- In [1]: #This is a supplementary material to the lecture "Introduction to ML" to quickly revise, whenever need ed
- In [2]: #In general computing, we need to pass the data and write the rules (program) to figure out the output #Machine learning in broad terms is about using some past data and corresponding output, let machine f igure out the rules and then

#using thode rules, predict the output for unseen data (supervised machine learning)

#There are some use cases, like categorising users on some specific traits, we just need to give data to machine and

#let it figure out the patterns in user traits and categorising them

- In [3]: #In supervised learning, we may have two types of problems to solve
 #one is Classification (where the output to be predicted is not continuous i.e. labels)
 #another is Regression (where the output to be predicted is continuous spectrum of values)
- In [4]: #Now, for solving any machine learning task, there are some general steps
 - # 1. Get the data
 - # 2. Preprocess/clean it to make it compatible with input, output formats
 - # 3. Train the model
 - # 4. Predict output for unseen data
- In [5]: #scikit-learn (sklearn) is the machine leraning library, we will use heavily in this course
- In [6]: #ok, enough of theory, let's the game begin!!
- In [7]: #let's first import required packages/libraries to read, manipulate the data and train the model
 import numpy as np
 import pandas as pd
 from sklearn.model_selection import train_test_split #for splitting our data to training and te
 sting
 from sklearn.linear_model import LinearRegression #to fit the linear model to the data
- In [8]: #let's work on simple boston house-prices dataset
 from sklearn import datasets
 data = datasets.load_boston()

In [9]: #Let's Look at the data we have Loaded data

```
Out[9]: {'data': array([[6.3200e-03, 1.8000e+01, 2.3100e+00, ..., 1.5300e+01, 3.9690e+02,
                  4.9800e+00],
                 [2.7310e-02, 0.0000e+00, 7.0700e+00, ..., 1.7800e+01, 3.9690e+02,
                  9.1400e+00],
                 [2.7290e-02, 0.0000e+00, 7.0700e+00, ..., 1.7800e+01, 3.9283e+02,
                  4.0300e+00],
                 [6.0760e-02, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9690e+02,
                  5.6400e+001.
                 [1.0959e-01, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9345e+02,
                  6.4800e+00],
                 [4.7410e-02, 0.0000e+00, 1.1930e+01, ..., 2.1000e+01, 3.9690e+02,
                  7.8800e+00]]),
          'target': array([24., 21.6, 34.7, 33.4, 36.2, 28.7, 22.9, 27.1, 16.5, 18.9, 15.,
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                 33.2, 27.5, 26.5, 18.6, 19.3, 20.1, 19.5, 19.5, 20.4, 19.8, 19.4,
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                 20.3, 20.5, 17.3, 18.8, 21.4, 15.7, 16.2, 18. , 14.3, 19.2, 19.6,
                 23. , 18.4, 15.6, 18.1, 17.4, 17.1, 13.3, 17.8, 14. , 14.4, 13.4,
                 15.6, 11.8, 13.8, 15.6, 14.6, 17.8, 15.4, 21.5, 19.6, 15.3, 19.4,
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                 25., 50., 23.8, 23.8, 22.3, 17.4, 19.1, 23.1, 23.6, 22.6, 29.4,
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                 20.3, 22.5, 29., 24.8, 22., 26.4, 33.1, 36.1, 28.4, 33.4, 28.2,
                 22.8, 20.3, 16.1, 22.1, 19.4, 21.6, 23.8, 16.2, 17.8, 19.8, 23.1,
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                 19.8, 17.1, 19.4, 22.2, 20.7, 21.1, 19.5, 18.5, 20.6, 19. , 18.7,
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                 18.6, 30.1, 18.2, 20.6, 17.8, 21.7, 22.7, 22.6, 25. , 19.9, 20.8,
                 16.8, 21.9, 27.5, 21.9, 23.1, 50., 50., 50., 50., 50., 13.8, 13.8, 15., 13.9, 13.3, 13.1, 10.2, 10.4, 10.9, 11.3, 12.3, 8.8,
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                 12.5, 8.5, 5., 6.3, 5.6, 7.2, 12.1, 8.3, 8.5, 5., 11.9,
                 27.9, 17.2, 27.5, 15., 17.2, 17.9, 16.3, 7., 7.2, 7.5, 10.4,
                  8.8, 8.4, 16.7, 14.2, 20.8, 13.4, 11.7, 8.3, 10.2, 10.9, 11.
                  9.5, 14.5, 14.1, 16.1, 14.3, 11.7, 13.4, 9.6, 8.7, 8.4, 12.8,
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                 20.6, 21.2, 19.1, 20.6, 15.2, 7., 8.1, 13.6, 20.1, 21.8, 24.5,
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          'feature_names': array(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX', 'PTRATIO', 'B', 'LSTAT'], dtype='<U7'),
          'DESCR': ".. _boston_dataset:\n\nBoston house prices dataset\n-----\n\n**Data
         Set Characteristics:** \n\n
                                          :Number of Instances: 506 \n\n :Number of Attributes: 13 numeric/c
         ategorical predictive. Median Value (attribute 14) is usually the target.\n\n
                                                                                               :Attribute Informati
         on (in order):\n
                                 - CRIM
                                              per capita crime rate by town\n
                                                                                      - ZN
                                                                                                   proportion of re
                                                                                  proportion of non-retail busines
         sidential land zoned for lots over 25,000 sq.ft.\n
                                                                     - INDUS
                                                Charles River dummy variable (= 1 if tract bounds river; 0 other
                                    - CHAS
         s acres per town\n
                       - NOX
                                    nitric oxides concentration (parts per 10 million)\n
                                                                                               - RM
         wise)\n
         age number of rooms per dwelling\n
                                                     - AGE
                                                                 proportion of owner-occupied units built prior t
                         - DIS
                                     weighted distances to five Boston employment centres\n
         ndex of accessibility to radial highways\n
                                                              - TAX
                                                                         full-value property-tax rate per $10,000
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Median value of owner-occupied homes in $1000's\n\n
                                                              :Missing Attribute Values: None\n\n
                                                                                                       :Creato
         r: Harrison, D. and Rubinfeld, D.L.\n\nThis is a copy of UCI ML housing dataset.\nhttps://archive.ic
         s.uci.edu/ml/machine-learning-databases/housing/\n\nThis dataset was taken from the StatLib library
         which is maintained at Carnegie Mellon University.\n\nThe Boston house-price data of Harrison, D. and
         Rubinfeld, D.L. 'Hedonic\nprices and the demand for clean air', J. Environ. Economics & Management,\n
         vol.5, 81-102, 1978. Used in Belsley, Kuh & Welsch, 'Regression diagnostics\n...', Wiley, 1980.
         N.B. Various transformations are used in the table on\npages 244-261 of the latter.\n\nThe Boston hou
         se-price data has been used in many machine learning papers that address regression\nproblems. \n
         \n.. topic:: References\n\n - Belsley, Kuh & Welsch, 'Regression diagnostics: Identifying Influenti
         al Data and Sources of Collinearity', Wiley, 1980. 244-261.\n - Quinlan,R. (1993). Combining Instan
         ce-Based and Model-Based Learning. In Proceedings on the Tenth International Conference of Machine Le
         arning, 236-243, University of Massachusetts, Amherst. Morgan Kaufmann.\n",
          'filename': 'C:\\Users\\NKS\\Anaconda3\\lib\\site-packages\\sklearn\\datasets\\data\\boston_house_pr
         ices.csv'}
In [10]: #we can see that it's a dictionary containing the data key (features) and a key target (output)
         x, y = data['data'], data['target']
In [11]: x.shape, y.shape
Out[11]: ((506, 13), (506,))
In [12]: #we have loaded the data and for this data, it's already cleaned, let's just go to splitting the data
          in training and testing part
         x_train, x_test, y_train, y_test = train_test_split(x, y)
In [13]: | #create an object for linear regression model
         alg = LinearRegression()
         #let's train it on training data
         alg.fit(x_train, y_train)
Out[13]: LinearRegression(copy X=True, fit intercept=True, n jobs=None, normalize=False)
In [14]: #let's predict output for the test data
         y_pred = alg.predict(x_test)
         y_pred
Out[14]: array([23.92063152, 21.70960302, 15.90137371, 25.26613301, 35.28140728,
                33.52524584, 31.5096118 , 24.7278648 , 29.78030644, 23.47682464,
                18.67509642, 16.09391054, 18.99758634, 31.0204188 , 24.4544231 ,
                33.14582508, 21.94666409, 21.50488414, 41.6312715 , 25.59723236,
                19.03071767, 15.74215299, 19.97454463, 8.22678384, 20.74759963,
                20.69842196, 23.62803176, 27.92068888, 16.77707254, 25.03078489,
                23.44771888, 32.09655476, 19.89498947, 22.31265674, 29.5992013,
                20.73430944, 18.21921299, 14.41814784, 33.49209035, 32.82080152,
                34.21850912, 21.03199176, 41.57949748, 31.34313733, 16.38879188,
                36.77031586, 19.86647289, 22.39533759, 20.76926633, 20.26947855,
                23.40805566, 15.02586201, 8.80571267, 30.6199747, 12.99512848,
                23.17095429, 19.90261325, 19.67699176, 20.61715063, 21.57080798,
                40.44213951, 20.77831271, 36.60525538, 33.12336125, 28.11597573,
                19.12842547, 21.95870278, 24.69522108, 21.64426877, 35.28076106,
                23.21838962, 21.3121438 , 32.52315044, 18.32394463, 24.89186364,
                14.86180983, 12.17746263, 18.18513725, 13.05267758, 28.18491413,
                17.53579646,\ 23.8675469\ ,\ 35.13050216,\ 19.91786559,\ 36.54741044,
                18.54715893, 13.89860166, 11.35470543, 21.1374334 , 17.19694955,
                11.76699982, 34.04578352, 22.88080089, 32.17612864, 13.76864937,
                12.12140298, 18.56446052, 21.17790522, 27.44023073, 15.11573552,
                25.51723534, 25.83393721, 18.67099273, 14.4901367 , 11.86075032,
                36.98801211, 18.62953052, 21.58013076, 19.31129993, 33.06459861,
                23.32722355, 23.77959932, 25.93054169, 24.86666654, 17.93431748,
                15.9819414 , 8.27879767, 31.62097212, 13.49420127, 28.91437617,
                32.55343849, 18.9068841 , 25.75440277, 20.84163537, 17.334071 ,
                33.49740441, 36.90388786])
In [15]: #Thanks, happy Coding!
```

- B

- LSTAT % lower status of the population\n

1000(Bk - 0.63)^2 where Bk is th

- PTRATIO pupil-teacher ratio by town\n

e proportion of blacks by town\n

In []: #To download .ipynb notebook, right click the following link and click save as https://ninjasfiles.s3.amazonaws.com/00000000003220.ipynb