



Poisson Regression

- In statistics, Poisson regression is a generalized linear model form of regression analysis used to model count data and contingency tables.
- Poisson regression assumes the response variable Y has a Poisson distribution, and assumes the logarithm of its expected value can be modeled by a linear combination of unknown parameters.
- A Poisson regression model is sometimes known as a log-linear model, especially when used to model contingency tables.
- Negative binomial regression is a popular generalization of Poisson regression because it loosens the highly restrictive assumption that the variance is equal to the mean made by the Poisson model.
- The traditional negative binomial regression model is based on the Poisson-gamma mixture distribution. This model is popular because it models the Poisson heterogeneity with a gamma distribution.
- Poisson regression models are generalized linear models with the logarithm as the (canonical) link function, and the Poisson distribution function as the assumed probability distribution of the response.

```
In [2]: ### Importing Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from sklearn.linear_model import PoissonRegressor
from sklearn.pipeline import Pipeline
from sklearn.metrics import accuracy_score, r2_score, mean_squared_error
```

```
In [3]: ### Import the Dataset
df = pd.read_csv(r'C:\Users\hp\Desktop\100DaysOfDataScience\Day 46\competition_awards_data.csv')
df.head()
```

```
Out[3]:
```

	Awards	Math Score
0	0	43
1	0	38
2	0	41
3	0	33
4	0	39

```
In [4]: df.shape ### Checking Shape
```

```
Out[4]: (200, 2)
```

```
In [5]: df.describe() ### Get information of the Dataset
```

```
Out[5]:
```

	Awards	Math Score
count	200.000000	200.000000
mean	0.630000	50.715000
std	1.052921	19.148029
min	0.000000	30.000000
25%	0.000000	35.000000
50%	0.000000	42.000000
75%	1.000000	66.000000
max	6.000000	91.000000

```
In [6]: df.columns ### Checking Columns
```

```
Out[6]: Index(['Awards', 'Math Score'], dtype='object')
```

```
In [7]: df.info() ### Checking Information About a DataFrame
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 2 columns):
#   Column      Non-Null Count  Dtype
---  -
0   Awards      200 non-null    int64
1   Math Score  200 non-null    int64
dtypes: int64(2)
memory usage: 3.3 KB
```

```
In [8]: df.isnull().sum() ### Checking Null Values in the Data
```

```
Out[8]: Awards      0
Math Score    0
dtype: int64
```

