Analysis of Covid 19 using Apache Spark

Importing Libraries

from pyspark.sql import SparkSession

from pyspark.sql.types import StructField,IntegerType,StructType,StringType

import pyspark.sql.functions as f

from pyspark.ml.regression import LinearRegression

from pyspark.ml.linalg import Vectors

from pyspark.ml.feature import VectorAssembler

import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

import plotly.graph_objects as go

import plotly.express as px

from plotly.subplots import make subplots

from pyspark.ml.classification import DecisionTreeClassifier, GBTClassifier, RandomForestClassifier

from pyspark.ml.regression import RandomForestRegressor, DecisionTreeRegressor, GBTRegressor

from pyspark.ml import Pipeline

from pyspark.ml.evaluation import RegressionEvaluator

from pyspark.ml.feature import HashingTF, Tokenizer

from pyspark.ml.tuning import ParamGridBuilder, TrainValidationSplit

from pyspark.ml.feature import VectorIndexer

Loading the dataset

In [2]:

spark = SparkSession.builder.appName("Project").getOrCreate()

In [3]:

df = spark.read.csv("country_wise_latest.csv", inferSchema =**True**, header=**True**) data = pd.read_csv("country_wise_latest.csv", index_col=0) world_data = pd.read_csv("worldometer_data.csv")

Data Exploration

In [4]:

df.toPandas().head()

													Out	t[4]:
	Country/Region	Confirmed	Deaths	Recovered	Active	New cases	New deaths	New recovered	Deaths / 100 Cases	Recovered / 100 Cases	Deaths / 100 Recovered	Confirmed last week	1 week change	
0	Afghanistan	36263	1269	25198	9796	106	10	18	3.50	69.49	5.04	35526	737	
1	Albania	4880	144	2745	1991	117	6	63	2.95	56.25	5.25	4171	709	
2	Algeria	27973	1163	18837	7973	616	8	749	4.16	67.34	6.17	23691	4282	
3	Andorra	907	52	803	52	10	0	0	5.73	88.53	6.48	884	23	
4	Angola	950	41	242	667	18	1	0	4.32	25.47	16.94	749	201	
4												1		•

In [5]:

world_data.head()

In [1]:

\cap	-[5]	٠
Out	1121	٠

	Country/Region	Continent	Population	TotalCases	NewCases	TotalDeaths	NewDeaths	TotalRecovered	NewRecovered	ActiveCases	•
0	USA	North America	3.311981e+08	5032179	NaN	162804.0	NaN	2576668.0	NaN	2292707.0	
1	Brazil	South America	2.127107e+08	2917562	NaN	98644.0	NaN	2047660.0	NaN	771258.0	
2	India	Asia	1.381345e+09	2025409	NaN	41638.0	NaN	1377384.0	NaN	606387.0	
3	Russia	Europe	1.459409e+08	871894	NaN	14606.0	NaN	676357.0	NaN	180931.0	
4	South Africa	Africa	5.938157e+07	538184	NaN	9604.0	NaN	387316.0	NaN	141264.0	
4										<u> </u>	
										In [6]]:

#Enables the user to check the column datatypes df.printSchema()

root

- |-- Country/Region: string (nullable = true)
- |-- Confirmed: integer (nullable = true)
- |-- Deaths: integer (nullable = true)
- |-- Recovered: integer (nullable = true)
- |-- Active: integer (nullable = true)
- |-- New cases: integer (nullable = true)
- |-- New deaths: integer (nullable = true)
- |-- New recovered: integer (nullable = true)
- |-- Deaths / 100 Cases: double (nullable = true)
- |-- Recovered / 100 Cases: double (nullable = true)
- |-- Deaths / 100 Recovered: string (nullable = true)
- |-- Confirmed last week: integer (nullable = true)
- |-- 1 week change: integer (nullable = true)
- |-- 1 week % increase: double (nullable = true)
- |-- WHO Region: string (nullable = true)

In [7]:

#Counting the total number of rows and column for primary dataset print((df.count(), len(df.columns)))

(187, 15)

In [8]:

#Printing the rows and column for secondary dataset world_data.shape

(209, 16)

Out[8]:

Data Pre-processing

In [9]:

#Changing the column datatype from string to integer
df = df.withColumn("Deaths / 100 Recovered", df["Deaths / 100 Recovered"].cast(IntegerType()))

