```
In [ ]: | # Imports
        from pyspark.sql import SparkSession
        from pyspark.sql import Row
        from pyspark.sql.functions import lit
        from pyspark.sql.types import StringType
        from pyspark.sql.types import DoubleType
        from pyspark.sql.functions import year
        from pyspark.ml.feature import VectorAssembler
        from pyspark.ml.regression import LinearRegression
        from pyspark.ml.feature import MinMaxScaler
        from pyspark.sql.functions import col
        from pyspark.sql.functions import concat
        import pyspark.sql.functions as fn
        from scipy import stats
        import pandas as pd
        import numpy as np
        import shapefile
        import six
```

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In [10]: # Linear regression analysis to find the relationship between the given two variable
         # Inbuilt linear regression
         def linear_regression_inbuilt(data, dependent_vars):
             vectorAssembler = VectorAssembler(inputCols = dependent_vars, outputCol = 'features')
             vector_df = vectorAssembler.transform(data)
             vector_df = vector_df.select(['features', 'crime_count'])
               glr = GeneralizedLinearRegression(family="binomial", link="logit", maxIter=10, regParam=0.0)
               lr model = glr.fit(data)
             lr = LinearRegression(featuresCol = 'features', labelCol='crime count', maxIter=10, regParam=0.3, el
         asticNetParam=0.8)
             lr_model = lr.fit(vector_df)
             return lr_model
         # Custom multivariate linear regression
         def linear regression(data, indexes):
             # Gathering the data for linear regression
             x = []
             y = []
             for each in data:
                 x_s = [ float(each[index]) for index in indexes if each[index] != None]
                 if len(x s) == len(indexes):
                     x.append(x_s)
                     y.append(float(each[1]))
             # Preparing the data for linear regression
             N = len(x)
             M = len(indexes)
             df = N - (1+M)
             X = np.reshape(x,(N,M))
             Y = np.reshape(y, (len(y), 1))
             if df <= 0:
                 return -1
             if N > 1:
                 X = (X - np.mean(X,axis=0))/np.std(X,axis=0)
                 Y = (Y - np.mean(Y)) / np.std(Y)
             # Linear regression
             X = np.hstack((X,np.ones((N,1))))
             X_t = np.transpose(X)
             X_inv = np.linalg.pinv(np.dot(X_t,X))
             weights = np.dot( np.dot(X_inv,X_t) ,Y)
             # Finding the p-value
             rss = np.sum(np.power((Y - np.dot(X, weights)), 2))
             s_squared = rss / df
             se = np.sum(np.power((X[:, 0]), 2))
             tt = (weights[0, 0] / np.sqrt(s squared / se))
             pval = stats.t.sf(np.abs(tt), df)
             # Returning the betas and pvalue
             return weights[0][0],pval
```

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In [7]: # Creating the spark context
         spark = SparkSession.builder.master("local[*]").getOrCreate()
         # Reading the data
         crime data = spark.read.json("hdfs://home/udit gupta 1/processed data/")
         demographics = spark.read.option("header", "true").csv("../Data/borough demographics.csv")
         # Preparing data for linear regression
         # Finding borough level aggregate
         complaints = crime data.rdd.filter(lambda row: row['RECORD TYPE'] == 'C').toDF()
         complaints_df = complaints.filter(col("Year").isin(keep_column))
         complaints df = complaints df.filter(col("BORO NM").isin(list(boro dict.values())))
         complaints_df = complaints_df.withColumn("Key",fn.concat(fn.col("BORO_NM"),fn.col("Year")))
         crime count = complaints df.groupby("Key").agg(fn.count(col('CMPLNT NUM')).alias('crime count'))
         # Casting the data to suitable types
         demographics = demographics.withColumn("unemployment rate", demographics["unemployment rate"].cast(Doubl
         eType()))
         demographics = demographics.withColumn("racial_diversity", demographics["racial_diversity"].cast(DoubleT
         demographics = demographics.withColumn("income diversity", demographics["income diversity"].cast(DoubleT
         ype()))
         demographics = demographics.withColumn("proverty rate", demographics["proverty rate"].cast(DoubleType())
         demographics = demographics.withColumn("population", demographics["population"].cast(DoubleType()))
         # Combining Data
         final data = crime count.join(demographics, crime count.Key == demographics.Demo Key)
         final data = final data.drop('Demo Key')
         demo crime data = final data.rdd.map(list).collect()
In [16]: # Correlation between the crime count and other demographics data
         for i in final data.columns:
             if not( isinstance(final data.select(i).take(1)[0][0], six.string types)):
                 print( "Correlation between crime_count and", i, final_data.stat.corr('crime_count',i))
         Correlation between crime count and crime count 1.0
         Correlation between crime count and proverty rate 0.1895440726873476
         Correlation between crime_count and income_diversity -0.19683924650147086
         Correlation between crime count and racial diversity 0.2940662008177049
         Correlation between crime_count and unemployment_rate -0.20042337200923163
         Correlation between crime count and population 0.3918328051254336
In [11]: # Inbuilt linear regression
         lr model = linear regression inbuilt(final data, ["unemployment rate"])
         model summary = lr model.summary
         print("r2: %f" % model_summary.r2)
         r2: 0.040170
```

## **Hyothesis Testing**

- Level of Significance is 0.05
- The null hypthesis states that demographic factor don't effect the crime count.
- The null hypothesis is rejected if the pvalue is less than 0.05.
- The null hypothesis is not rejected if the pvalue is greater than 0.05.

Below we are printing the pvalues for linear regression between crime rate and various demographic factors.

```
In [19]: print("Significance of various demographic factors with crime_rate")
    print("crime_rate vs proverty_rate "+str(linear_regression(demo_crime_data, [4])[1]))
    print("crime_rate vs income_diversity "+ str(linear_regression(demo_crime_data, [5])[1]))
    print("crime_rate vs racial_diversity "+str(linear_regression(demo_crime_data, [6])[1]))
    print("crime_rate vs unemployment_rate "+str(linear_regression(demo_crime_data, [7])[1]))

print("\n\significance of various demographic factors with crime_rate controlled by population")
    print("crime_rate vs proverty_rate controlled by population "+str(linear_regression(demo_crime_data, [4, 8])[1]))
    print("crime_rate vs income_diversity controlled by population "+ str(linear_regression(demo_crime_data, [5,8])[1]))
    print("crime_rate vs racial_diversity controlled by population "+str(linear_regression(demo_crime_data, [6,8])[1]))
    print("crime_rate vs unemployment_rate controlled by population "+str(linear_regression(demo_crime_data, [7,8])[1]))
```

```
Significance of various demographic factors with crime_rate crime_rate vs proverty_rate 0.06523546120848842 crime_rate vs income_diversity 0.03606532612160858 crime_rate vs racial_diversity 0.008711275823851098 crime rate vs unemployment rate 0.05471047391610688
```

Significance of various demographic factors with crime\_rate controlled by population crime\_rate vs proverty\_rate controlled by population 0.1829580286423675 crime\_rate vs income\_diversity controlled by population 0.04857684388345955 crime\_rate vs racial\_diversity controlled by population 0.00022642815530583585 crime rate vs unemployment rate controlled by population 0.012688870210739571