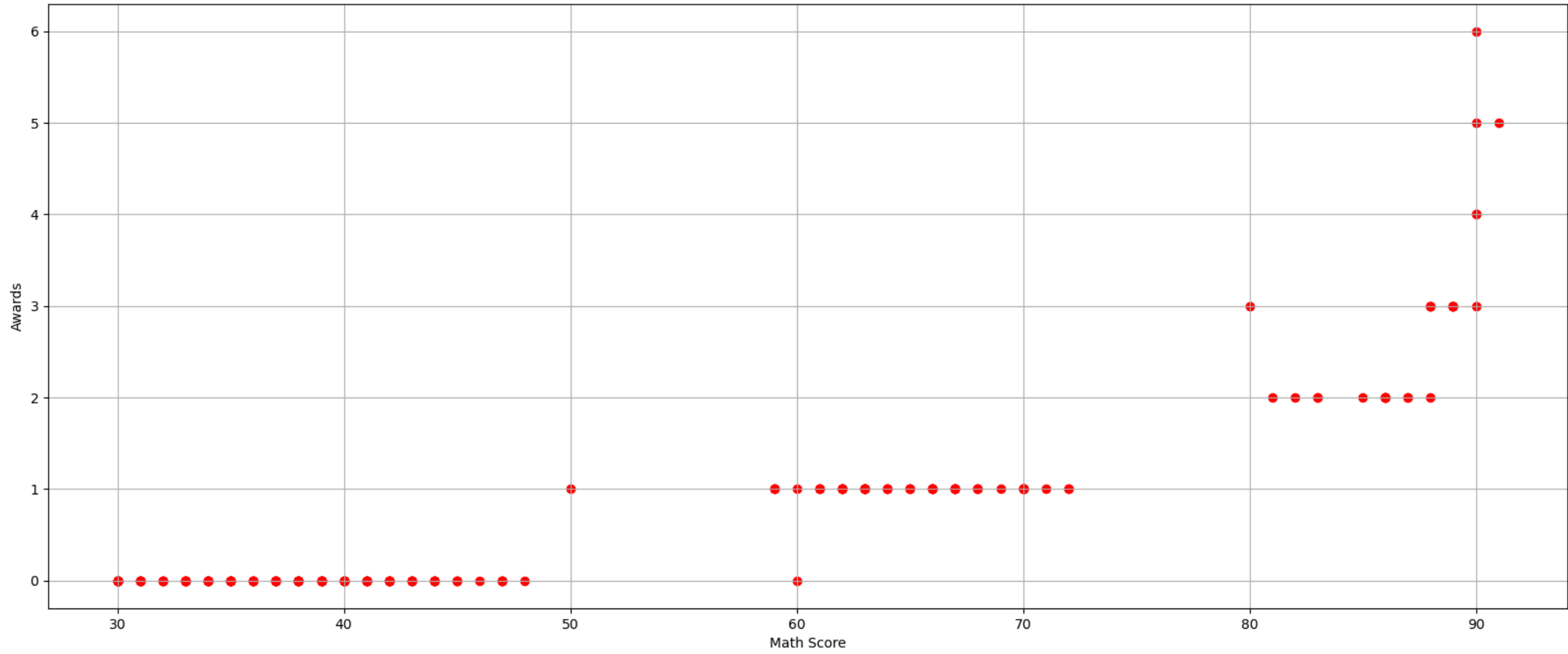
```
In [9]: df1 = pd.DataFrame.copy(df)
df1.shape
```

```
Out[9]: (200, 2)
```

```
In [10]: for i in df1.columns:
        print({i:df1[i].unique()}) ### Checking Unique values in each columns
```

```
{'Awards': array([0, 1, 3, 2, 5, 4, 6], dtype=int64)}
{'Math Score': array([43, 38, 41, 33, 39, 35, 36, 60, 30, 32, 37, 44, 45, 34, 40, 42, 64,
                    62, 50, 65, 68, 31, 47, 89, 70, 66, 61, 83, 59, 48, 69, 63, 86, 72,
                    67, 88, 71, 80, 82, 90, 87, 46, 81, 91, 85], dtype=int64)}
```

```
In [15]: fig, ax = plt.subplots(figsize=(20,8))
        plt.grid()
        ax.set_ylabel("Awards")
        ax.set_xlabel("Math Score")
        ax.scatter( df1['Math Score'],df1.Awards,color='red')
        plt.show()
```



```
In [27]: ### Splitting Data into X and y
        X = df1['Math Score'].values.reshape(-1, 1)
        y = df1.Awards
        print('X:',X.shape)
        print('*' * 10)
        print('y:',y.shape)
```

```
X: (200, 1)
*****
y: (200,)
```

```
In [28]: y = y.astype(int) #convert y in to integer always perform this operation
```

```
In [33]: ### Splitting into Training and Testing Data
        from sklearn.model_selection import train_test_split
        X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=1)

        print("X_train: ",X_train.shape)
        print("X_test: ",X_test.shape)
        print("y_train: ",y_train.shape)
        print("y_test: ",y_test.shape)
```

```
X_train: (160, 1)
X_test: (40, 1)
y_train: (160,)
y_test: (40,)
```

```
In [34]: #create a model object
        pipeline = Pipeline([['model', PoissonRegressor()]])
        #train the model object
        pipeline.fit(X_train, y_train)
        #predict using the model
        y_pred = pipeline.predict(X_test)
        print(y_pred)
```

```
[0.07497373 0.04367845 0.60249917 0.05505896 3.29156503 0.09450829
 0.09450829 0.08098962 0.4779645  4.14918936 3.84098829 0.06940469
 0.04043402 0.04367845 0.51631639 0.1501729  0.51631639 0.75948163
 3.84098829 0.11913263 0.05505896 0.12869184 0.10209164 0.08748823
 0.06940469 3.29156503 0.06424932 0.08098962 4.48212049 0.40959542
 0.08098962 0.0594769  0.8862532  3.55568035 0.75948163 0.10209164
 0.04043402 0.04043402 0.04043402 3.04706815]
```

```
In [38]: # Checking r2 score for the model
        r2_test = r2_score(y_test, y_pred)
        r2_test
```

