

VISVESVARAYA TECHNOLOGICAL UNIVERSITY

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LAB REPORT

on

Machine Learning

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in partial fulfillment for the award of the degree of
BACHELOR OF ENGINEERING
in
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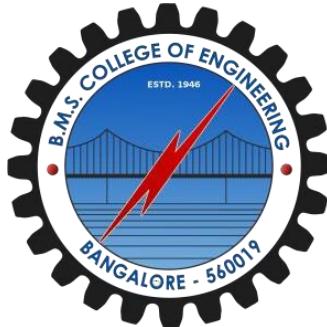
B.M.S. COLLEGE OF ENGINEERING

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CERTIFICATE

This is to certify that the Lab work entitled "**Machine Learning**" carried out by **Nachiketha (1BM21CS109)**, who is a bonafide student of **B. M. S. College of Engineering**. It is in partial fulfillment for the award of **Bachelor of Engineering in Computer Science and Engineering** of the Visvesvaraya Technological University, Belgaum during the year 2024. The Lab report has been approved as it satisfies the academic requirements in respect of **Machine Learning - (22CS6PCMAL)** work prescribed for the said degree.

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1. Course Outcomes

CO1: Apply machine learning techniques in computing systems.

CO2: Evaluate the model using metrics.

CO3: Design a model using machine learning to solve a problem.

CO4: Conduct experiments to solve real-world problems using appropriate machine learning techniques

2. Experiments

2.1 Experiment - 1

2.1.1 Question:

Write a python program to import and export data using Pandas library functions.

2.1.2 Code with Output:

```
import pandas as pd
import numpy as np

california_housing_train_data = pd.read_csv("/content/sample_data/california_housing_train.csv")

# View the first 5 rows

california_housing_train_data.head()
```

| | longitude | latitude | housing_median_age | total_rooms | total_bedrooms | population | households | median_income | median_house_value |
|---|-----------|----------|--------------------|-------------|----------------|------------|------------|---------------|--------------------|
| 0 | -114.31 | 34.19 | 15.0 | 5612.0 | 1283.0 | 1015.0 | 472.0 | 1.4936 | 66900.0 |
| 1 | -114.47 | 34.40 | 19.0 | 7650.0 | 1901.0 | 1129.0 | 463.0 | 1.8200 | 80100.0 |
| 2 | -114.56 | 33.69 | 17.0 | 720.0 | 174.0 | 333.0 | 117.0 | 1.6509 | 85700.0 |
| 3 | -114.57 | 33.64 | 14.0 | 1501.0 | 337.0 | 515.0 | 226.0 | 3.1917 | 73400.0 |
| 4 | -114.57 | 33.57 | 20.0 | 1454.0 | 326.0 | 624.0 | 262.0 | 1.9250 | 65500.0 |

```
▶ import pandas as pd
▶ import numpy as np

url = "https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data"

# Define the column names

col_names = ["sepal_length_in_cm",
             "sepal_width_in_cm",
             "petal_length_in_cm",
             "petal_width_in_cm",
             "class"]

# Read data from URL

iris_data = pd.read_csv(url, names=col_names)
iris_data.head()
```

| | sepal_length_in_cm | sepal_width_in_cm | petal_length_in_cm | petal_width_in_cm | class |
|---|--------------------|-------------------|--------------------|-------------------|-------------|
| 0 | 5.1 | 3.5 | 1.4 | 0.2 | Iris-setosa |
| 1 | 4.9 | 3.0 | 1.4 | 0.2 | Iris-setosa |
| 2 | 4.7 | 3.2 | 1.3 | 0.2 | Iris-setosa |
| 3 | 4.6 | 3.1 | 1.5 | 0.2 | Iris-setosa |
| 4 | 5.0 | 3.6 | 1.4 | 0.2 | Iris-setosa |

```
[3] iris_data.to_csv("cleaned_iris_data.csv")
```

2.2 Experiment - 2

2.2.1 Question:

End-to-end ML Project.

2.2.2 Code with Output:

Download the Data

```
In [1]: import os
import tarfile
import urllib

In [2]: DOWNLOAD_ROOT = "https://raw.githubusercontent.com/ageron/handson-ml2/master/"
HOUSING_PATH = os.path.join("data", "01")
HOUSING_URL = DOWNLOAD_ROOT + "datasets/housing/housing.tgz"

In [3]: def fetch_housing_data(housing_url=HOUSING_URL, housing_path=HOUSING_PATH):
    os.makedirs(name=housing_path, exist_ok=True)
    tgz_path = os.path.join(housing_path, "housing.tgz")
    urllib.request.urlretrieve(url=housing_url, filename=tgz_path)
    housing_tgz = tarfile.open(name=tgz_path)
    housing_tgz.extractall(path=housing_path)
    housing_tgz.close()
```

Download the data:

```
In [4]: fetch_housing_data()
```

Load the data using pandas:

```
In [5]: import pandas as pd

In [6]: def load_housing_data(housing_path=HOUSING_PATH):
    data_path = os.path.join(housing_path, "housing.csv")
    return pd.read_csv(data_path)
```

Data Structure

```
In [7]: housing = load_housing_data()
```

```
In [8]: housing.head()
```

```
Out[8]:   longitude  latitude  housing_median_age  total_rooms  total_bedrooms  population  households  median_income  median_house_value
0      -122.23     37.88           41.0        880.0         129.0       322.0        126.0      8.3252      452600.0
1      -122.22     37.86           21.0        7099.0        1106.0      2401.0        1138.0     8.3014      358500.0
2      -122.24     37.85           52.0        1467.0         190.0       496.0        177.0      7.2574      352100.0
3      -122.25     37.85           52.0        1274.0         235.0       558.0        219.0      5.6431      341300.0
4      -122.25     37.85           52.0        1627.0         280.0       565.0        259.0      3.8462      342200.0
```

```
In [9]: housing.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
 #   Column            Non-Null Count  Dtype  
--- 
 0   longitude         20640 non-null   float64
 1   latitude          20640 non-null   float64
 2   housing_median_age 20640 non-null   float64
 3   total_rooms        20640 non-null   float64
 4   total_bedrooms     20433 non-null   float64
 5   population         20640 non-null   float64
 6   households         20640 non-null   float64
 7   median_income      20640 non-null   float64
 8   median_house_value 20640 non-null   float64
 9   ocean_proximity    20640 non-null   object  
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

There exist 20,640 instances (rows) in the dataset. Which means that it is fairly small data sample by machine learning standards.

207 districts are missing the `total_bedrooms` attribute, we will need to take care of this later.

On the other hand, all attributes are numerical, except `ocean_proximity`

Since we noticed repeated `ocean_proximity` values for the top 5 rows, we suspect that it is a categorical column, let's check it out:

```
In [10]: housing['ocean_proximity'].value_counts()
```

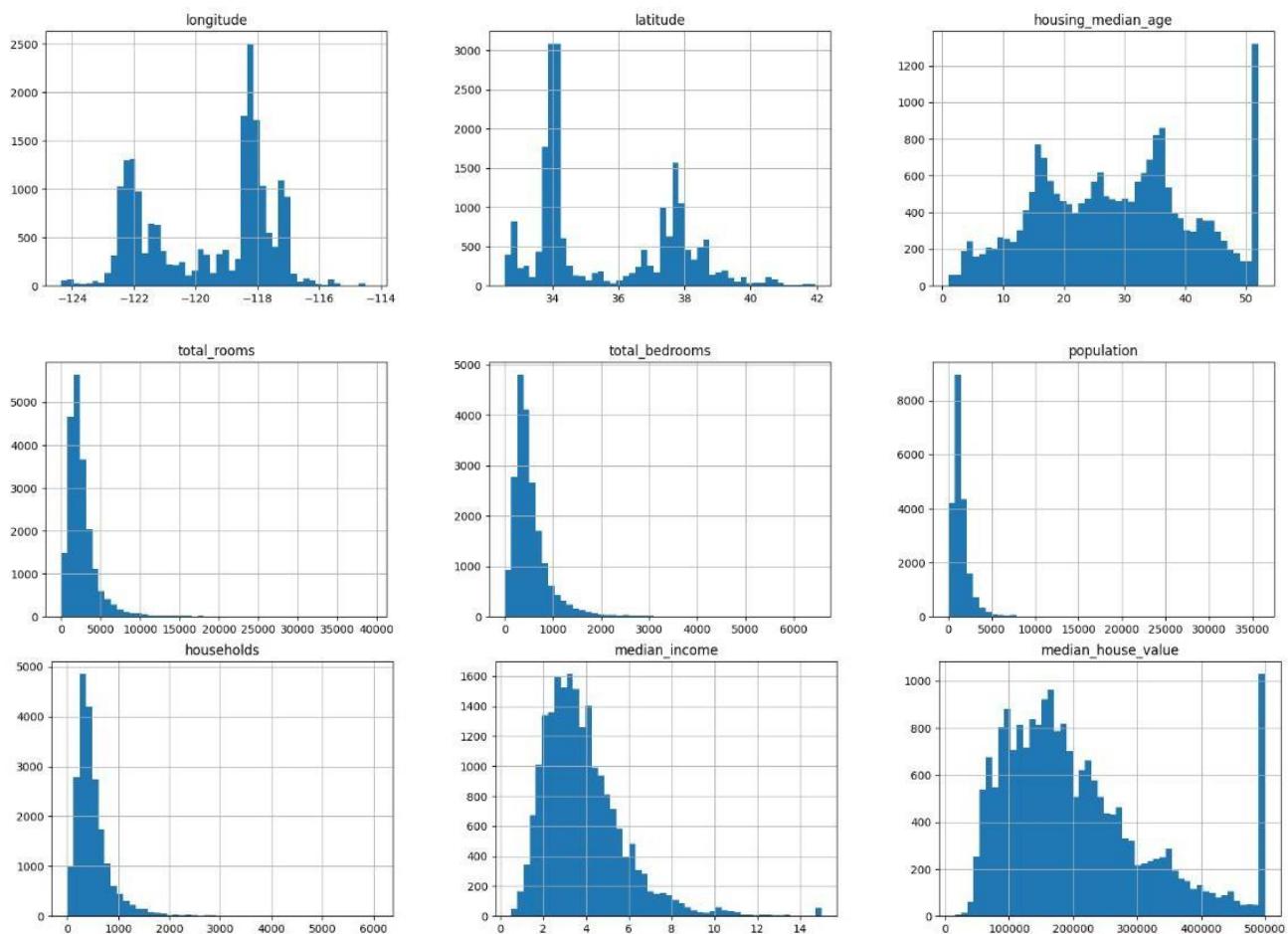
```
Out[10]: ocean_proximity
<1H OCEAN    9136
INLAND       6551
NEAR OCEAN    2658
NEAR BAY      2290
ISLAND        5
Name: count, dtype: int64
```

```
In [11]: housing.describe()
```

| | longitude | latitude | housing_median_age | total_rooms | total_bedrooms | population | households | median_income | me |
|--------------|--------------|--------------|--------------------|--------------|----------------|--------------|--------------|---------------|----|
| count | 20640.000000 | 20640.000000 | 20640.000000 | 20640.000000 | 20433.000000 | 20640.000000 | 20640.000000 | 20640.000000 | |
| mean | -119.569704 | 35.631861 | 28.639486 | 2635.763081 | 537.870553 | 1425.476744 | 499.539680 | 3.870671 | |
| std | 2.003532 | 2.135952 | 12.585558 | 2181.615252 | 421.385070 | 1132.462122 | 382.329753 | 1.899822 | |
| min | -124.350000 | 32.540000 | 1.000000 | 2.000000 | 1.000000 | 3.000000 | 1.000000 | 0.499900 | |
| 25% | -121.800000 | 33.930000 | 18.000000 | 1447.750000 | 296.000000 | 787.000000 | 280.000000 | 2.563400 | |
| 50% | -118.490000 | 34.260000 | 29.000000 | 2127.000000 | 435.000000 | 1166.000000 | 409.000000 | 3.534800 | |
| 75% | -118.010000 | 37.710000 | 37.000000 | 3148.000000 | 647.000000 | 1725.000000 | 605.000000 | 4.743250 | |
| max | -114.310000 | 41.950000 | 52.000000 | 39320.000000 | 6445.000000 | 35682.000000 | 6082.000000 | 15.000100 | |

```
In [12]:  
import matplotlib.pyplot as plt  
import seaborn as sns
```

```
In [13]:  
housing.hist(bins=50, figsize=(20,15))  
plt.show()
```



Create a Test Set

```
In [14]:  
import numpy as np
```

```
In [15]:  
def split_train_test(data, test_ratio=0.2):  
    shuffled_indices = np.random.permutation(len(data))  
    test_set_size = int(len(data) * test_ratio)  
    test_indices = shuffled_indices[:test_set_size]  
    train_indices = shuffled_indices[test_set_size:]  
    return data.iloc[train_indices], data.iloc[test_indices]
```

```
In [16]:  
# you can then use the function like this  
train_set, test_set = split_train_test(data=housing)  
len(train_set), len(test_set)
```

```
Out[16]: (16512, 4128)
```

```
In [17]: from zlib import crc32
```

```
In [18]: def test_set_check(identifier, test_ratio=.2):
    total_size = 2**32
    hex_repr = crc32(np.int64(identifier)) & 0xffffffff
    in_test = hex_repr < (test_ratio * total_size)
    return in_test
```

```
In [19]: [test_set_check(i) for i in range(10)]
```

```
Out[19]: [False, False, True, False, False, True, False, False, False, False]
```

```
In [20]: def split_train_test_by_id(data, test_ratio, id_column):
    ids = data[id_column]
    in_test_set = ids.apply(lambda id_: test_set_check(id_, test_ratio))
    return data.loc[~in_test_set], data.loc[in_test_set]
```

Unfortunately, the housing dataset does not have an identifier column. We will use the row index as an identifier:

```
In [21]: housing_with_id = housing.reset_index()
```

```
In [22]: train_set, test_set = split_train_test_by_id(data=housing_with_id, test_ratio=0.2, id_column="index")
train_set.shape, test_set.shape
```

```
Out[22]: ((16512, 11), (4128, 11))
```

```
In [23]: def from_Z_to_N(z):
    if z >= 0:
        n = 2 * z
    else:
        n = -2 * z - 1
    return n
```

```
In [24]: def cantor_pairing(n1, n2):
    n = ( (n1 + n2) * (n1 + n2 + 1) ) / 2 + n2
    return n
```

```
In [25]: def lat_lon_to_index(lat, lon):
    lat, lon = int(lat*100), int(lon*100)
    lat, lon = from_Z_to_N(lat), from_Z_to_N(lon)
    index = cantor_pairing(lat, lon)
    return np.int64(index)
```

```
In [26]: housing['id'] = housing.apply(lambda row: lat_lon_to_index(row['latitude'], row['longitude']), axis=1)
```

```
In [27]: housing['id'].value_counts()
```

```
Out[27]: id
513289261    24
513481522    20
513417431    18
513353344    18
463609694    14
..
513032709     1
513417159     1
519523778     1
519459311     1
515855387     1
Name: count, Length: 11573, dtype: int64
```

We still get duplicate indexes, and at the same time, we have duplicate (lat,lon) tuples as follows:

```
In [28]: housing.groupby(by=['longitude', 'latitude']).count()['total_rooms'].sort_values()
```

```
Out[28]: longitude  latitude
-124.35      40.54      1
-118.90      34.41      1
          35.26      1
          35.41      1
-118.89      34.22      1
..
-122.41      37.75     10
-122.42      37.75     10
-122.44      37.78     11
-122.42      37.80     11
-122.41      37.80     15
Name: total_rooms, Length: 12590, dtype: int64
```

```
In [29]: del(housing['id'])
```

```
In [30]: housing_with_id["id"] = housing["longitude"] * 1000 + housing["latitude"]
```

```
In [31]: train_set, test_set = split_train_test_by_id(data=housing_with_id, test_ratio=0.2, id_column='id')
train_set.shape, test_set.shape
```

```
Out[31]: ((16322, 12), (4318, 12))
```

Split the dataset

```
In [32]: from sklearn.model_selection import train_test_split
```

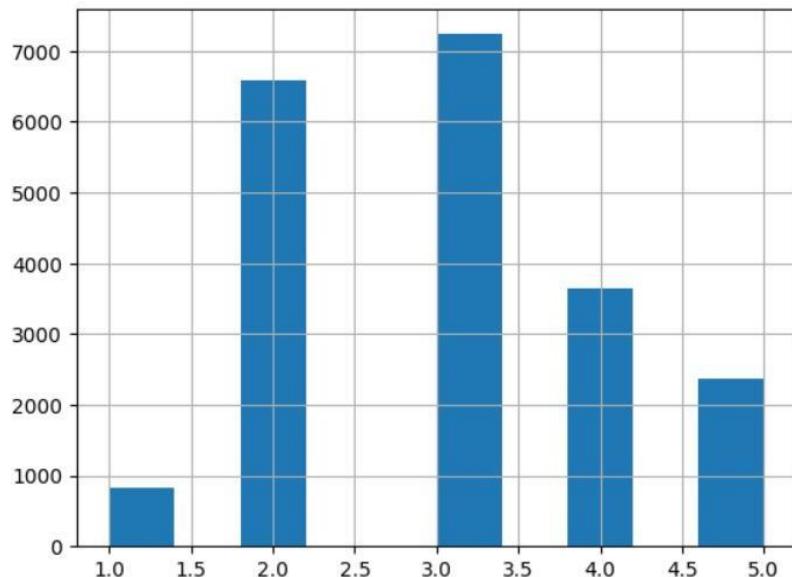
```
In [33]: train_set, test_set = train_test_split(housing, test_size=0.2, random_state=42)
train_set.shape, test_set.shape
```

```
Out[33]: ((16512, 10), (4128, 10))
```

```
In [34]: housing['income_cat'] = pd.cut(x=housing['median_income'], bins=[0, 1.5, 3, 4.5, 6, np.inf], labels=[1, 2, 3, 4, 5])
```

```
In [35]: # visualize the categories  
housing['income_cat'].hist()
```

```
Out[35]: <Axes: >
```



Now we are ready to do stratified sampling based on income category:

```
In [36]: from sklearn.model_selection import StratifiedShuffleSplit
```

```
In [37]: split = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=42)
```

```
In [38]: for train_index, test_index in split.split(X=housing, y=housing['income_cat']):  
    strat_train_set = housing.loc[train_index]  
    strat_test_set = housing.loc[test_index]
```

checking the proportions of income categories in the test set:

```
In [39]: strat_test_set['income_cat'].value_counts() / len(strat_test_set)
```

