



SMARTBRIDGE
Let's Bridge the Gap

Summer Internship Report

Predicting Life Expectancy Using Machine Learning

Submitted By: -

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Internship Title: Predicting Life Expectancy using Machine Learning - SB37181

Project ID: SPS_PRO_215

Project Mentor: - Miss. Supriya Punna

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1. INTRODUCTION

Life expectancy is a statistical measure of the average time an organism is expected to live, based on the year of its birth, its current age, and other demographic factors including gender. The most commonly used measure is life expectancy at birth. A typical Regression Machine Learning project leverages historical data to predict insights into the future. This problem statement is aimed at predicting Life Expectancy rate of a country given various features.

1.1 Overview

Life expectancy is estimation of someone's life span, that any person lives some amount of years. It further depends on some demographic factors like Mental illness, Physical illness, Education Sex differences, Regional variation, Economic circumstances, Education, Year of birth etc. This problem statement provides a way to predict the average life expectancy when various factors such as GDP, year, BMI, alcohol intake of people in country and some specific disease related to death in country are given.

In order to predict life expectancy rate of a given country, we will be using Machine Learning algorithms to draw inferences from the given dataset and give an output. For better usability by the customer, we are also going to be creating a UI for the user to interact with using Node-Red.

1.2 Purpose:

This project tries to create a modal that predict the life expectancy of different countries in years provided by data of WHO. This data offers a timeframe from 200 to 2015. This helps to determine the life expectancy of a region and to take necessary medical precautions if there are any diseases.

Predicting life expectancy would play a vital role in judging the growth and development of the economy. Across countries, high life expectancy is associated with high income per capital. Increase in life expectancy also leads to an increase in the "manpower" of a country. The knowledge asset of a country increases with the number of individuals in a country.

Helps the government bodies take appropriate measures to control the population growth and also direct the utilization of the increase in human resources and skillset acquired by people over many years.

2. LITERATURE SURVEY

2.1 Existing problem:

We have to predict life expectancy of a country in a year and having some factors that affect life expectancy. Some existing technology predict life expectancy and some fails to give the right answer. There are even some other approaches smart devices which involves human intervention. TO overcome this, we can some latest evolving techniques like ML, AI etc. to predict life expectancy instead of calculating manually.

2.2 Proposed Solution:

Machine learning helps us to have a lot of models with different degrees and choices. In order to make regression models we need to use a lot of libraries and tools like stats models, Linear Regression and train test split from sklearn besides Pandas, Numpy, Matplotlib, etc. in Python. I will use some Variance Analysis in Regression models in order to determine whether regression models are accurate or misleading. Following a flawed model is a bad idea, so it is important that we can quantify how accurate our model is.

I made this research based on Life Expectancy data set which is published by The Global Health Observatory (GHO) data repository under World Health Organization (WHO) keeps track of the health status, as well as many other related factors for all countries. The datasets are made available to the public for the purpose of health data analysis.

The dataset related to life expectancy, health factors for 193 countries have been collected from the same WHO data repository website and its corresponding economic data was collected from the United Nation website.

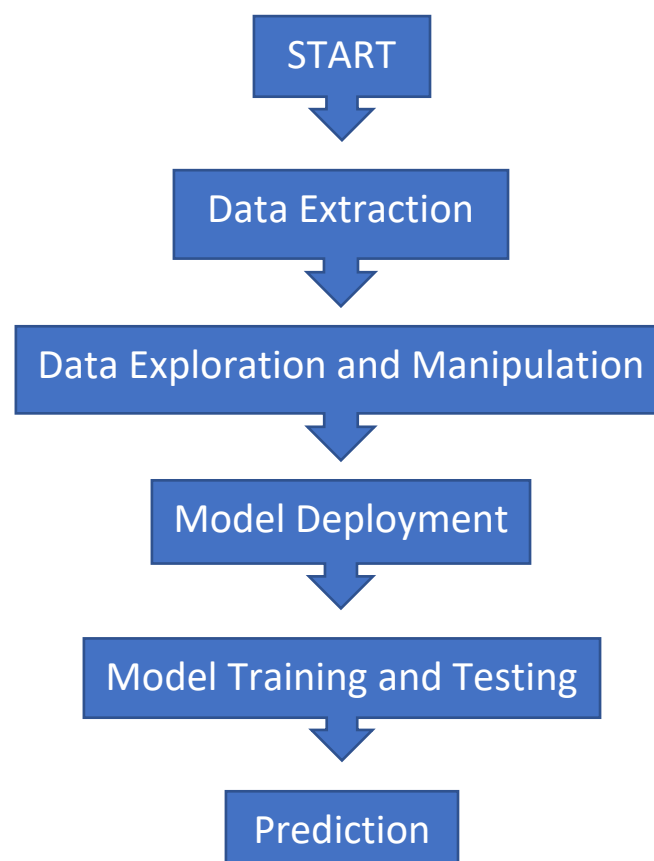
We will see our values from the year 2000 till 2015 for 193 countries. In order to have an accurate filling on missing values and a clear view of the data external data set has been merged together into a single dataset to predict the life expectancy of a country in a particular year we are going to use IBM cloud.

IBM cloud solution for a Regression Machine Learning project leverages historical data to predict insights into the future. This problem statement is aimed at predicting Life Expectancy rate of a country given various features using node-RED user interface.

Life expectancy is a statistical measure of the average time a human being is expected to live, Life expectancy depends on various factors: Regional variations, Economic Circumstances, Sex Differences, Mental Illnesses, Physical Illnesses, Education, Year of their birth and other demographic factors. My responsibility is to work on IBM Watson Studio and Auto AI to provides a way to predict average life expectancy of people living in a country when various factors such as year, GDP, education, alcohol intake of people in the country, expenditure on healthcare system and some specific disease related deaths that happened in the country are given.

3. THEORITICAL ANALYSIS

3.1 Block diagram

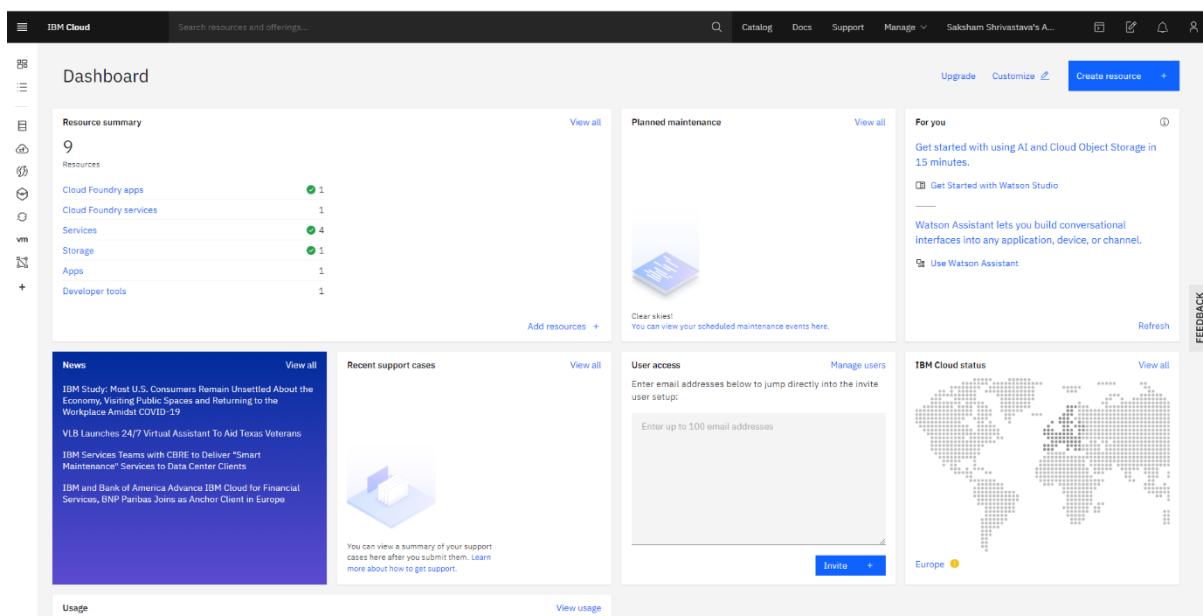


3.2 Hardware / Software designing:

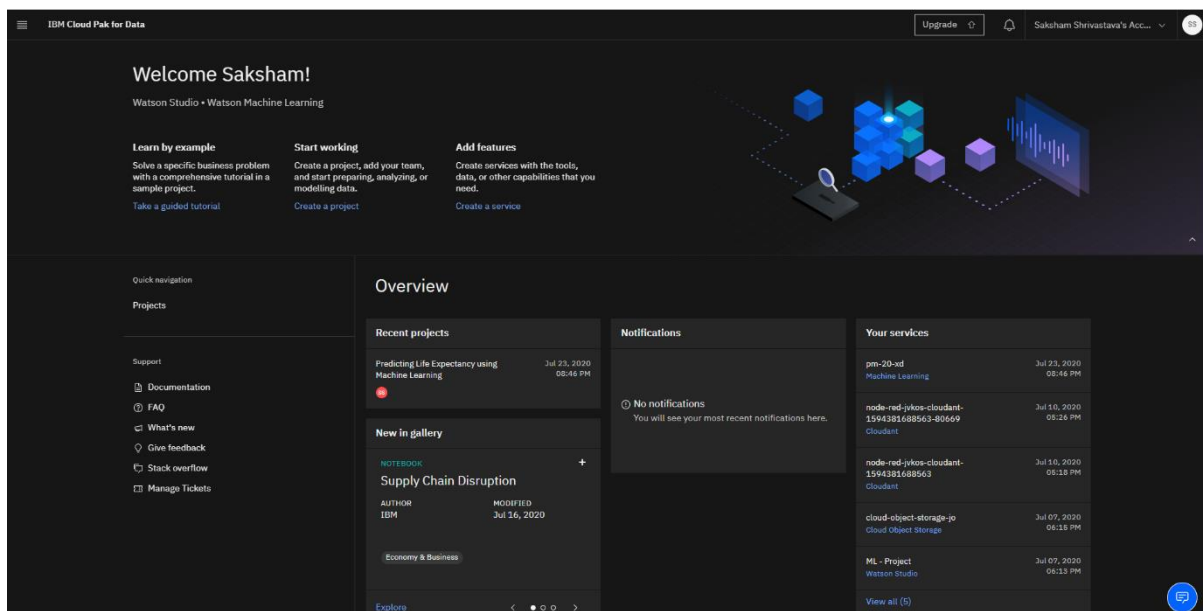
First, we have to evaluate our dataset like data exploration, manipulation, EDA (exploratory data analysis), train and test split, using multiple regression for prediction, creating deployments and then the regression model built in python is deployed on IBM cloud. The Node- RED application then sends HTTP request with all the required parameters to the trained model. The model then sends the HTTP response which is then parsed and displayed on the UI.

Model Designing (Watson Studio): -

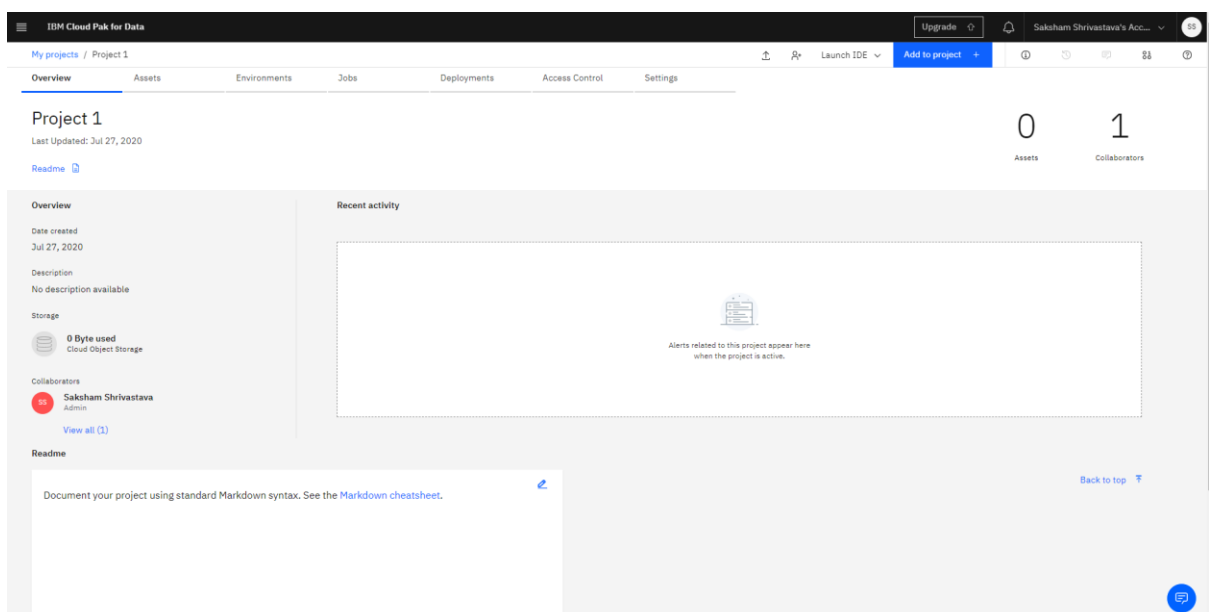
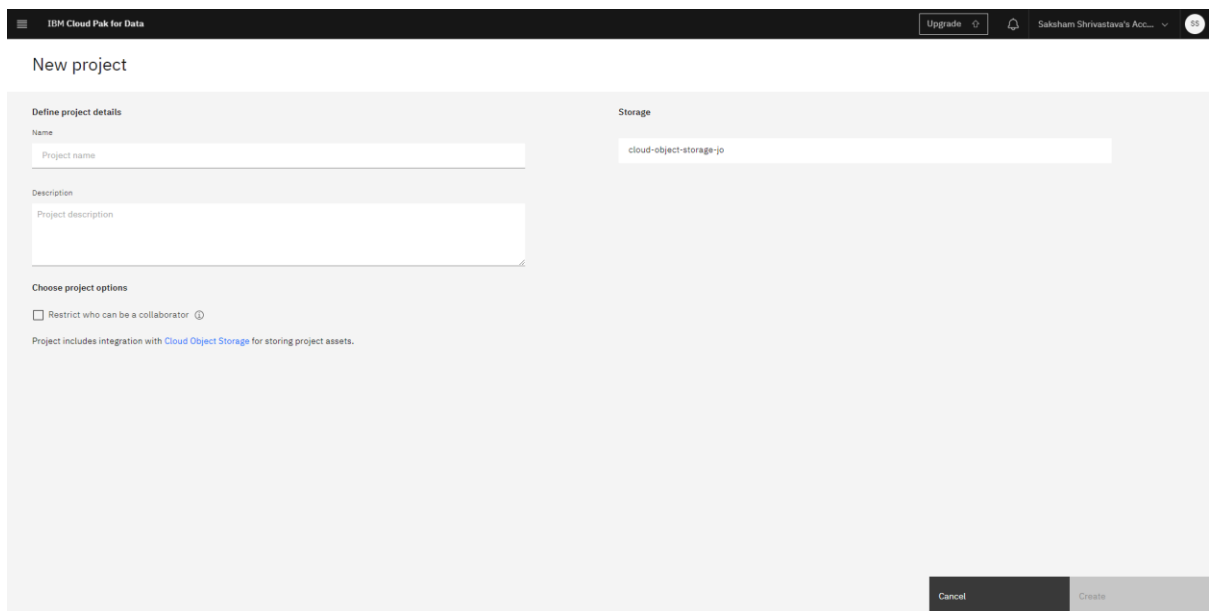
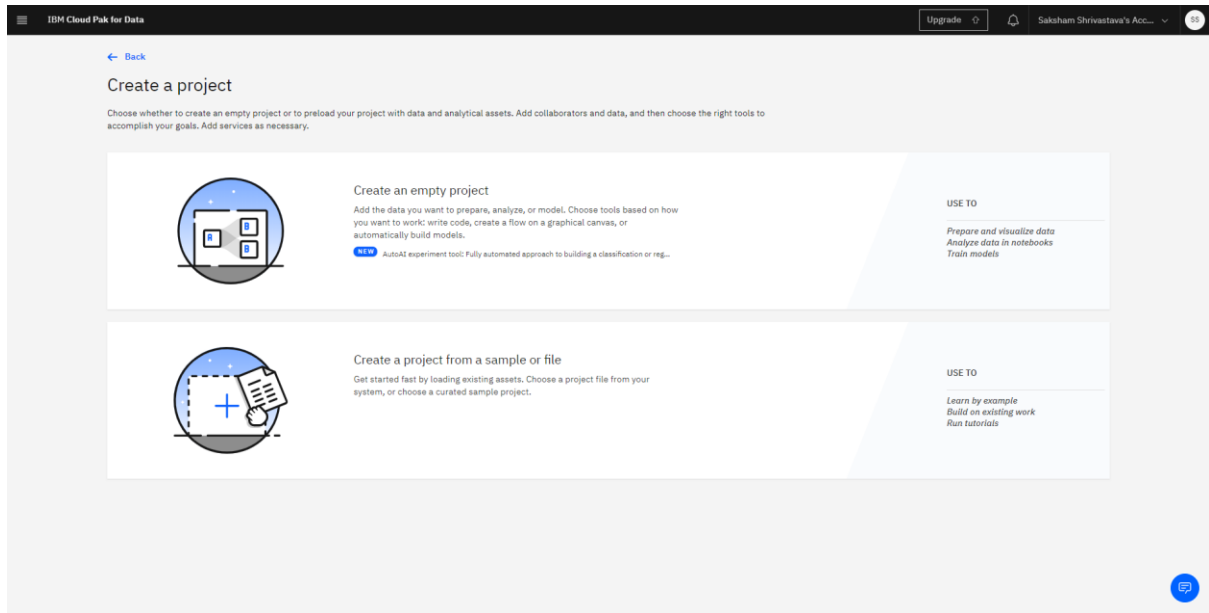
1. Login to your IBM cloud account:

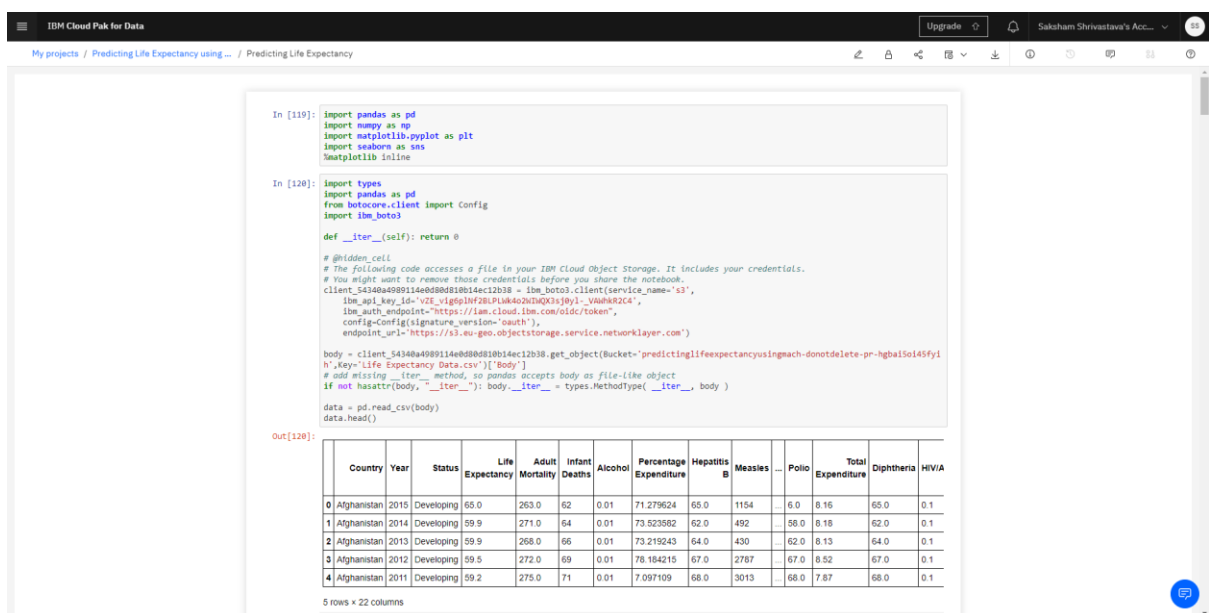
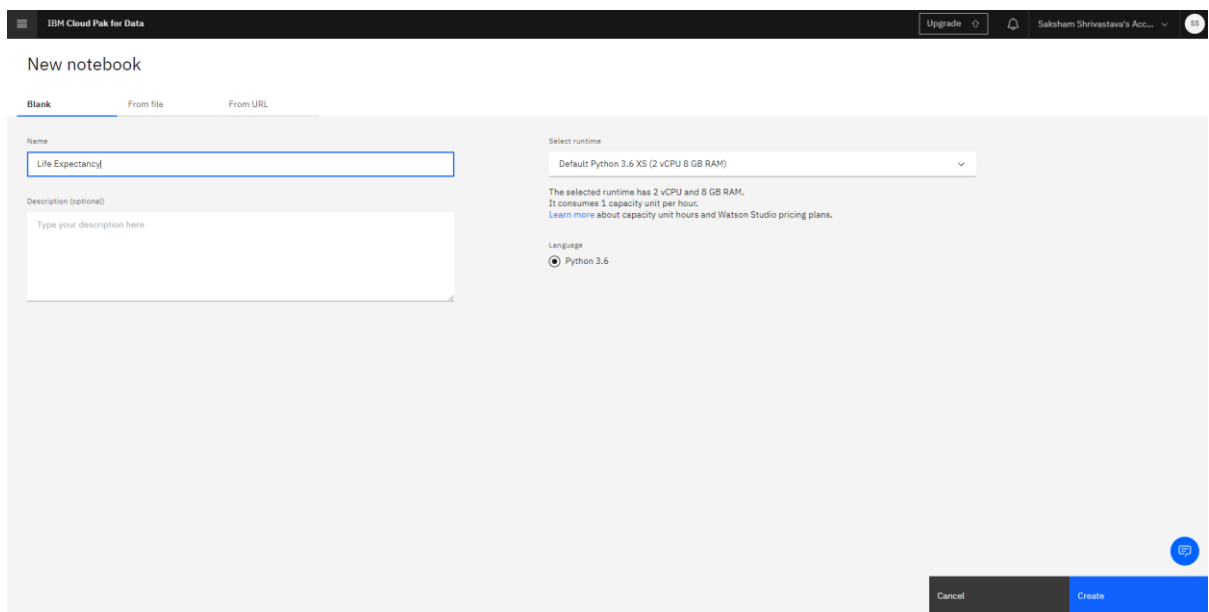
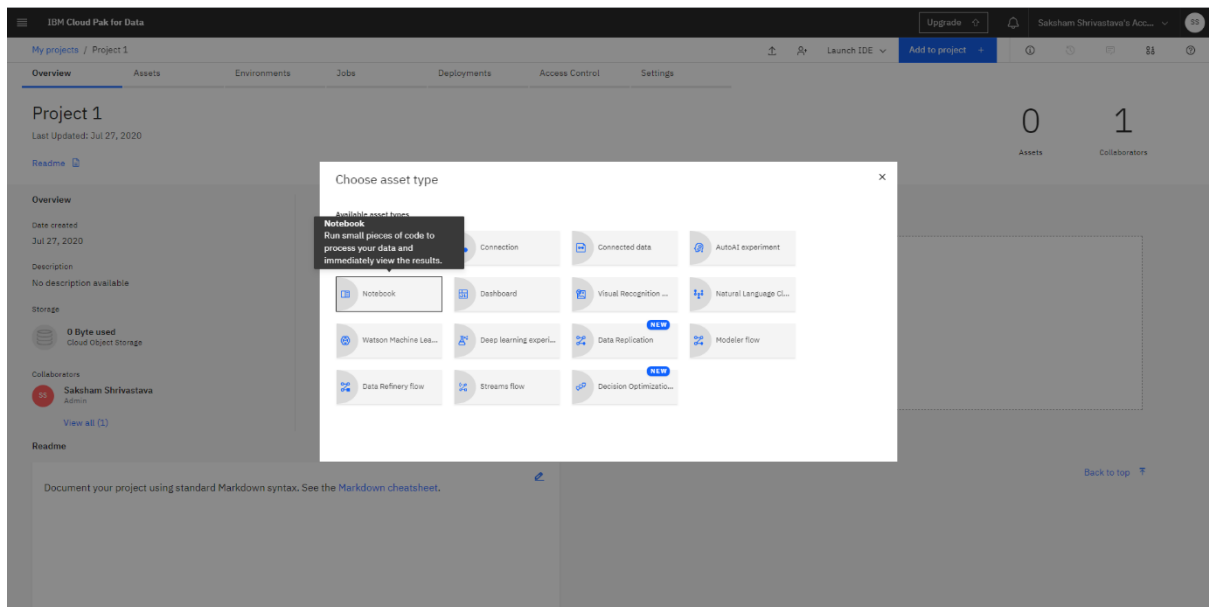


2. Open Watson Studio (Via Resource List):



3. Create new project and open it in notebook:





4. Scoring Endpoint

```
IBM Cloud Pak for Data

My projects / Predicting Life Expectancy using ... / Predicting Life Expectancy

In [139]: from watson_machine_learning_client import WatsonMachineLearningAPIClient

In [140]: wml_credentials={
    "apikey": "d908xh3M4VIZ788Indx_tSRbv9uie3w3L3t4Kxq791C",
    "instance_id": "728e34c25-baa3-486f-bd65-99f79705734f",
    "url": "https://eu-gb.ml.cloud.ibm.com"
}

In [141]: client = WatsonMachineLearningAPIClient(wml_credentials)

In [142]: model_props = {client.repository.ModelMetadata.AUTHOR_NAME: "Saksham Shrivastava",
    client.repository.ModelMetadata.AUTHOR_EMAIL: "sakshamshri99@gmail.com",
    client.repository.ModelMetadata.NAME: "Life Expectancy Prediction"}

In [143]: model_artifact = client.repository.store_model(rfr, meta_props=model_props)

In [144]: published_model_uid = client.repository.get_model_uid(model_artifact)

In [145]: published_model_uid
Out[145]: '4ff58118-a6c9-4865-80c0-823c193c098e'

In [ ]: deployment = client.deployments.create(published_model_uid, name="Life Expectancy Prediction")

#####
Synchronous deployment creation for uid: '4ff58118-a6c9-4865-80c0-823c193c098e' started
#####

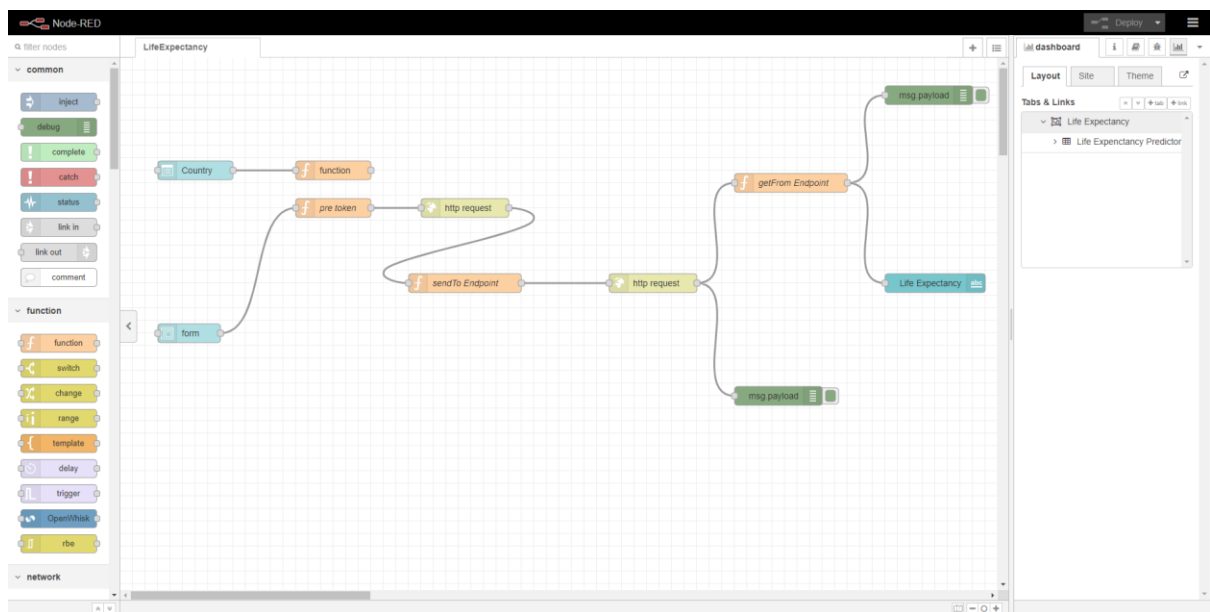
INITIALIZING

In [ ]: scoring_endpoint = client.deployments.get_scoring_url(deployment)

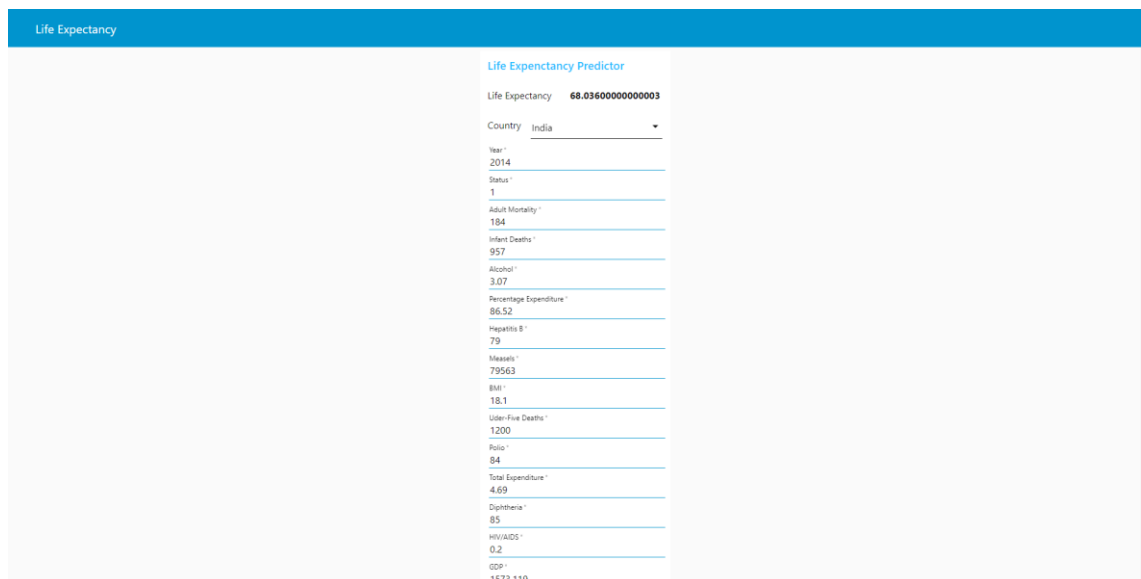
In [ ]: scoring_endpoint

In [ ]:
```

5. Create a Node Red Flow:



6. Deploy your model and predict the output:



The screenshot shows a web application titled "Life Expectancy Predictor". It features a list of input fields for various factors, each with a corresponding value. The factors and their values are:

Factor	Value
Life Expectancy	68.03600000000003
Country	India
Year	2014
Status	1
Adult Mortality	184
Infant Deaths	957
Alcohol	3.07
Percentage Expenditure	86.52
Hepatitis B	79
Measles	79563
BMI	18.1
Under-Five Deaths	1200
Polio	84
Total Expenditure	4.69
Diphtheria	85
HIV/AIDS	0.2
GDP	1573.119

4. EXPERIMENTAL ANALYSIS

We have to analyse various features of the dataset to create an accurate model. This will help us to improve the efficiency and performance of our model. In this project we are going to investigate a model for prediction of life expectancy of a country by given factors in the dataset. A typical Regression Machine Learning project leverages historical data to predict insights into the future. Analysis of various methods of regression gives insight that random forest regression can achieve a higher accuracy compared to other methods. These various factors provide us to predict the average life of a country.

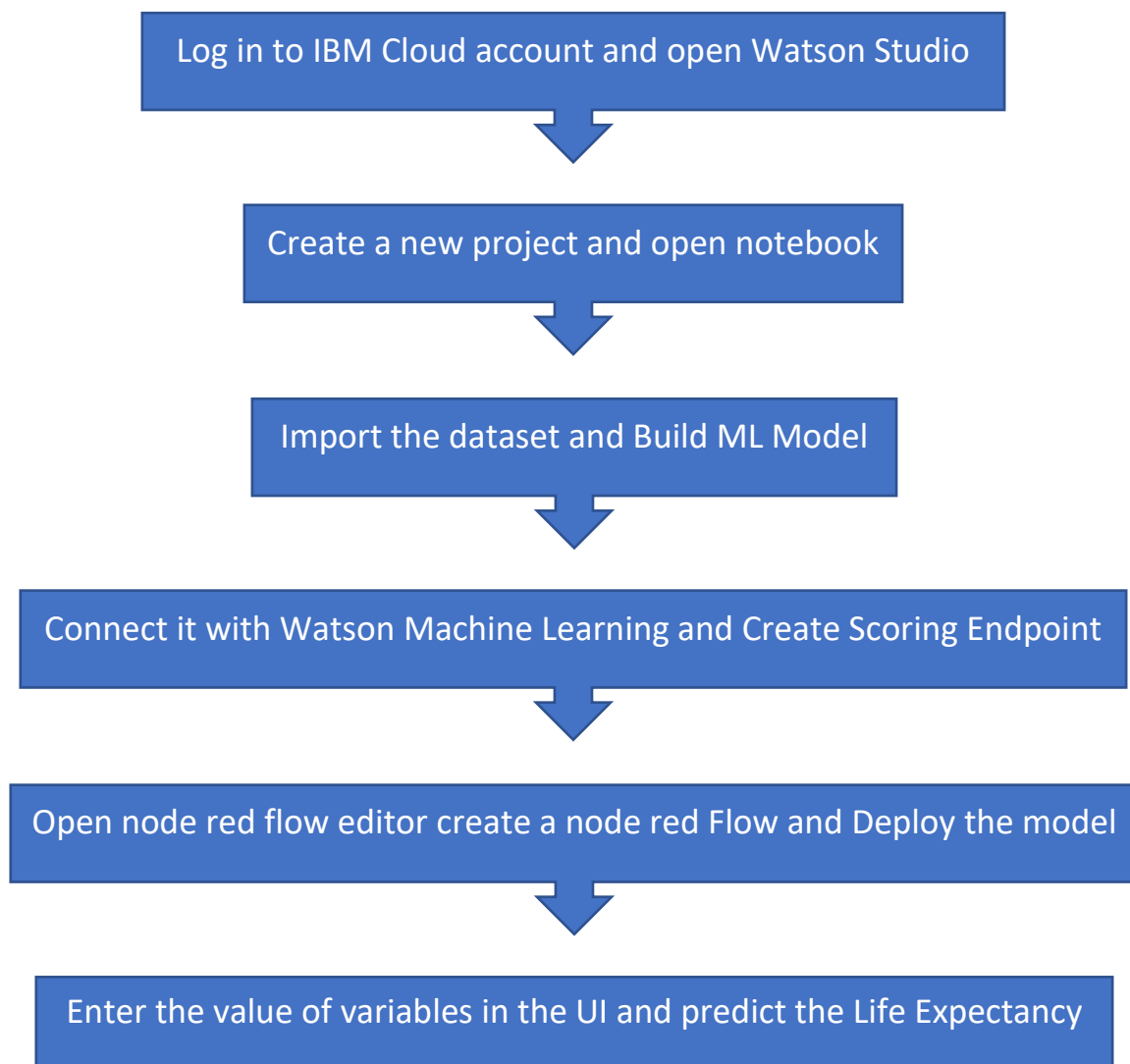
Factors that affects life expectancy: -

- Adult Mortality
- BMI
- GDP
- Alcohol intake
- Total Expenditure
- Hepatitis B
- Infant Deaths
- Percentage Expenditure
- Measles
- Under Five Deaths
- Thinness 1-19 years
- Thinness 5-9 years
- Polio
- Diphtheria

- Population
- HIV/AIDS
- Year
- Status
- Income composition of resources
- Schooling

5. FLOWCHART

To build this project we are going to follow some steps. When we represent these steps in a diagram that is the workflow for a project is the flowchart. These are the steps that we are going to follow to make this project with python: -



6. RESULT

After building the ML model and creating a node red flow. We deploy the model in the UI we enter the value of all factors that affect life expectancy and then we get the predicted life expectancy.

Predicting Life Expectancy using Python

Life Expectancy **68.03600000000003**

Country India ▼

Year *

2014

Status *

1

Adult Mortality *

184

Infant Deaths *

957

Alcohol *

3.07

Percentage Expenditure *

86.52

Hepatitis B *

79

Measels *

79563

BMI *

18.1

Uder-Five Deaths *

1200

Polio *

84

Total Expenditure *

4.69

Diphtheria *

85

HIV/AIDS *

0.2

GDP *

1573.119

Population *

1293853294

Thinness 10-19 Years *

26.8

Thinness 5-9 Years *

27.4

Income Composition of Resources *

0.607

Schooling *

11.6

PREDICT

RESET

7. ADVANTAGES & DISADVANTAGES

Advantages: -

- Creating a node red flow and do the prediction on UI is very simple. We can create a user interface easily with help of Node-RED and give the input to the model and predicts the Life expectancy.
- We can easily use IBM cloud to build this project with the help of Watson studio, Watson machine learning and node red flow.
- With the help of IBM cloud, we can use this and build our project efficiently with the help of all the services of IBM cloud.

Disadvantages: -

- Random forest has been observed to over fit on some datasets with some noisy regression and classification task.

- When the size of the data fed to the machine learning is very large, the computational cost and the time taken to train the model on the data increases drastically. This can increase the cost of resources required to implement the application on a large scale. So, ML could be very time consuming.

8. APPLICATIONS

- Life expectancy predictions have the potential to be beneficial to individuals, health service providers and governments.
- The solution would require input from specialists including demographers, health scientists, data scientists, IT specialists, programmers, medical professionals and statisticians. While the collection of enough data will be challenging, we can likely expect to see advances in this area in the coming years.
- they would make people more aware of their general health, and its improvement or deterioration over time. This may motivate them to make healthier lifestyle choices.

9. CONCLUSION

We aimed to advance the understanding of what is needed for automatic processing of electronic medical records, and to explore the use of unstructured clinical text for predicting life expectancy. The potential use of automatic prognostication is not limited to health care in practice, but could also be useful in other clinical applications such, such as clinical trials. In clinical trials, outcomes often depend on prognostic factors. Automatic processing of medical records would enable quick and systematic stratification of patients based on their prognoses, which could be used to further reduce biases.

This research should be considered to be exploratory. In order to replicate and extend this research, we are currently expanding the dataset substantially, by collecting additional data of both deceased and active patients. This will allow us to zoom in on specific illness trajectories, and to rephrase the task in such a way that it will match clinical settings more closely, for example by aiming to make predictions about patients while they are still active. We plan to compare a range of predictive models, alternative patient representations, and (interpretations of) output variables in future work.

10. FUTURE SCOPE

Life expectancy plays a major role in development of a country, hence, using predictions and trends, the health infrastructure can be improved. If this model

can help government to predict the life expectancy then government can plan health services better using the data and future predictions. A mobile application can be developed that uses personal health data and historical data of the country that user lives in and predict the expected life span of that user.

11. BIBILOGRAPHY

IBM cloud products and services

<https://cloud.ibm.com/>

https://dataplatform.cloud.ibm.com/home?context=wdp&apps=data_science_experience&nocache=true

<https://node-red-croes.eu-gb.mybluemix.net/red/#flow/b220a319.74907>

Dataset Reference

<https://www.kaggle.com/kumarajarshi/life-expectancy-who>

Predicting Life expectancy with python

<https://www.youtube.com/watch?v=Jtej3Y6uUng>

<https://www.youtube.com/watch?v=-CUI8GezG1I&list=PLzpeuWUENMK2PYtasCaKK4bZjaYzhW23L&index=2>

<https://bookdown.org/caoying4work/watsonstudio-workshop/jn.html#deploy-model-as-web-service>

12. Appendix

Source Code (Python)

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

import types
import pandas as pd
from botocore.client import Config
import ibm_boto3

def __iter__(self): return 0

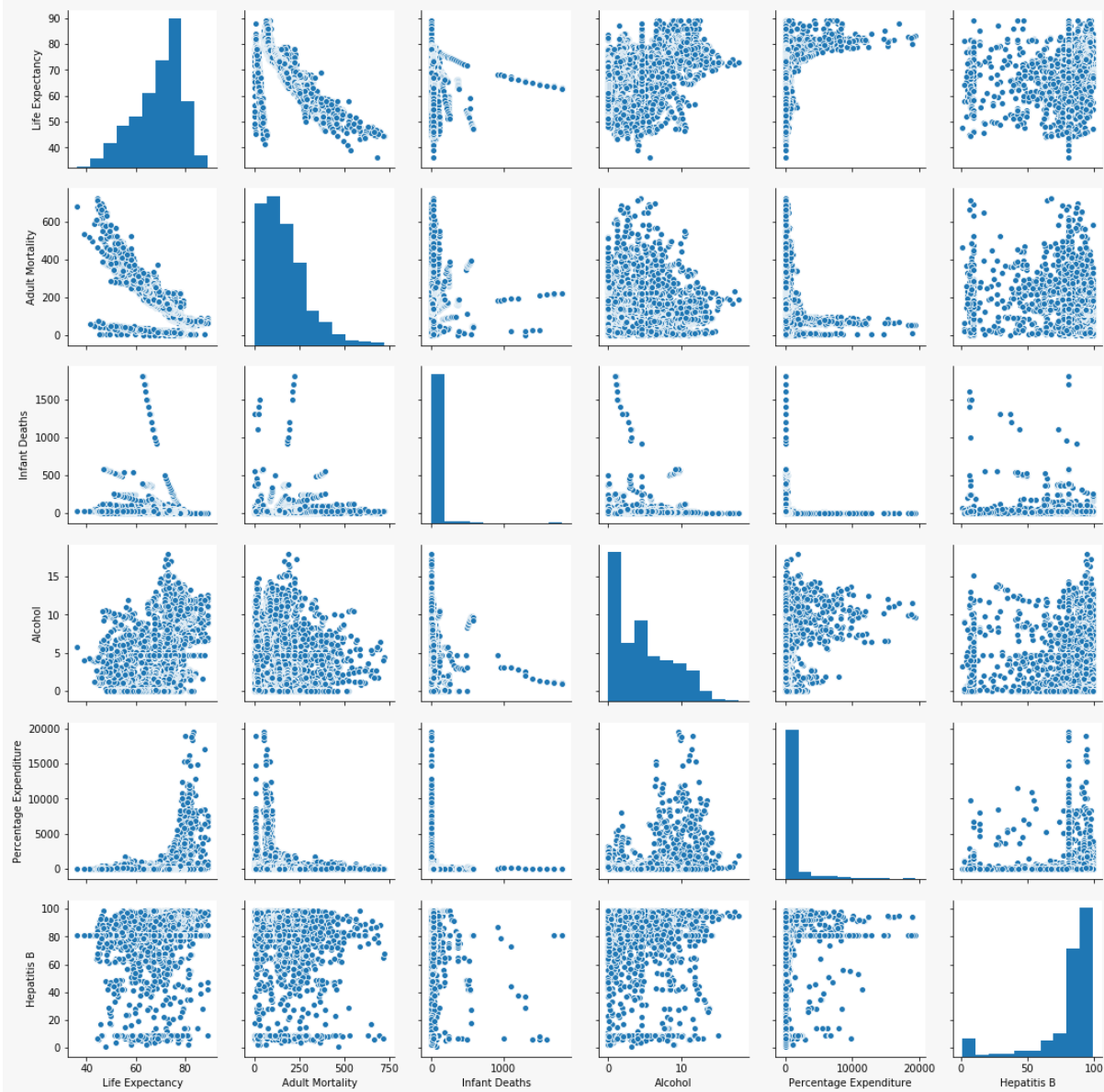
# @hidden_cell
# The following code accesses a file in your IBM Cloud Object Storage. It includes your
# credentials.
# You might want to remove those credentials before you share the notebook.
client_54340a4989114e0d80d810b14ec12b38 = ibm_boto3.client(service_name='s3',
    ibm_api_key_id='vZE_vig6plNf2BLPLWk4o2WIWQX3sj0yl-_VAWhkR2C4',
    ibm_auth_endpoint="https://iam.cloud.ibm.com/oidc/token",
    config=Config(signature_version='oauth'),
    endpoint_url='https://s3.eu-geo.objectstorage.service.networklayer.com')

body = client_54340a4989114e0d80d810b14ec12b38.get_object(Bucket='predictinglifeexpecta
ncyusingmach-donotdelete-pr-hgbai5oi45fyih',Key='Life Expectancy Data.csv')['Body']
# add missing __iter__ method, so pandas accepts body as file-like object
if not hasattr(body, "__iter__"): body.__iter__ = types.MethodType( __iter__, body )

data = pd.read_csv(body)

data.isnull().sum()
data.fillna(value = data.mean(), inplace = True)
data.isnull().sum()

sns.pairplot(data, vars = ['Life Expectancy','Adult Mortality','Infant Deaths','Alc
ohol','Percentage Expenditure','Hepatitis B'])
```

```
plt.figure(figsize = (15,12))
```

```
sns.heatmap(data.corr(),annot =True)
```



```
factors = data.drop('Life Expectancy', axis = 1)
lexp = data['Life Expectancy']
```

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
factors['Status'] = le.fit_transform(factors['Status'])
factors['Country'] = le.fit_transform(factors['Country'])
factors.head()
```

```
from sklearn.model_selection import train_test_split
factors_train, factors_test, lexp_train, lexp_test = train_test_split(factors, lexp, test_size=0.20, random_state=101)
```

```
from sklearn.linear_model import LinearRegression
lr = LinearRegression()
lr.fit(factors_train, lexp_train)
```

```
lexp_pred = lr.predict(factors_test)
```

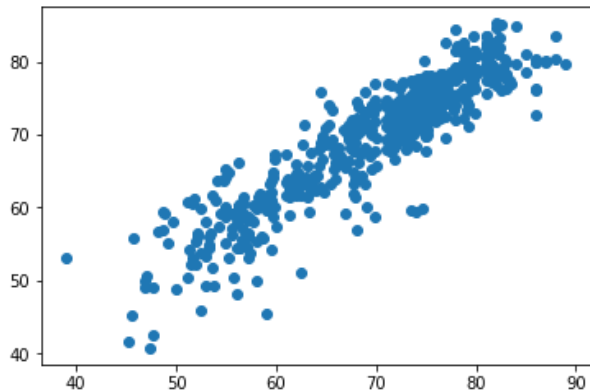
```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
mae = mean_absolute_error(lexp_test, lexp_pred)
mse = mean_squared_error(lexp_test, lexp_pred)
rmse = np.sqrt(mse)
r2 = r2_score(lexp_test, lexp_pred)
```

```

print("Mean Absolute Error = ",mae)
print("Mean Squared Error = ",mse)
print("Root Mean Squared Error = ",rmse)
print("R2 Score = ",r2)

```

```
plt.scatter(lexp_test,lexp_pred)
```



```

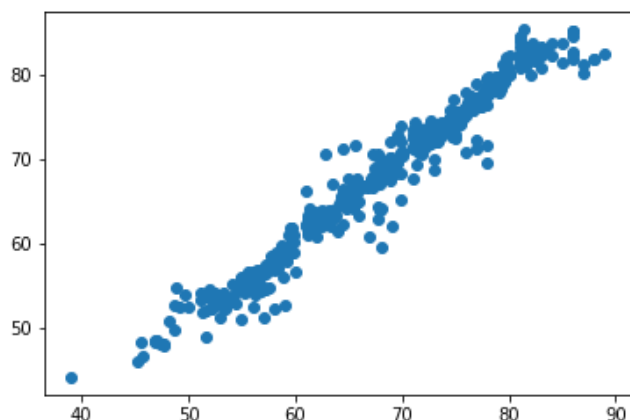
from sklearn.ensemble import RandomForestRegressor
rfr = RandomForestRegressor(n_estimators=200, random_state=0)
rfr.fit(factors_train, lexp_train)
lexp_pr = rfr.predict(factors_test)

from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
mae = mean_absolute_error(lexp_test, lexp_pr)
mse = mean_squared_error(lexp_test, lexp_pr)
rmse = np.sqrt(mse)
r2 = r2_score(lexp_test, lexp_pr)

print("Mean Absolute Error = ",mae)
print("Mean Squared Error = ",mse)
print("Root Mean Squared Error = ",rmse)
print("R2 Score = ",r2)

```

```
plt.scatter(lexp_test,lexp_pr)
```



```
!pip install watson-machine-learning-client
```

```
from watson_machine_learning_client import WatsonMachineLearningAPIClient
```

```
wml_credentials={
```

```

    "apikey": "dPO8xhjNWiYIZ7BBIrdx_t5Rbv9uIe3wL3Lt4rXq79IC",
    "instance_id": "28e34c25-9ae3-486f-bdd5-99f79703734f",
    "url": "https://eu-gb.ml.cloud.ibm.com"
}

client = WatsonMachineLearningAPIClient( wml_credentials )

model_props = {client.repository.ModelMetaNames.AUTHOR_NAME: "Saksham Shrivastava",
               client.repository.ModelMetaNames.AUTHOR_EMAIL: "sakshamshri99@gmail.com",
               client.repository.ModelMetaNames.NAME: "Life Expectancy Prediction"}

model_artifact =client.repository.store_model(rfr, meta_props=model_props)

published_model_uid = client.repository.get_model_uid(model_artifact)

deployment = client.deployments.create(published_model_uid, name="Life Expectancy Prediction")

scoring_endpoint = client.deployments.get_scoring_url(deployment)

```

Source Code (Flow)

```

[{"id":"625cfd02.949d64","type":"tab","label":"LifeExpectancy","disabled":false,
"info":""},{ "id":"bc6387a6.3acca8","type":"ui_form","z":"625cfd02.949d64","name":"","label":"","group":"3e6e9eb6.8ba222","order":0,"width":"0","height":"0",
"options":[{"label":"Year","value":"b","type":"number","required":true,"rows":null}, {"label":"Status","value":"c","type":"number","required":true,"rows":null},
{"label":"Adult Mortality\t","value":"d","type":"number","required":true,"rows":null}, {"label":"Infant Deaths","value":"e","type":"number","required":true,"rows":null}, {"label":"Alcohol","value":"f","type":"number","required":true,"rows":null}, {"label":"Percentage Expenditure","value":"g","type":"number","required":true,"rows":null}, {"label":"Hepatitis B","value":"h","type":"number","required":true,"rows":null}, {"label":"Measels","value":"i","type":"number","required":true,"rows":null}, {"label":"BMI","value":"j","type":"number","required":true,"rows":null}, {"label":"Uder-Five Deaths","value":"k","type":"number","required":true,"rows":null}, {"label":"Polio","value":"l","type":"number","required":true,"rows":null}, {"label":"Total Expenditure","value":"m","type":"number","required":true,"rows":null}, {"label":"Diphtheria","value":"n","type":"number","required":true,"rows":null}, {"label":

```

"HIV/AIDS","value":"o","type":"number","required":true,"rows":null},{ "label":"GDP","value":"p","type":"number","required":true,"rows":null},{ "label":"Popula
tion","value":"q","type":"number","required":true,"rows":null},{ "label":"Thinne
ss 10-19
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ess 5-9
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Resources","value":"t","type":"number","required":true,"rows":null},{ "label":"S
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ct", "cancel":"Reset", "topic":"","x":110,"y":440,"wires":[["2d4e4116.61dd1e"]]}, {
"id":"2d4e4116.61dd1e", "type":"function", "z":"625cfd02.949d64", "name":"pre
token", "func":"//make user given values as global
variables\nnglobal.set(\"b\",msg.payload.b);\nnglobal.set(\"c\",msg.payload.c);\nnglobal.set(\"d\",msg.payload.d);\nnglobal.set(\"e\",msg.payload.e);\nnglobal.set(\"f\",msg.payload.f);\nnglobal.set(\"g\",msg.payload.g);\nnglobal.set(\"h\",msg.pa
yload.h);\nnglobal.set(\"i\",msg.payload.i);\nnglobal.set(\"j\",msg.payload.j);\nnglo
bal.set(\"k\",msg.payload.k);\nnglobal.set(\"l\",msg.payload.l);\nnglobal.set(\"m\"
,msg.payload.m);\nnglobal.set(\"n\",msg.payload.n);\nnglobal.set(\"o\",msg.paylo
ad.o);\nnglobal.set(\"p\",msg.payload.p);\nnglobal.set(\"q\",msg.payload.q);\nnglo
bal.set(\"r\",msg.payload.r);\nnglobal.set(\"s\",msg.payload.s);\nnglobal.set(\"t\",
msg.payload.t);\nnglobal.set(\"u\",msg.payload.u);\n\n//following are required
to receive a token\nvar
apikey=\"dPO8xhjNWiyIZ7BBIrdx_t5Rbv9ule3wL3Lt4rXq79IC\";\nmsg.headers={
\"content-type\":\"application/x-www-form-
urlencoded\"};\nmsg.payload={\"grant_type\":\"urn:ibm:params:oauth:grant-
type:apikey\", \"apikey\":apikey};\nreturn
msg;\n\", \"outputs\":1, \"noerr\":0, \"initialize\":\"\", \"finalize\":\"\", \"x\":340, \"y\":240, \"wires\"
:[["3e544724.d4bf78"]]}, { \"id\":\"fdf240d9.c1aba\", \"type\":\"http
request\", \"z\":\"625cfd02.949d64\", \"name\":\"\", \"method\":\"POST\", \"ret\":\"obj\", \"payto
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99f79703734f/deployments/e5cc688c-fac5-42b9-979b-
7b475d375f7a/online\", \"tls\":\"\", \"persist\":false, \"proxy\":\"\", \"authType\":\"basic\", \"x\":
850, \"y\":360, \"wires\":[[\"d1b4be2f.26ec8\", \"c0b1dc76.b4afa\"]]}, { \"id\":\"67951ae.83f
6ae4\", \"type\":\"debug\", \"z\":\"625cfd02.949d64\", \"name\":\"\", \"active\":true, \"tosideba
r\":true, \"console\":false, \"tostatus\":false, \"complete\":\"payload\", \"targetType\":\"msg

```
,"statusVal":"","statusType":"auto","x":1290,"y":60,"wires":[]},{ "id":"c0b1dc76.
b4afa","type":"function","z":"625cfd02.949d64","name":"getFrom
Endpoint","func":"msg.payload=msg.payload.values[0][0];\nreturn
msg;","outputs":1,"noerr":0,"initialize":"","finalize":"","x":1070,"y":200,"wires":
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token and make headers\nvar token=msg.payload.access_token;\nvar
instance_id=\"28e34c25-9ae3-486f-bdd5-
99f79703734f\"\nmsg.headers={'Content-Type':
'application/json','Authorization':\"Bearer \"+token,\"ML-Instance-
ID\":instance_id}\n\n//get variables that are set earlier\nvar a =
global.get(\"a\");\nvar b = global.get(\"b\");\nvar c = global.get(\"c\");\nvar d =
global.get(\"d\");\nvar e = global.get(\"e\");\nvar f = global.get(\"f\");\nvar g =
global.get(\"g\");\nvar h = global.get(\"h\");\nvar i = global.get(\"i\");\nvar j =
global.get(\"j\");\nvar k = global.get(\"k\");\nvar l = global.get(\"l\");\nvar m =
global.get(\"m\");\nvar n = global.get(\"n\");\nvar o = global.get(\"o\");\nvar p =
global.get(\"p\");\nvar q = global.get(\"q\");\nvar r = global.get(\"r\");\nvar s =
global.get(\"s\");\nvar t = global.get(\"t\");\nvar u = global.get(\"u\");\n//send
the user values to service endpoint\nmsg.payload =
\n{\"fields\":[\"Country\", \"Year\", \"Status\", \"Adult Mortality\", \"Infant
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B\", \"Measles\", \"BMI\", \"Under-Five Deaths\", \"Polio\", \"Total
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