In [10]:

df.printSchema()

```
root
```

- |-- Country/Region: string (nullable = true)
- |-- Confirmed: integer (nullable = true)
- |-- Deaths: integer (nullable = true)
- |-- Recovered: integer (nullable = true)
- |-- Active: integer (nullable = true)
- |-- New cases: integer (nullable = true)
- |-- New deaths: integer (nullable = true)
- |-- New recovered: integer (nullable = true)
- |-- Deaths / 100 Cases: double (nullable = true)
- |-- Recovered / 100 Cases: double (nullable = true)
- |-- Deaths / 100 Recovered: integer (nullable = true)
- |-- Confirmed last week: integer (nullable = true)
- |-- 1 week change: integer (nullable = true)
- |-- 1 week % increase: double (nullable = true)
- |-- WHO Region: string (nullable = true)

In [11]:

df.describe().toPandas()

Out[11]:

	summary	Country/Region	Confirmed	Deaths	Recovered	Active	New cases	ı
0	count	187	187	187	187	187	187	
1	mean	None	88130.935828877	3497.51871657754	50631.48128342246	34001.935828877	1222.957219251337	28.9572
2	stddev	None	383318.6638306154	14100.00248201848	190188.18964313966	213326.17337142891	5710.374790280563	120.03717
3	min	Afghanistan	10	0	0	0	0	
4	max	Zimbabwe	4290259	148011	1846641	2816444	56336	
4								F

In [12]:

#Selecting the growth factor column to determine the increase of covid cases per week df.select("1 week % increase").show()

```
|1 week % increase|
```

•
++
2.07
17.0
18.07
2.6
26.84
13.16
28.02
1
6.89
23.13
4.13
9.16
119.54
6.89
9.05
3.77
1.57
3.64
20.0
1
10.49
10.0
++

only showing top 20 rows

In [13]:

type(df["1 week % increase"])

Out[13]:

pyspark.sql.column.Column

In [14]:

#Rename the column since it is considered as label df = df.withColumnRenamed("1 week % increase", "growth_factor")

Country/Region|Confirmed|Deaths|Recovered|Active|New cases|New deaths|New recovered|Deaths / 100 Cases|Recovered / 100 Cases| Deaths / 100 Recovered|Confirmed last week|1 week change|growth_factor| WHO Region Afghanistan| 36263| 1269| 25198| 9796| 106 10| 18| 3.5 69.49 35526 5| 737 2.07|Eastern Mediterra...| Albania| 4880| 144| 2745| 1991| 6 63| 2.95 56.25 5 4171| 117 709 17.0 Europe 27973 | 1163 | 18837| 7973| 8 749 4.16 67.34 6 23691| Algeria| 616 4282 18.07 Africal Andorra| 907| 52| 803| 52| 10| 0| 0 5.73 88.53 6 884 23 2.6 Europe Angola| 950| 41| 242 | 667 | 18 11 0 4.32 25.47 16 749 201| 26.84 Africa 4| |Antigua and Barbuda| 5| 3.49| 75.581 4 10 861 31 65| 18| 0 76 13.16 Americas| 167416| 3059| 72575| 91782| 4890 120| 2057 43.35 Argentina| 1.83 4 13077 4| 366421 28.02 Americas| 37390| 711| 26665| 10014| 73| 6 187 1.9 71.32 2 34981| Armenia| 2409 6.89 Europe Australial 15303| 167| 9311 | 5825 | 368 6 137 1.09 60.84 12428 1 2875 23.13 Western Pacific 20558| 713| 18246| 1599| 37| 88.75 3| 19743 86 1| 3.47 Austria 815 4.13 Europe Azerbaijan| 30446| 423| 23242| 6781| 396 6 558 1.39 76.34 1| 27890 2556 9.16 Europe Bahamas 382 11 91| 280| 40| 0| 0 2.88 23.82 12| 174 20 8 119.54 Americas| 39482| 141| 36110| 3231| 351| 91.46 1| 421| 0.36 0 36936 Bahrainl 2546 6.89|Eastern Mediterra...| Bangladesh| 226225| 2965| 125683| 97577| 2772 37| 1801| 1.31| 55.56 2 2074 53| 18772 9.05 South-East Asia Barbados| 110 7 94| 9| 0 0 0| 6.36 85.45 7| 106 4| 3.77 Americas| 67251| 538| 89.95 Belarus| 60492 6221 119 4 67| 0.8 0| 66213 1038 1.57 Europe 66428| 9822| 17452| 39154| 4021 14| 14.79 26.27 56 64094 Belgium| 1 2334 3.64 Europe 4.17 54.17 7| 40| Belize| 48 2 26 20| 0 0 0 8 20.0 Americas 1770| 35| 1036 | 699 | 0| 0| 0 1.98 58.53 31 1602 168| Benin| 10.49 Africa| Bhutanl 991 01 86| 13| 41 0.0 86.87 01 901 91 0 1| South-East Asia ----+------+

In [16]:

#Fill all the null values present in the dataset with 0 df = df.na.fill("0", subset = ['New cases',

only showing top 20 rows

In [17]:

df.select("growth_factor").show()

^{&#}x27;New deaths'.