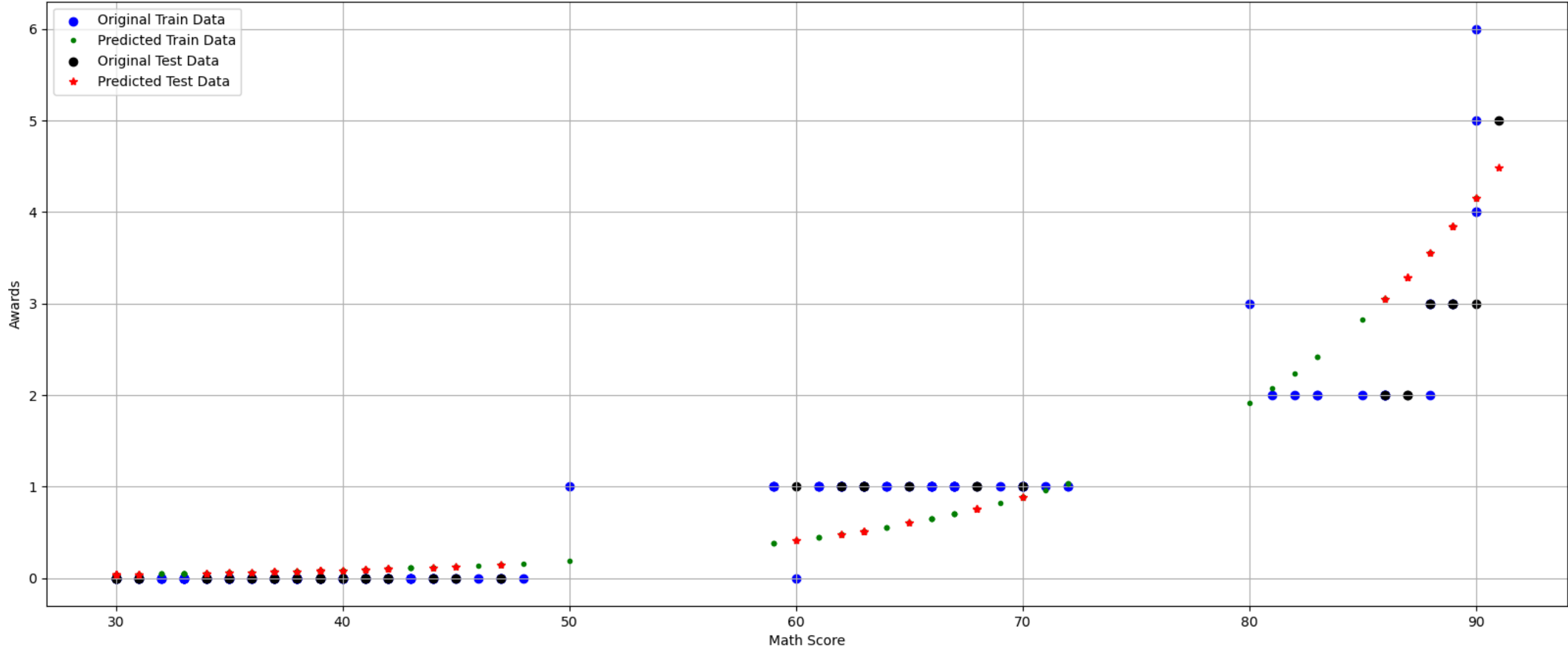
Out[38]: 0.8371373661390169

```
In [40]: # training performance
        y_pred_train = pipeline.predict(X_train)
        r2_train = r2_score(y_train, y_pred_train)
        r2_train
```

Out[40]: 0.8586107885977591

In [43]: *# plot predictions and actual values against Math score*

```
fig, ax = plt.subplots(figsize=(20,8))
plt.grid()
ax.set_xlabel("Math Score")
ax.set_ylabel("Awards")
# train data in blue
ax.scatter(X_train, y_train,color='blue',label="Original Train Data")
ax.plot(X_train, y_pred_train, '.', color='green',label="Predicted Train Data")
# test data
ax.scatter(X_test, y_test,color='black',label="Original Test Data")
ax.plot(X_test, y_pred, '*', color='red',label="Predicted Test Data")
ax.legend()
plt.show()
```



In [44]: `eval = pd.DataFrame({'y_pred': [round(y, 0) for y in y_pred], 'y': y_test}).reset_index()`
`eval.head()`

Out[44]:

	index	y_pred	y
0	58	0.0	0
1	40	0.0	0
2	34	1.0	1
3	102	0.0	0
4	184	3.0	2

In [46]: `print('Frequency table')`
`eval.groupby(['y', 'y_pred']).agg('count').reset_index().pivot(index='y', columns='y_pred', values='index').fillna(0)`

Frequency table

Out[46]:

	y_pred	0.0	1.0	3.0	4.0
y					
0	24.0	0.0	0.0	0.0	
1	2.0	6.0	0.0	0.0	
2	0.0	0.0	3.0	0.0	
3	0.0	0.0	0.0	4.0	
5	0.0	0.0	0.0	1.0	

Made with ❤ by Zahid Salim Shaikh

In []: