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CS 7394

Imports

In [1]:

```
import pandas as pd
import numpy as np
from sklearn.linear_model import LinearRegression
import warnings
warnings.filterwarnings('ignore')
```

Data Processing

Source: World Bank (https://data.worldbank.org/indicator/SP.POP.TOTL)

In [2]:

```
data = pd.read_csv('World3.csv')
data.head()
```

Out[2]:

	Country Name	1960	1961	1962	1963	1964	1965	1966	
0	Afghanistan	8996967.0	9169406.0	9351442.0	9543200.0	9744772.0	9956318.0	10174840.0	1039
1	Albania	1608800.0	1659800.0	1711319.0	1762621.0	1814135.0	1864791.0	1914573.0	196
2	Algeria	11057864.0	11336336.0	11619828.0	11912800.0	12221675.0	12550880.0	12902626.0	1327
3	American Samoa	20127.0	20605.0	21246.0	22029.0	22850.0	23675.0	24473.0	2
4	Andorra	13410.0	14378.0	15379.0	16407.0	17466.0	18542.0	19646.0	2

5 rows × 62 columns

In [3]:

```
data.shape
```

Out[3]:

```
(217, 62)
```

In [4]:

```
data[data.isnull().any(axis=1)]
```

Out[4]:

	Country Name	1960	1961	1962	1963	1964	1965	1966	1967
61	Eritrea	1007586.0	1033320.0	1060489.0	1088859.0	1118152.0	1148188.0	1178875.0	1210304.0
106	Kuwait	269026.0	300581.0	337346.0	378756.0	423900.0	472032.0	523169.0	577164.0

	Country Name	1960	1961	1962	1963	1964	1965	1966	1967
213	West Bank and Gaza	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

3 rows × 62 columns

In [5]:
```
data.dropna(inplace=True)
```

In [6]:
```
data.shape
```

Out[6]:
```
(214, 62)
```

In [7]:
```
data = data.drop(columns=['Country Name'])
```

Model Fit and Predict

In [8]:
```
def build_model(train, modType):
    x = train.iloc[:, 0].values.reshape(-1,1)
    y = train.iloc[:, 1].values.reshape(-1,1)
    model = modType().fit(x,y)
    return model

def predict(model, year):
    return model.predict([[year]])[0][0]
```

Predict World Population in 2122

Method #1:

Create one model for the total population

In [9]:
```
data2 = pd.read_csv('totalPop.csv')
data2.head()
```

Out[9]:

	Series Name	Country Name	1960	1961	1962	1963	1964	1965	
0	Population, total	World	3032156070	3071596055	3124561005	3189655687	3255145692	3322046795	339

1 rows × 63 columns

In [10]:
```
data2 = data2.drop(columns=['Series Name' ,'Country Name'])
```

In [11]:
```
data_tuples = list(zip(data2.columns.values,data2.iloc[0, : ]))
tempDf = pd.DataFrame(data_tuples, columns=['Year','Population'])
```

In [12]:
```
linReg = build_model(tempDf, LinearRegression)


predLin1 = predict(linReg, 2122)
print("Linear Regression #1 population prediction = ", np.floor(predLin1))
```

```
Linear Regression #1 population prediction =  15953694673.0
```

Model plot

In [13]:
```
from matplotlib import pyplot as plt
import seaborn as sns

X = tempDf.iloc[:, 0].values
Y = tempDf.iloc[:, 1].values
x = X.reshape(-1,1)
```

In [14]:
```
y_pred = linReg.predict(x)
y_pred = y_pred.reshape(1,-1)
```

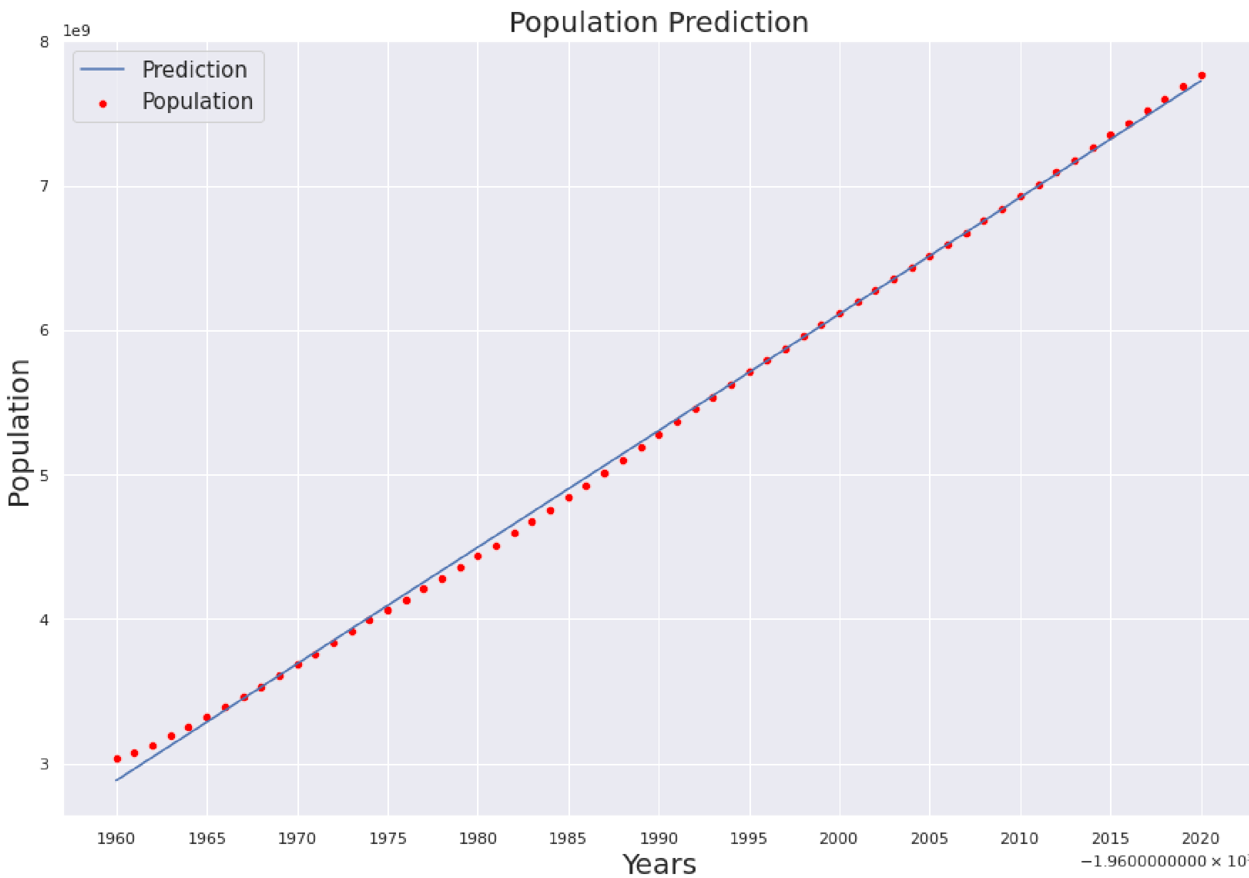
In [15]:
```
import matplotlib.ticker as ticker


plt.figure(figsize=(15, 10))


sns.set()


ax = sns.scatterplot(X, Y, color = 'red')
sns.lineplot(X, y = y_pred[0])
ax.xaxis.set_major_locator(ticker.MultipleLocator(5))
ax.xaxis.set_major_formatter(ticker.ScalarFormatter(-1960,-2020))
plt.title('Population Prediction', fontsize=20)
plt.xlabel('Years', fontsize=20)
plt.ylabel('Population', fontsize=20)
plt.legend(['Prediction', 'Population'], fontsize=15 )
plt.savefig("model.png")


plt.show()
```



In [16]:

```
from sklearn.metrics import mean_squared_error

rms = mean_squared_error(Y, linReg.predict(x), squared=False)
rms
print("RMSE of the linear regression model =", rms)
```

```
RMSE of the linear regression model = 41276568.06427081
```

Method #2:

- Model the population growth of each country
- Predict the population of one country
- Sum the predictedtions

In [17]:

```
predLin2 = 0
for index in range(data.shape[0]):
    data_tuples = list(zip(data.columns.values,data.iloc[index, : ]))
    data_tuples

    tempDf = pd.DataFrame(data_tuples, columns=['Year','Population'])
    model = build_model(tempDf, LinearRegression)

    pred = predict(model, 2122)
    predLin2 = predLin2 + pred
```

```
print("Linear Regression #1 population prediction = ", np.floor(predLin2))
```

```
Linear Regression #1 population prediction =  15874354113.0
```

Method #2 yields a slightly lower prediction than Method #1 which makes it the better method, but still not enough.

Ridge Regression

In [18]:
```
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
```

Method #1:

In [19]:
```
data_tuples = list(zip(data2.columns.values,data2.iloc[0, : ]))
tempDf = pd.DataFrame(data_tuples, columns=['Year','Population'])

x = tempDf.iloc[:, 0].values.reshape(-1,1)
y = tempDf.iloc[:, 1].values.reshape(-1,1)

ridge = Ridge(alpha=1.0)
# fit
ridge.fit(x, y)
# predict

predRidge1 = predict(ridge, 2122)

predRidge1
```

Out[19]:
```
15953131404.865936
```

In [20]:
```
rms2 = mean_squared_error(Y, ridge.predict(x), squared=False)
print("RMSE of the ridge regression model =", rms2)
```

```
RMSE of the ridge regression model = 41276636.44146911
```

Method #2:

In [21]:
```
predRidge2 = 0
for index in range(data.shape[0]):
    data_tuples = list(zip(data.columns.values,data.iloc[index, : ]))
    data_tuples

    tempDf = pd.DataFrame(data_tuples, columns=['Year','Population'])
```

```
    model = build_model(tempDf, Ridge)

    pred = predict(model, 2122)
    predRidge2 = predRidge2 + pred
    #print(pred)
print("Ridge Regression population prediction = ", predRidge2)
```

```
Ridge Regression population prediction =  15873793727.353664
```

I was curious to see how differently ridge regression will perform on this problem. In both methods it produced almost the same result as the linear regression models, with prediction values lower than that of LR by around 500K.

Conclusion

Linear Regression is not the optimal solution for our problem. It tends to provide high predictions because it follows population growth data from over the past 80 years only, during which world population boomed. Between 1960 and 2020 (the dataset limits), the world population more than doubled, growing from 3 billion to almost 8 billion. It is reasonable for a linear model to predict that the population doubles in 100 years, given only these information.

The information extracted from the population data is not enough to make a reliable prediction 100 years in the future. We probably need to look for more data features that contribute to population growth/decline. Such features include (but not limited to): fertility rates, mortality rates, death rates, gross reproduction rates, migration rates, deforestation, climate change, etc.... These features could be consalidated with dimentionality reduction algorithms to extract the most information out of the data that indicate a trend. We then train a neural network on the extracted features. This approach would provide more reliable and data driven predictions.

Experimenting with time series forcasting models

ARIMA Model:

In [22]:

```
from statsmodels.tsa.arima.model import ARIMA
def parser(x):
    return pd.datetime.strptime(x, '%Y')
years = []
years = [parser(x) for x in data2.columns.values]
```

In [23]:

```
series = pd.DataFrame(list(data2.iloc[0, : ]), columns=['Population'])
series
```

Out[23]:

	Population

	Population
0	3032156070
1	3071596055
2	3124561005
3	3189655687
4	3255145692
...	...
56	7433569330
57	7519183459
58	7602454161
59	7683372259
60	7761620146

61 rows × 1 columns

In [24]:

```
series.index = years
series.index = series.index.to_period('Y')
series
```

Out[24]:

	Population
1960	3032156070
1961	3071596055
1962	3124561005
1963	3189655687
1964	3255145692
...	...
2016	7433569330
2017	7519183459
2018	7602454161
2019	7683372259
2020	7761620146

61 rows × 1 columns

In [25]:

```
model = ARIMA(series, order=(1,2,0))
fitted_Model = model.fit()
print(fitted_Model.summary())
```

```
                           SARIMAX Results
==============================================================================
Dep. Variable:             Population   No. Observations:                   61
Model:                 ARIMA(1, 2, 0)   Log Likelihood                -949.309
Date:                Mon, 07 Feb 2022   AIC                           1902.618
Time:                        16:01:32   BIC                           1906.773
Sample:                    12-31-1960   HQIC                          1904.240
                         - 12-31-2020
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.0045      0.011     -0.418      0.676      -0.026       0.017
sigma2      3.093e+12   5.23e-16   5.91e+27      0.000    3.09e+12    3.09e+12
===================================================================================
Ljung-Box (L1) (Q):                   1.92   Jarque-Bera (JB):               439.95
Prob(Q):                              0.17   Prob(JB):                         0.00
Heteroskedasticity (H):               0.18   Skew:                             2.56
Prob(H) (two-sided):                  0.00   Kurtosis:                        15.36
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 7.07e+42. Stan
dard errors may be unstable.
```

```
/home/sam/anaconda3/envs/aplML/lib/python3.9/site-packages/statsmodels/base/model.py:60
4: ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check mle_ret
vals
  warnings.warn("Maximum Likelihood optimization failed to "
```

In [26]:

```python
start_index = pd.datetime.strptime('2122','%Y')
end_index = pd.datetime.strptime('2122','%Y')
forecast = fitted_Model.predict(start=start_index, end=end_index)
print("Prediction: ")
forecast
```

```
Prediction:
```

Out[26]:

```
2122    1.574412e+10
Freq: A-DEC, dtype: float64
```

Holt-Winters Model:

In [27]:

```python
from statsmodels.tsa.holtwinters import SimpleExpSmoothing
```

In [28]:

```python
f = SimpleExpSmoothing(series).fit(smoothing_level=0.5,optimized=True,use_brute=True)
print("Prediction: ")
f.predict(start=start_index, end=end_index)
```

```
Prediction:
```

Out[28]:
```
2122    7.681143e+09
Freq: A-DEC, dtype: float64
```