^{&#}x27;New recovered',

^{&#}x27;Deaths / 100 Cases'.

^{&#}x27;Recovered / 100 Cases',

^{&#}x27;Deaths / 100 Recovered'])

```
|growth_factor|
     2.07
     17.0
     18.07
      2.6
     26.84
     13.16
     28.02
     6.89
     23.13|
     4.13|
     9.16
    119.54
     6.89
     9.05
     3.77|
     1.57
     3.64
     20.0
     10.49
     10.0
only showing top 20 rows
#Filtering out the column growth factor
df.filter("growth_factor == 0").select(["Country/Region","New cases","growth_factor"]).show()
```

```
Country/Region|New cases|growth_factor|
        Brunei|
                           0.0
       Dominica|
                            0.0
                               0.0
  Equatorial Guinea
         Fiji|
                        0.0
        Grenada|
                            0.0
       Holy See|
                    0
                            0.0
    Liechtenstein|
                     0
                             0.0
|Saint Kitts and N...|
                              0.0
                      0
      San Marino|
                     0|
                             0.0
       Tanzania|
                     0
                            0.0
                             0.0
     Timor-Leste|
                     0
                       0|
   Western Sahara
                               0.0
```

In [19]:

In [18]:

new_df = df.filter(df["growth_factor"] > 0).sort("growth_factor", ascending = True)

In [20]:

new_df.select("growth_factor").show()

```
|growth_factor|
     0.13|
     0.26
     0.29
     0.49
     0.64
     0.68
     0.7|
     0.78
     0.79
     0.82
     1.08
     1.12
     1.18
     1.36
     1.45
     1.54
     1.57
     1.6
     1.73
     1.86
```

only showing top 20 rows

new_df.describe().toPandas()

Out[21]:

In [21]:

	summary	Country/Region	Confirmed	Deaths	Recovered	Active	New cases	
0	count	174	174	174	174	174	174	
1	mean	None	94682.02298850575	3758.080459770115	54396.84482758621	36527.097701149425	1314.2816091954023 31.12	2(
2	stddev	None	396678.03033529996	14586.544569931522	196683.77697176125	220987.46339036332	5910.842358130151 124.1	15
3	min	Afghanistan	14	0	0	1	0	
4	max	Zimbabwe	4290259	148011	1846641	2816444	56336	
_				400000000000000000000000000000000000000				

In [22]:

new_df.printSchema()

root

- |-- Country/Region: string (nullable = true)
- |-- Confirmed: integer (nullable = true)
- |-- Deaths: integer (nullable = true)
- |-- Recovered: integer (nullable = true)
- |-- Active: integer (nullable = true)
- |-- New cases: integer (nullable = true)
- |-- New deaths: integer (nullable = true)
- |-- New recovered: integer (nullable = true)
- |-- Deaths / 100 Cases: double (nullable = true)
- |-- Recovered / 100 Cases: double (nullable = true)
- |-- Deaths / 100 Recovered: integer (nullable = true) |-- Confirmed last week: integer (nullable = true)
- |-- 1 week change: integer (nullable = true)
- |-- growth_factor: double (nullable = true)
- |-- WHO Region: string (nullable = true)

In [23]:

new_df.toPandas().head()

	Country/Region	Confirmed	Deaths	Recovered	Active	New cases	New deaths	New recovered	Deaths / 100 Cases	Recovered / 100 Cases	Deaths / 100 Recovered	Confirmed last week		gro
0	New Zealand	1557	22	1514	21	1	0	1	1.41	97.24	1.0	1555	2	
1	Guinea-Bissau	1954	26	803	1125	0	0	0	1.33	41.10	3.0	1949	5	
2	Mauritius	344	10	332	2	0	0	0	2.91	96.51	3.0	343	1	
3	Ireland	25892	1764	23364	764	11	0	0	6.81	90.24	7.0	25766	126	
4	Estonia	2034	69	1923	42	0	0	1	3.39	94.54	3.0	2021	13	
4														F

Data Visualization

In [24]:

part = data.iloc[:10, :5] part

Out[24]:

	Confirmed	Deaths	Recovered	Active	New cases
Country/Region					
Afghanistan	36263	1269	25198	9796	106
Albania	4880	144	2745	1991	117
Algeria	27973	1163	18837	7973	616
Andorra	907	52	803	52	10
Angola	950	41	242	667	18
Antigua and Barbuda	86	3	65	18	4
Argentina	167416	3059	72575	91782	4890
Armenia	37390	711	26665	10014	73
Australia	15303	167	9311	5825	368
Austria	20558	713	18246	1599	86

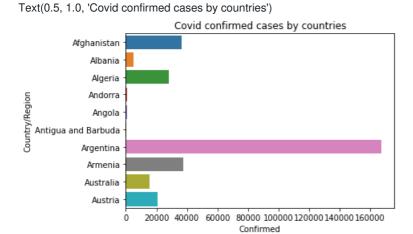
In [25]:

#Displaying the number of confirmed cases for the first 10 countries by default sns.barplot(part['Confirmed'], part.index).set_title('Covid confirmed cases by countries')

/home/muz/.local/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

warnings.warn(

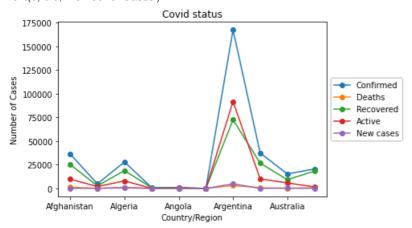
Out[25]:



In [26]:

Displaying the Deaths, Recovered and Active Cases across different countries[first 5] part.plot(style='o-') plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5)) plt.title("Covid status")

Text(0, 0.5, 'Number of Cases')



In [27]:

Visualization of Total Confirmed cases, Total Deaths and Total Active cases for top 20 countries fig=px.bar(world_data.iloc[:20,:],y='Country/Region',x='TotalCases',color='TotalCases',text="TotalCases') fig.update_layout(template="plotly_dark",title_text="Top 20 countries of Total confirmed cases") fig.show()

fig=px.bar(world_data.sort_values('TotalDeaths',ascending=**False**).iloc[:20,:],y='Country/Region',x='TotalDeaths',color='TotalDeaths',text="To fig.update_layout(template="plotly_dark",title_text="Top 20 countries of Total deaths") fig.show()

fig=px.bar(world_data.sort_values('ActiveCases',ascending=**False**).iloc[:20,:],y='Country/Region',x='ActiveCases',color='ActiveCases',text='ActiveCases',color='ActiveCases',text='ActiveCases',color='ActiveCases',text='ActiveCases',color='ActiveCases',text='ActiveCases',color='ActiveCases',text='ActiveCases',color='ActiveCases',text='A

fig=px.bar(world_data.sort_values('TotalRecovered',ascending=False).iloc[:20,:],y='Country/Region',x='TotalRecovered',color='TotalRecoverefig.update_layout(template="plotly_dark",title_text="Top 20 countries of Total Recovered") fig.show()

In [28]:

#Avg of growthfactor used to predict the percentile of week 2 con_sum = new_df.groupBy("Confirmed").sum() death_sum = new_df.groupBy("Deaths").sum() rec_sum = new_df.groupBy("Recovered").sum()

avg_growth = new_df.groupBy("growth_factor").sum()

In [29]:

avg_growth.toPandas().head()

Out[29]:

	growth_factor	sum(Confirmed)	sum(Deaths)	sum(Recovered)	sum(Active)	sum(New cases)	sum(New deaths)	sum(New recovered)	sum(Deaths / 100 Cases)	sum(Recovered / 100 Cases)
0	0.13	1557	22	1514	21	1	0	1	1.41	97.24
1	0.26	1954	26	803	1125	0	0	0	1.33	41.10
2	0.29	344	10	332	2	0	0	0	2.91	96.51
3	0.49	25892	1764	23364	764	11	0	0	6.81	90.24
4	0.64	2034	69	1923	42	0	0	1	3.39	94.54
4										<u> </u>

ML algorithms applied using Spark

Determining the label and feature column to split the dataset

In [30]:

for item in new_df.head(1)[0]:
 print(item)

Western Pacific

2 0.13

In [31]:

new_df.columns

Out[31]: ['Country/Region', 'Confirmed', 'Deaths', 'Recovered', 'Active'. 'New cases', 'New deaths', 'New recovered', 'Deaths / 100 Cases', 'Recovered / 100 Cases', 'Deaths / 100 Recovered', 'Confirmed last week', '1 week change', 'growth_factor', 'WHO Region'] In [32]: assembler = VectorAssembler(inputCols=['Confirmed','1 week change', 'Confirmed last week'], outputCol='features') In [33]: output = assembler.transform(new_df) In [34]: output.printSchema() root |-- Country/Region: string (nullable = true) |-- Confirmed: integer (nullable = true) |-- Deaths: integer (nullable = true) |-- Recovered: integer (nullable = true) |-- Active: integer (nullable = true) |-- New cases: integer (nullable = true) |-- New deaths: integer (nullable = true) |-- New recovered: integer (nullable = true) |-- Deaths / 100 Cases: double (nullable = true) |-- Recovered / 100 Cases: double (nullable = true) |-- Deaths / 100 Recovered: integer (nullable = true) |-- Confirmed last week: integer (nullable = true) |-- 1 week change: integer (nullable = true) |-- growth_factor: double (nullable = true) |-- WHO Region: string (nullable = true) |-- features: vector (nullable = true) In [35]: final_data = output.select("features", "growth_factor") In [36]: final_data.show()

features growth	
+	0.13
[1954.0,5.0,1949.0]	0.26
[344.0,1.0,343.0]	0.29
[25892.0,126.0,25	0.49
[2034.0,13.0,2021.0]	0.64
[246286.0,1662.0,	0.68
[289.0,2.0,287.0]	0.7
[5059.0,39.0,5020.0]	0.78
[7398.0,58.0,7340.0]	0.79
[1854.0,15.0,1839.0]	0.82
[9132.0,98.0,9034.0]	1.08
[4599.0,51.0,4548.0]	1.12
[8904.0,104.0,880	1.18
[86783.0,1161.0,8 [3297.0,47.0,3250.0]	1.36 1.45
[2513.0,38.0,2475.0]	1.54
[67251.0,1038.0,6]	1.57
[301708.0,4764.0,	1.6
[79395.0,1347.0,7	1.73
[207112.0,3787.0,	1.86
+	
only showing top 20 row	'S
, , ,	
#Splitting the Dataset	
train_data,test_data = 1	inal_data.randomSplit([0.8,0.2]
Linear Regression	
	d accion to an object
#Initialize the model an	
	abelCol="growth_factor")
Ir = LinearRegression(I	abelCol="growth_factor")
Ir = LinearRegression(I #Training the model us	abelCol="growth_factor") ing train dataset
Ir = LinearRegression(I	abelCol="growth_factor") ing train dataset
Ir = LinearRegression(I #Training the model us	abelCol="growth_factor") ing train dataset
Ir = LinearRegression(I #Training the model us Ir_model = Ir.fit(train_date)	abelCol="growth_factor") ing train dataset ata)
Ir = LinearRegression(I #Training the model us Ir_model = Ir.fit(train_di #Evaluating the model	abelCol="growth_factor") ing train dataset ata) using the test dataset
Ir = LinearRegression(I #Training the model us Ir_model = Ir.fit(train_date)	abelCol="growth_factor") ing train dataset ata) using the test dataset
Ir = LinearRegression(I #Training the model us Ir_model = Ir.fit(train_date) #Evaluating the model	abelCol="growth_factor") ing train dataset ata) using the test dataset

test_results.residuals.show()

```
residuals|
|-10.342908548530055|
|-12.445341418826391
|-12.310432666992382|
|-12.260911291083795|
| -9.626351699311964|
|-10.381571672499517|
| -11.34272449071033|
| -10.10315486688515|
|-10.668273608717577|
| -10.25259971267764|
|-10.001995004429709|
 -9.53787584771572
 -9.526679406361826|
-6.876238894182514|
| -5.439312032681437|
| -5.709388615431024|
| -5.408952467318873|
| -5.082417514962112|
|-2.6663941275472656|
| -2.558042692802866|
only showing top 20 rows
                                                                                                                           In [42]:
#Rootmeansquared error
print("RMSE for Linear Regression")
print(test_results.rootMeanSquaredError)
RMSE for Linear Regression
13.743615446702012
                                                                                                                           In [43]:
#Returning the coefficient of determination
print("R Squared Value for Linear Regression")
print(test_results.r2)
R Squared Value for Linear Regression
0.04899621536079357
                                                                                                                           In [44]:
final_data.describe().show()
|summary| growth_factor|
+----+
| count|
 mean|14.644827586206901|
| stddev|25.103550073060976|
| min|
              0.13
             226.32
| max|
+----+
                                                                                                                           In [45]:
#Data prediction using the Feature column
unlabled_data = test_data.select("features")
                                                                                                                           In [46]:
unlabled_data.show()
```

```
features
[109597.0,2560.0,...]
[[1132.0,27.0,1105.0]]
[4448.0,109.0,433...]
 [350.0,9.0,341.0]
[116458.0,3533.0,...]
|[59177.0,1984.0,5...|
|[2532.0,86.0,2446.0]|
[66428.0,2334.0,6...]
|[1783.0,72.0,1711.0]|
|[7235.0,314.0,692...|
[6208.0,285.0,592...]
[18752.0,908.0,17...
|[1455.0,74.0,1381.0]|
| [148.0,11.0,137.0]|
[81161.0,6541.0,7...]
|[9764.0,816.0,894...
[15655.0,1343.0,1...]
[23154.0,2039.0,2...]
[431.0,47.0,384.0]
|[3369.0,370.0,299...|
only showing top 20 rows
                                                                                                                                  In [47]:
prediction = Ir model.transform(unlabled data)
                                                                                                                                  In [48]:
# Growth Factor prediction
prediction.show()
     features| prediction|
|[109597.0,2560.0,...|12.732908548530055|
|[1132.0,27.0,1105.0]| 14.88534141882639|
|[4448.0,109.0,433...|14.820432666992382|
 [350.0,9.0,341.0]|14.900911291083796|
|[116458.0,\!3533.0,\!...|12.756351699311965|
|[59177.0,1984.0,5...|13.851571672499517|
|[2532.0,86.0,2446.0]| 14.86272449071033|
|[66428.0,2334.0,6...| 13.74315486688515|
|[1783.0,72.0,1711.0]|14.878273608717576|
|[7235.0,314.0,692...|14.792599712677639|
|[6208.0,285.0,592...|14.811995004429708|
|[18752.0,908.0,17...| 14.62787584771572|
|[1455.0,74.0,1381.0]|14.886679406361825|
[148.0,11.0,137.0]|14.906238894182513|
|[81161.0,6541.0,7...|14.209312032681437|
|[9764.0,\!816.0,\!894...|14.829388615431023|
|[15655.0,1343.0,1...|14.788952467318873|
|[23154.0,2039.0,2...|14.742417514962112|
[431.0,47.0,384.0]|14.906394127547266|
|[3369.0,370.0,299...|14.898042692802866|
-------
only showing top 20 rows
Decision Tree Regressor
                                                                                                                                  In [49]:
#Intialize the decision tree regressor
featureIndexer = VectorIndexer(inputCol="features", outputCol="indexedFeatures", maxCategories=4).fit(final data)
dtr = DecisionTreeRegressor(labelCol= "growth_factor",featuresCol= "features")
                                                                                                                                  In [50]:
pipeline = Pipeline(stages=[featureIndexer, dtr])
                                                                                                                                  In [51]:
dtr_model = pipeline.fit(train_data)
```

```
In [52]:
 dtr_predictions = dtr_model.transform(test_data)
                                                                                                                                      In [53]:
 dtr_predictions.select("prediction", "growth_factor", "features").show(5)
    prediction|growth_factor| features|
      -----+
| 6.615172413793103| 2.39|[109597.0,2560.0,...|
|2.5714285714285716|

|1.5219999999999999999|

|2.5714285714285716|

|6.615172413793103|

|2.51|[132.0,27.0,1105.0]|

2.51|[4448.0,109.0,433...]

2.64| [350.0,9.0,341.0]|

3.13|[116458.0,3533.0,...]
+-----+
only showing top 5 rows
                                                                                                                                      In [58]:
 #Evaluate the model that has been trianed using the train dataset where label is growth factor
 print("Root Mean Squared Error (RMSE) for Decision Tree on test data")
 dtr_evaluator = RegressionEvaluator(
    labelCol="growth_factor", predictionCol="prediction", metricName="rmse")
 dtr rmse = dtr evaluator.evaluate(dtr predictions)
 print(dtr_rmse)
Root Mean Squared Error (RMSE) for Decision Tree on test data
10.34182489586513
                                                                                                                                      In [59]:
 #Summary of the model
 dtr_treeModel = dtr_model.stages[1]
 print(dtr_treeModel)
DecisionTreeRegressionModel: uid=DecisionTreeRegressor_ef24775c252f, depth=5, numNodes=53, numFeatures=3
RandomForest Tree regressor
                                                                                                                                      In [60]:
 #Initalize the Randomforest Regressor
 rfr = RandomForestRegressor(numTrees= 100,labelCol= "growth_factor", featuresCol= "features")
 rfr_pipeline = Pipeline(stages=[featureIndexer, rfr])
 rfr model = rfr pipeline.fit(train data)
 rfr_predictions = rfr_model.transform(test_data)
                                                                                                                                      In [61]:
 rfr_predictions.select("prediction", "growth_factor", "features").show(5)
    prediction|growth_factor| features|
+-----+
| 10.191944281248436| | 2.39|[109597.0,2560.0,...| | 4.681050535452821| | 7.367222753089058| | 2.51|[4448.0,109.0,433...|
+-----+-----
only showing top 5 rows
                                                                                                                                      In [64]:
 #Evaluate the model that has been trianed using the train dataset where label is growth factor
 print("Root Mean Squared Error (RMSE) for Random Forest on test data")
 rfr_evaluator = RegressionEvaluator(
    labelCol="growth_factor", predictionCol="prediction", metricName="rmse")
 rfr_rmse = rfr_evaluator.evaluate(rfr_predictions)
 print(rfr_rmse)
Root Mean Squared Error (RMSE) for Random Forest on test data
12.460239542681974
                                                                                                                                      In [65]:
 #Summary of the model
 rfr_treeModel = rfr_model.stages[1]
```

RandomForestRegressionModel: uid=RandomForestRegressor_f22d1d717bdd, numTrees=100, numFeatures=3

Gradient Boost Tree Regressor

```
#Initialize Gradient Booster Regressor
gbr = GBTRegressor(labelCol= "growth_factor", featuresCol= "features")
gbr_pipeline = Pipeline(stages=[featureIndexer, gbr])
gbr_model = gbr_pipeline.fit(train_data)
gbr_predictions = gbr_model.transform(test_data)
                                                                                                                                   In [67]:
gbr_predictions.select("prediction", "growth_factor", "features").show(5)
+-----+
    prediction|growth_factor| features|
+-----+
| 5.169092022645198| 2.39|[109597.0,2560.0,...| 2.680869028166836| 2.44|[1132.0,27.0,1105.0]|
| 1.806442660961181| | 2.51|[4448.0,109.0,433...| | 1.5040683028236084| | 5.4472733099287804| | 3.13|[116458.0,3533.0,...|
+-----+
only showing top 5 rows
                                                                                                                                   In [69]:
#Evaluate the model that has been trianed using the train dataset where label is growth factor
print("Root Mean Squared Error (RMSE) for Gradient Boost on test data")
gbr_evaluator = RegressionEvaluator(
   labelCol="growth_factor", predictionCol="prediction", metricName="rmse")
gbr_rmse = gbr_evaluator.evaluate(gbr_predictions)
print(gbr_rmse)
Root Mean Squared Error (RMSE) for Gradient Boost on test data
7.833917524401471
                                                                                                                                   In [70]:
#Summary of the model
gbr_treeModel = gbr_model.stages[1]
print(gbr_treeModel)
GBTRegressionModel: uid=GBTRegressor_66dd9e38cacb, numTrees=20, numFeatures=3
                                                                                                                                   In [71]:
#Data prediction using the Feature column[if new entries were added to the current dataset]
unlabled_data = test_data.select("features")
                                                                                                                                   In [72]:
unlabled_data.show()
```

In [66]:

```
features
[109597.0,2560.0,...]
|[1132.0,27.0,1105.0]|
[4448.0,109.0,433...]
 [350.0,9.0,341.0]
[116458.0,3533.0,...]
|[59177.0,1984.0,5...|
|[2532.0,86.0,2446.0]|
[66428.0,2334.0,6...]
[1783.0,72.0,1711.0]
|[7235.0,314.0,692...|
[6208.0,285.0,592...]
[18752.0,908.0,17...
|[1455.0,74.0,1381.0]|
| [148.0,11.0,137.0]|
[81161.0,6541.0,7...]
|[9764.0,816.0,894...
|[15655.0,1343.0,1...
[23154.0,2039.0,2...]
 [431.0,47.0,384.0]
|[3369.0,370.0,299...|
only showing top 20 rows
```

prediction 2 = gbr model.transform(unlabled data)

Growth Factor prediction prediction_2.show()

features| indexedFeatures| prediction| +----+ $|[109597.0,2560.0,...|[109597.0,2560.0,...|\ 5.169092022645198]$ |[1132.0,27.0,1105.0]|[1132.0,27.0,1105.0]| 2.680869028166836| |[4448.0,109.0,433...|[4448.0,109.0,433...| 1.806442660961181| [350.0,9.0,341.0]| [350.0,9.0,341.0]|1.5040683028236084| |[116458.0,3533.0,...|[116458.0,3533.0,...|5.4472733099287804]||[59177.0,1984.0,5...|[59177.0,1984.0,5...| 2.388992576577857| |[2532.0,86.0,2446.0]|[2532.0,86.0,2446.0]| 5.126350710171436| |[66428.0,2334.0,6...|[66428.0,2334.0,6...| 6.337634515145746| |[1783.0,72.0,1711.0]|[1783.0,72.0,1711.0]| 4.924440456738263| |[7235.0,314.0,692...|[7235.0,314.0,692...| 6.242074332209283| |[6208.0,285.0,592...|[6208.0,285.0,592...]||[18752.0,908.0,17...|[18752.0,908.0,17...| 4.424208005309042| $|[1455.0,74.0,1381.0]|[1455.0,74.0,1381.0]|\ 4.924440456738263|$ [148.0,11.0,137.0]| [148.0,11.0,137.0]| 5.818553586633133| |[81161.0,6541.0,7...|[81161.0,6541.0,7...| 8.745725271437182| |[9764.0,816.0,894...|[9764.0,816.0,894...| 8.313693109334517| |[15655.0,1343.0,1...|[15655.0,1343.0,1...| 14.27559875845944| [23154.0,2039.0,2...|[23154.0,2039.0,2...| 15.78728864959134] | [431.0,47.0,384.0]| [431.0,47.0,384.0]| 5.515408268537896| |[3369.0,370.0,299...|[3369.0,370.0,299...| 11.08392957885411| +-----+ only showing top 20 rows

Hyperparameter Tuning using Train Validation Split

#Renaming the growth_factor column to its default name final_data = final_data.withColumnRenamed('growth_factor','label') final_data.show(5)

In [73]:

In [74]:

In [75]:

```
features|label|
+----+
| [1557.0,2.0,1555.0]| 0.13|
[1954.0,5.0,1949.0]| 0.26|
[344.0,1.0,343.0] 0.29
|[25892.0,126.0,25...|\ 0.49|
|[2034.0,13.0,2021.0]| 0.64|
+----+
only showing top 5 rows
                                                                                                                               In [76]:
#Splitting the dataset into train and test
train, test = final_data.randomSplit([0.8, 0.2], seed=12345)
                                                                                                                               In [77]:
#Initialize linear regression model
Ir2 = LinearRegression( maxIter=10)
train.show(5)
+----+
  features|label|
+----+
| [1557.0,2.0,1555.0]| 0.13|
[1954.0,5.0,1949.0] 0.26
[344.0,1.0,343.0] | 0.29
|[25892.0,126.0,25...| 0.49|
|[2034.0,13.0,2021.0]| 0.64|
+----+
only showing top 5 rows
                                                                                                                               In [78]:
test.show(5)
  features|label|
|[246286.0,1662.0,...| 0.68|
|[9132.0,98.0,9034.0]| 1.08|
|[2513.0,38.0,2475.0]| 1.54|
|[301708.0,4764.0,...| 1.6|
| [462.0,11.0,451.0]| 2.44|
+----+
only showing top 5 rows
                                                                                                                               In [79]:
paramGrid = ParamGridBuilder()\
   .addGrid(Ir.regParam, [0.1, 0.01]) \
   .addGrid(Ir.fitIntercept, [False, True])\
   .addGrid(Ir.elasticNetParam, [0.0, 0.5, 1.0])\
   .build()
                                                                                                                               In [80]:
tvs = TrainValidationSplit(estimator=lr2,
                estimatorParamMaps=paramGrid,
                evaluator=RegressionEvaluator(),
                trainRatio=0.8)
                                                                                                                               In [81]:
# Run TrainValidationSplit, and choose the best set of parameters.
model = tvs.fit(train)
                                                                                                                               In [82]:
model.transform(test)\
   .select("features", "label", "prediction")\
   .show()
```

features|label| prediction| |[246286.0,1662.0,...| 0.68| 9.241321131457799| $|[9132.0,98.0,9034.0]|\ 1.08|14.336751651536426|$ |[2513.0,38.0,2475.0]| 1.54|14.475933105974457| |[301708.0,4764.0,...| 1.6| 8.558165394245743|[462.0,11.0,451.0]| 2.44|14.517500925236522| $|[1132.0,\!27.0,\!1105.0]|\ 2.44|14.505253860410901|$ $\mid \ [907.0,\!23.0,\!884.0] \mid \ 2.6 | 14.509621400458085 |$ $|[14203.0,387.0,13...| \ \ 2.8|14.275203958824356|$ |[227019.0,6447.0,...| 2.92|10.566486739971866| |[50299.0,1528.0,4...| 3.13|13.667154199699686| |[116458.0,3533.0,...| 3.13|12.536674567540102| | [701.0,24.0,677.0]| 3.55|14.514484979615759| $|[2305.0, 94.0, 2211.0]| \ 4.25|14.491044737615399|$ [24.0,1.0,23.0]| 4.35| 14.52559249112532| [[1167.0,60.0,1107.0]] 5.42|14.510580622108927| [853.0,44.0,809.0] 5.44|14.514743243676852| [114.0,6.0,108.0]| 5.56|14.524476183406323| [265.0,14.0,251.0]| 5.58|14.522531127284006| |[50838.0,2803.0,4...| 5.84|13.891429601715728| |[39482.0,2546.0,3...| 6.89|14.101640130619082|

only showing top 20 rows

In []:

In []: