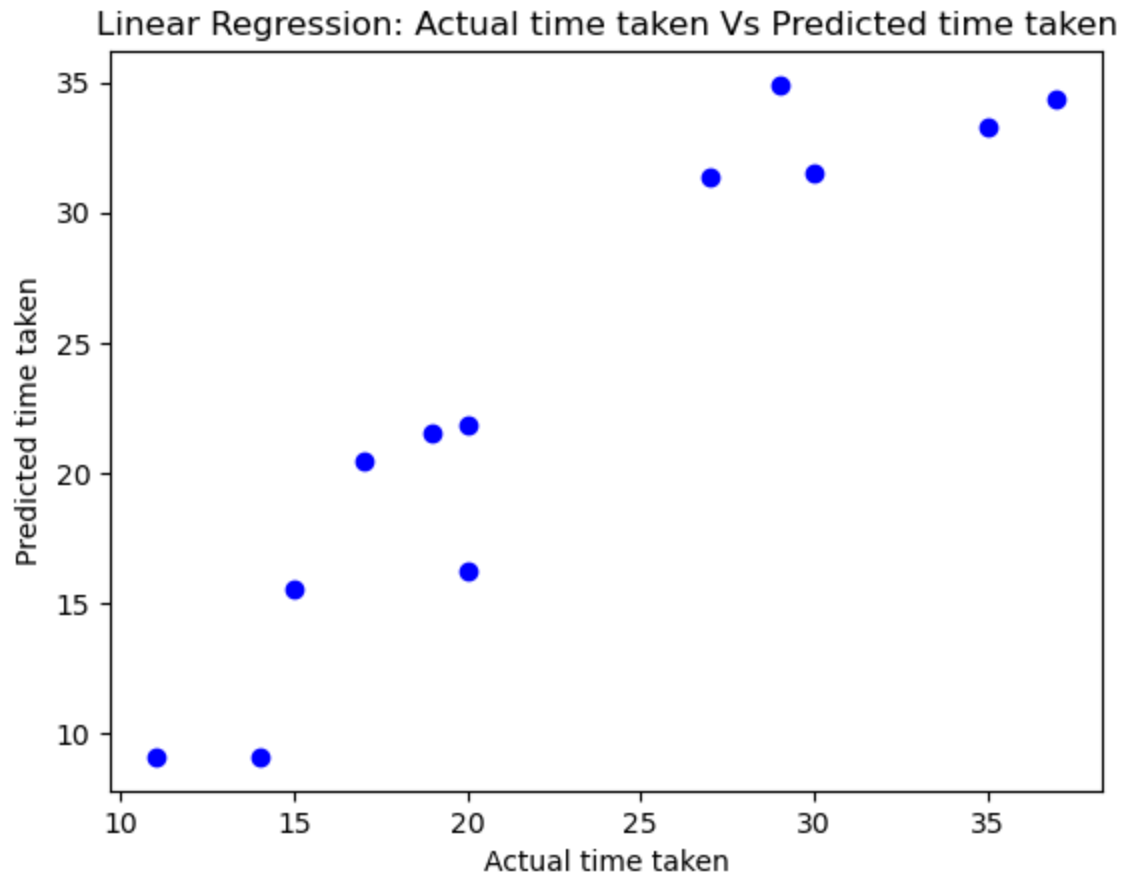
```
Out[25]: ▼ LinearRegression
LinearRegression()
```

```
In [26]: # Getting the predictions on test data
linear_reg_pred = linear_reg_model.predict(X_test)
```

```
In [27]: print('MAE for Linear Regression on Test set:', np.mean(np.abs(Y_test - linear_reg_pred)))
MAE for Linear Regression on Test set: 2.9245569115559626
```

```
In [28]: print('Linear regression R-square accuracy on Test set:', round(calculate_r_square(Y_test, linear_reg_pred)))
Linear regression R-square accuracy on Test set: 83.767 %
```

```
In [29]: plt.scatter(Y_test, linear_reg_pred, color='b')
plt.title('Linear Regression: Actual time taken Vs Predicted time taken')
plt.xlabel('Actual time taken')
plt.ylabel('Predicted time taken')
plt.show()
```



### Step 6: Fitting Poisson Regression model

Since we have to predict time which is positive integer number, we are assuming the distribution to be poisson

```
In [30]: # Poisson regression implementation
def calculate_error(y, y_pred):
    return y - y_pred

def compute_gradient(X, y, W):
    error = calculate_error(y, np.exp(np.dot(X, W)))
    gradient = np.dot(X.T, error)
    return gradient

def predict_Y(X, W):
    return np.exp(np.dot(X, W))

def initialize_weights(num_features):
    W = np.zeros(num_features)
    return W

W = np.zeros(X_train.shape[1])
learning_rate = 0.001
num_of_epochs = 10000
for i in range(num_of_epochs):
    gradient = compute_gradient(X_train, Y_train, W)
    W = W + (learning_rate * gradient)
print("Estimated Weight vector:", W)
```

```
Estimated Weight vector: [0.56260827 0.47469721 0.40701259 0.41703202 0.55830723 0.56
93132
0.52130315 1.79397869 1.71629499 0.68410359 1.27178736 1.23064244
0.32374029]
```

```
In [31]: predicted_poi_y = predict_Y(X_test, W)
print("Predicted Ys:", predicted_poi_y)
```

```
Predicted Ys: [16.73379959 33.09288606 30.61942568 34.67171655 34.68785326 14.5898670
1
21.06042065 11.55418677 20.82990119 20.07319666 11.55418677 30.11774005]
```

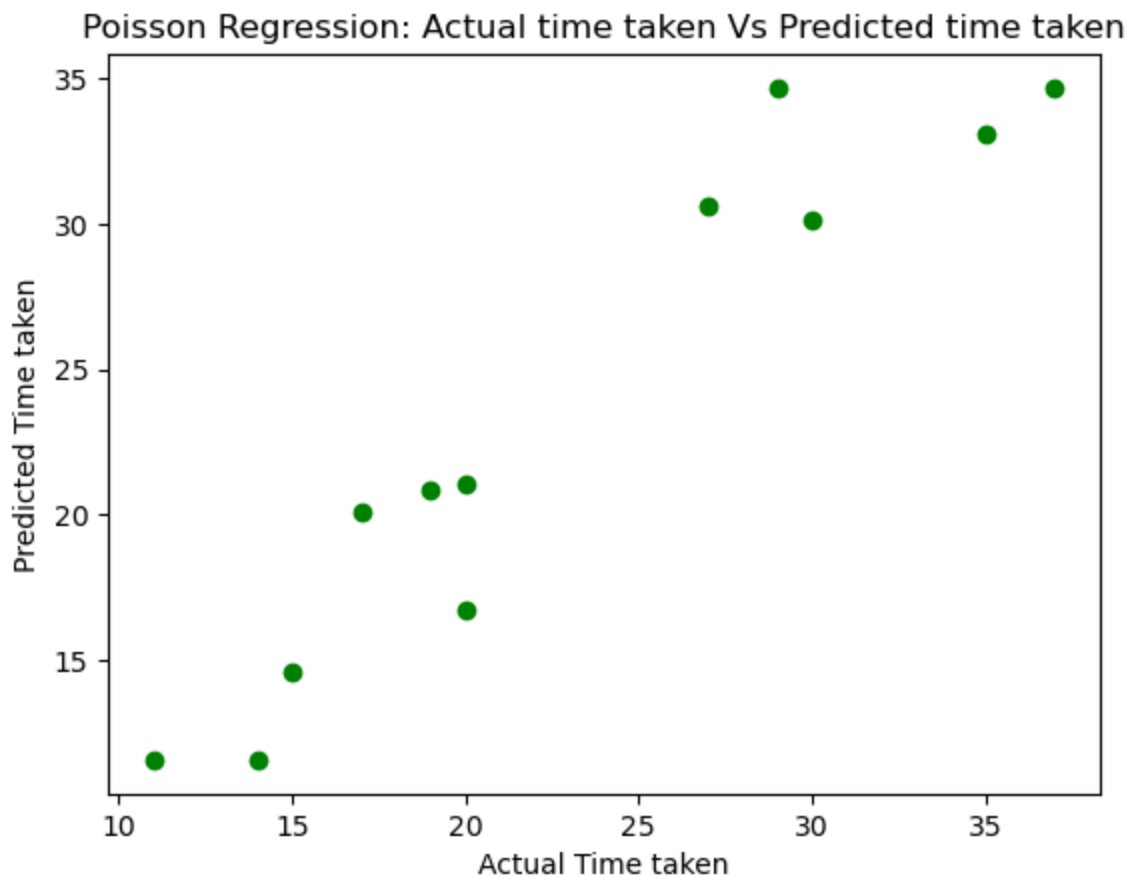
```
In [32]: print('MAE Poisson regression:', np.mean(np.abs((Y_test - predicted_poi_y))))
```

```
MAE Poisson regression: 2.1916890234455826
```

```
In [33]: print('Poisson regression R-square accuracy:', round(calculate_r_square(Y_test, predict
```

```
Poisson regression R-square accuracy: 89.3 %
```

```
In [34]: plt.scatter(Y_test, predicted_poi_y, color='g')
plt.title('Poisson Regression: Actual time taken Vs Predicted time taken')
plt.xlabel('Actual Time taken')
plt.ylabel('Predicted Time taken')
plt.show()
```



### Step 7: Comparing Linear regression and Poisson regression performance



```
In [35]: print('Linear regression R-square accuracy on Test set:', round(calculate_r_square(Y_test, predicted_linear_y), 3))  
print('Poisson regression R-square accuracy on Test set:', round(calculate_r_square(Y_test, predicted_poi_y), 3))
```

Linear regression R-square accuracy on Test set: 83.767 %

Poisson regression R-square accuracy on Test set: 89.3 %

```
In [36]: print('MAE for Linear Regression on Test set:', np.mean(np.abs(Y_test - linear_reg_pred)))  
print('MAE Poisson regression on Test set:', np.mean(np.abs((Y_test - predicted_poi_y))))
```

MAE for Linear Regression on Test set: 2.9245569115559626

MAE Poisson regression on Test set: 2.1916890234455826

### Observation:

**Based on above 2 metrics MAE (Mean Absolute Error) and R-square, poisson regression is performing better than linear regression**