```
Out[39]: income_cat  
3    0.350533  
2    0.318798  
4    0.176357  
5    0.114341  
1    0.039971  
Name: count, dtype: float64
```

Now that we have a test set that is representative of `income_cat`'s distribution, it's time to remove it:

```
In [40]: for set_ in (strat_train_set, strat_test_set):  
    set_.drop('income_cat', axis=1, inplace=True)
```

3. Discover & Visualize the Data to Gain Insights

Exploring the training set:

```
In [41]: strat_train_set.shape, strat_test_set.shape
```

```
Out[41]: ((16512, 10), (4128, 10))
```

```
In [43]: strat_test_set.reset_index().to_feather(fname='data/01/strat_test_set.f')
```

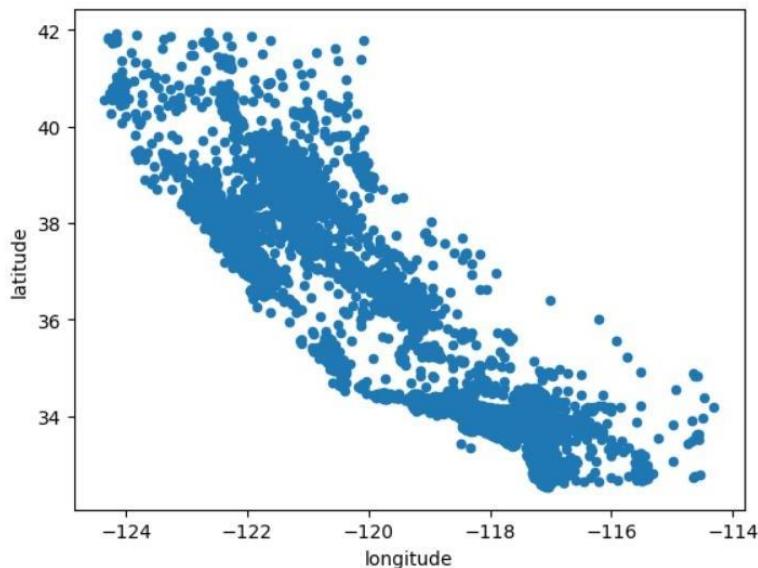
```
-----  
TypeError                                 Traceback (most recent call last)  
<ipython-input-43-044385fea95e> in <cell line: 1>()  
----> 1 strat_test_set.reset_index().to_feather(fname='data/01/strat_test_set.f')  
  
TypeError: DataFrame.to_feather() missing 1 required positional argument: 'path'
```

Let's create a copy of the training set to test without harming the original one:

```
In [44]: housing = strat_train_set.copy(); housing.shape
```

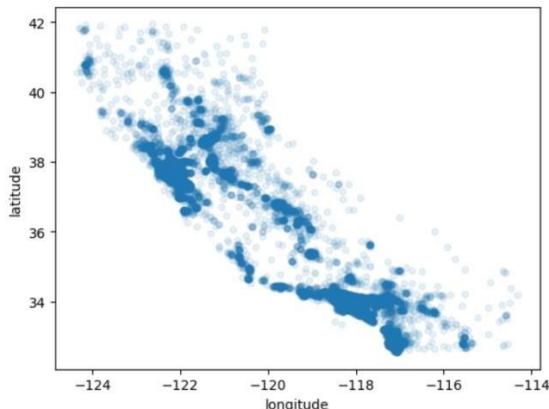
```
Out[44]: (16512, 10)
```

```
In [45]: housing.plot(kind='scatter', x='longitude', y='latitude')  
plt.show()
```



This looks like California, but other than that, we can't really see any other pattern. Setting the alpha to 0.1 makes it much easier to estimate densities:

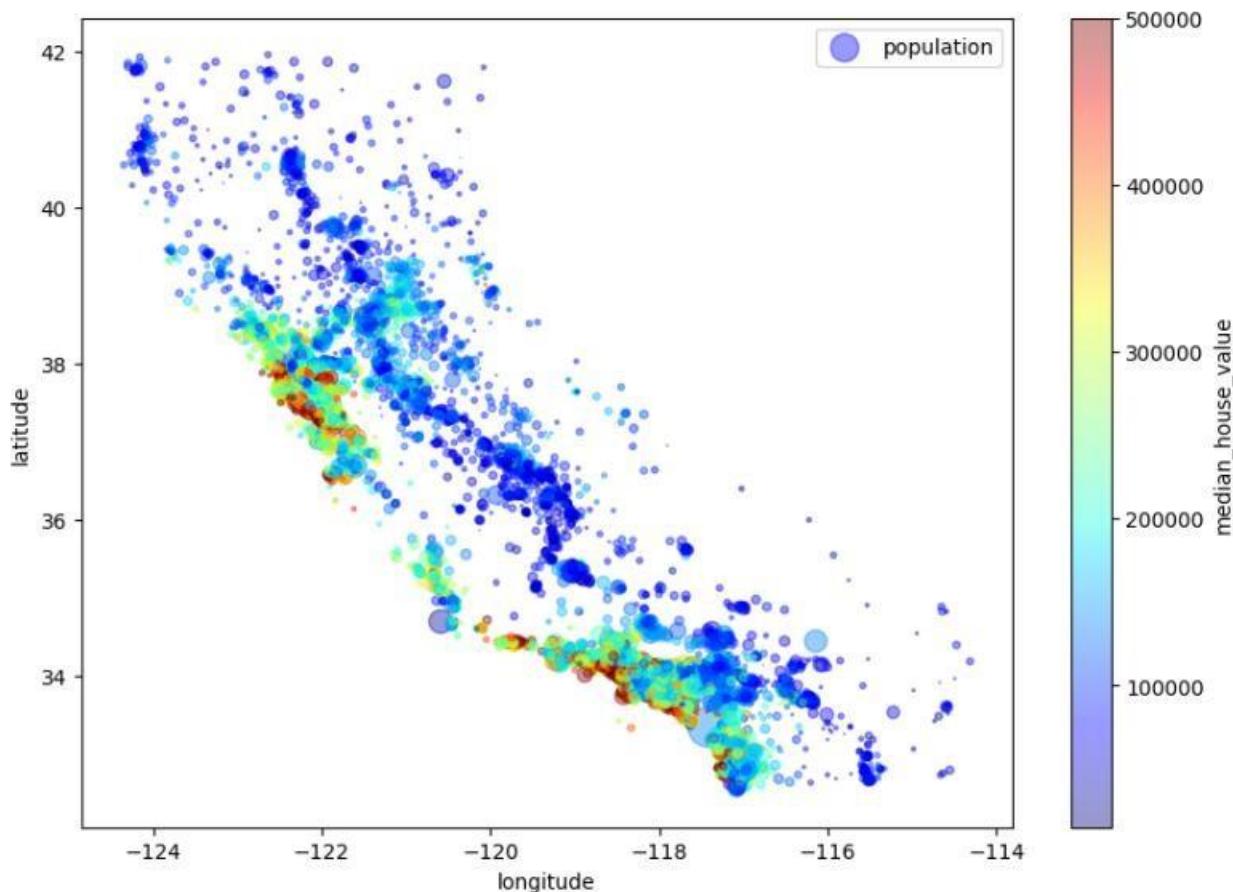
```
In [46]: housing.plot(kind='scatter', x='longitude', y='latitude', alpha=0.1)  
plt.show()
```



In the following figure, the radius of each circle represents the district's population (option `s`). The color represents the price (option `c`). We will also use a pre-defined color map called `jet` (option `cmap`) which ranges from `blue` (low levels) to `red` (high level).

```
In [47]: housing.plot(kind='scatter', x='longitude', y='latitude', alpha=.4, s=housing['population']/100.,  
label='population', figsize=(10, 7), c='median_house_value', cmap=plt.get_cmap(name='jet'), colorbar=True,  
plt.legend()
```

```
Out[47]: <matplotlib.legend.Legend at 0x7a8306385630>
```



Experimenting with Attribute Combinations

We may want to transform tail heavy distributions using the logarithm function (`log(.)`).

```
In [56]: housing['rooms_per_household'] = housing['total_rooms']/housing['households']  
housing['bedrooms_per_room'] = housing['total_bedrooms']/housing['total_rooms']  
housing['population_per_household'] = housing['population']/housing['households']
```

Look at the correlation matrix again:

```
In [57]: corr_matrix = housing.corr()  
corr_matrix['median_house_value'].sort_values(ascending=False)
```

We notice that `bedrooms_per_room` is much more correlated with `median_house_value`, meaning that the more expensive the house, the less the `bedrooms_per_room` ratio. `rooms_per_household` have a moderate positive correlation with `median_house_value`, the more expensive a house is, the more rooms it will have.

4. Prepare the Data for Machine Learning Algorithms

```
In [58]: housing = strat_train_set.drop("median_house_value", axis=1)
housing_labels = strat_train_set["median_house_value"].copy()
housing.shape, housing_labels.shape
```

```
Out[58]: ((16512, 9), (16512,))
```

Data Cleaning

We saw earlier that `total_bedrooms` have missing values, we have 3 options:

1. Get rid of the corresponding districts
 - `housing.dropna(subset='total_bedrooms')`
2. Get rid of the whole attribute (feature)
 - `housing.drop('total_bedrooms', axis=1)`
3. Set the missing values to some value (zero, mean, median, regressor preds,...)
 - `median = housing['total_bedrooms'].median()`
 - `housing['total_bedrooms'].fillna(median, inplace=True)`

We can also use `scikit-learn`'s `SimpleImputer`:

```
In [59]: from sklearn.impute import SimpleImputer
```

```
In [60]: imputer = SimpleImputer(strategy='median')
```

Since the imputer can only work on numerical attributes, we need to create a copy of the DataFrame without the `OCEAN_PROXIMITY` text attribute:

```
In [61]: housing_num = housing.drop("ocean_proximity", axis=1)
```

```
In [61]: housing_num = housing.drop("ocean_proximity", axis=1)
```

Now we can just fit the imputer to the dataframe:

```
In [62]: imputer.fit(housing_num)
```

```
Out[62]: SimpleImputer(strategy='median')
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

The imputer has calculated the median of all attributes and stored them in `.statistics_`.

```
In [63]: imputer.statistics_
```

```
Out[63]: array([-118.51    ,   34.26    ,   29.      ,  2119.      ,   433.      ,
 1164.      ,   408.      ,   3.54155])
```

```
In [64]: housing_num.median().values
```

```
Out[64]: array([-118.51    ,   34.26    ,   29.      ,  2119.      ,   433.      ,
 1164.      ,   408.      ,   3.54155])
```

Now we can use the "trained or fitted" imputer to transform the numerical attributes by replacing missing values with their corresponding medians:

```
In [65]: X = imputer.transform(housing_num)
X.shape
```

```
Out[65]: (16512, 8)
```

The result is a numpy array containing the transformed features. If we want to put it back into a Pandas DataFrame, it's simple:

```
In [66]: housing_tr = pd.DataFrame(data=X, index=housing_num.index, columns=housing_num.columns)
housing_tr.head()
```

```
Out[66]:    longitude  latitude  housing_median_age  total_rooms  total_bedrooms  population  households  median_income
12655      -121.46     38.52            29.0       3873.0          797.0      2237.0        706.0      2.1736
15502      -117.23     33.09             7.0       5320.0          855.0      2015.0        768.0      6.3373
2908       -119.04     35.37            44.0       1618.0          310.0       667.0        300.0      2.8750
14053      -117.13     32.75            24.0       1877.0          519.0       898.0        483.0      2.2264
20496      -118.70     34.28            27.0       3536.0          646.0      1837.0        580.0      4.4964
```

Handling Text & Categorical Attributes

```
In [67]: housing_cat = housing[['ocean_proximity']]
housing_cat.head(10)
```

```
Out[67]:    ocean_proximity
12655      INLAND
15502      NEAR OCEAN
2908       INLAND
14053      NEAR OCEAN
20496      <1H OCEAN
1481       NEAR BAY
18125      <1H OCEAN
5830       <1H OCEAN
17989      <1H OCEAN
4861       <1H OCEAN
```

```
In [68]: housing_cat['ocean_proximity'].value_counts()
```

```
Out[68]: ocean_proximity
<1H OCEAN    7277
INLAND       5262
NEAR OCEAN   2124
NEAR BAY     1847
ISLAND        2
Name: count, dtype: int64
```

Most ML algorithms prefer to work with numbers, so let's convert the text into **ordinal categorical** numbers:

```
In [69]: from sklearn.preprocessing import OrdinalEncoder
```

```
In [70]: ordinal_encoder = OrdinalEncoder()
```

```
In [71]: housing_cat_encoded = ordinal_encoder.fit_transform(housing_cat.values)
housing_cat_encoded.shape
```

```
Out[71]: (16512, 1)
```

```
In [72]: housing_cat_encoded[:10]
```

```
Out[72]: array([[1.],
 [4.],
 [1.],
 [4.],
 [0.],
 [3.],
 [0.],
 [0.],
 [0.],
 [0.]])
```

We can get the list of categories using the `categories_` attribute of the `OrdinalEncoder`:

```
In [73]: ordinal_encoder.categories_
```

```
Out[73]: [array(['<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN'],
      dtype=object)]
```

One issue with this representation is that the encoder will assume that two nearby categories are more similar than distant ones, but this is not the case for us (ex. categories 0 and 4 are clearly more similar than 0 and 1). To fix this issue, we create one binary attribute per category:

- One attribute is equal to `1` if the category is equal to `<1H OCEAN` and `0` otherwise.
- One attribute is equal to `1` if the category is equal to `INLAND` and `0` otherwise.
- ...

This is called 1-hot encoding because, for any row, only one binary attribute will be equal to 1 (hot), while the others are 0s (cold).

The new attributes are sometimes called dummy attributes, let's create them:

```
In [75]: from sklearn.preprocessing import OneHotEncoder

In [76]: one_hot_encoder = OneHotEncoder()

In [77]: housing_cat_1hot = one_hot_encoder.fit_transform(housing_cat.values)
housing_cat_1hot

Out[77]: <16512x5 sparse matrix of type '<class 'numpy.float64'>'  
with 16512 stored elements in Compressed Sparse Row format>
```

The output is a sparse scipy matrix instead of a numpy array. If we use numpy, we have to store all of the zeros in memory, comprising of most of the array. Instead, we store the information as a Scipy sparse matrix which only stores the locations of the non-zeros (which is more efficient).

We can mostly use it as a normal `2D` array, but if we want to convert it into a dense numpy array:

```
In [78]: housing_cat_1hot.toarray()

Out[78]: array([[0., 1., 0., 0., 0.],
 [0., 0., 0., 0., 1.],
 [0., 1., 0., 0., 0.],
 ...,
 [1., 0., 0., 0., 0.],
 [1., 0., 0., 0., 0.],
 [0., 1., 0., 0., 0.]])
```



```
In [79]: one_hot_encoder.categories_

Out[79]: [array(['<1H OCEAN', 'INLAND', 'ISLAND', 'NEAR BAY', 'NEAR OCEAN'],
 dtype=object)]
```

Custom Transformers

Although `scikit-learn` provide many useful transformers, we will need to write our own for custom tasks such as data cleanup or feature engineering. We'll want our transformer to easily work with other scikit-learn functionalities (such as Pipelines).

All we need to do is create a class with 3 methods: `fit`, `transform`, `fit_transform`. We can get `fit_transform` for free by adding `TransformerMixin` as a base class.

If we add `BaseEstimator` as another base class & avoid the use of `args` and `kwargs`, we get two extra methods (`.get_params()` & `.set_params()`).

```
In [80]: from sklearn.base import TransformerMixin, BaseEstimator

In [81]: rooms_ix, bedrooms_ix, population_ix, households_ix = 3, 4, 5, 6
```

```
In [82]: class CombinedAttributesAdder(BaseEstimator, TransformerMixin):
    def __init__(self, add_bedrooms_per_room=True):
        self.add_bedrooms_per_room = add_bedrooms_per_room

    def fit(self, X, y=None):
        return self # We don't have any internal parameters. Only interested in transforming data.

    def transform(self, X, y=None):
        rooms_per_household = X[:, rooms_ix] / X[:, households_ix]
        population_per_household = X[:, population_ix] / X[:, households_ix]
        if self.add_bedrooms_per_room:
            bedrooms_per_room = X[:, bedrooms_ix] / X[:, rooms_ix]
            return np.c_[X, rooms_per_household, population_per_household, bedrooms_per_room]
        else:
            return np.c_[X, rooms_per_household, population_per_household]
```

```
In [83]: attr_adder = CombinedAttributesAdder(add_bedrooms_per_room=False)
```

```
In [84]: housing_extra_attribs = attr_adder.transform(housing.values)
```

The `add_bedrooms_per_room` hyper-parameter will easily help us find out whether adding the attributes helps the ML algorithm or not.

We can add hyper-parameters to control any pre-processing step that we're not sure about. The more we automate these data preprocessing steps, the more combinations we get to try out.

Transformation Pipelines

```
In [85]: from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
```

```
In [86]: num_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy='median')),
    ('attribs_adder', CombinedAttributesAdder()),
    ('std_scaler', StandardScaler())
])
```

```
In [87]: housing_num_tr = num_pipeline.fit_transform(housing_num)
housing_num_tr.shape
```

```
Out[87]: (16512, 11)
```

So far, we have handled categorical/continuous columns separately. It would be better if we had a single transformer that is able to transform all columns.

`ColumnTransformer` is to the rescue:

```
In [88]: from sklearn.compose import ColumnTransformer
```

```
In [89]: num_attribs = housing_num.columns.tolist()
cat_attribs = ["ocean_proximity"]
```

```
In [90]: full_pipeline = ColumnTransformer([
    ("num", num_pipeline, num_attribs),
    ("cat", OneHotEncoder(), cat_attribs)
])
```

```
In [91]: housing_prepared = full_pipeline.fit_transform(housing)
housing_prepared.shape
```

5. Select & Train a Model

Training & Evaluating on the Training Set

Train a Linear Regression model:

```
In [92]: from sklearn.linear_model import LinearRegression  
  
In [93]: lin_reg = LinearRegression()  
  
In [94]: lin_reg.fit(X=housing_prepared, y=housing_labels)  
  
Out[94]: LinearRegression()  
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.  
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.
```

Let's try the model on a few instances from the training set:

```
In [95]: some_data = housing.iloc[:5]  
  
In [96]: some_labels = housing_labels.iloc[:5]  
  
In [97]: some_data_prepared = full_pipeline.transform(some_data)  
  
In [98]: print("Predictions: ", lin_reg.predict(some_data_prepared))  
  
Predictions: [ 85657.90192014 305492.60737488 152056.46122456 186095.70946094  
244550.67966089]  
  
In [99]: print("Labels: ", some_labels.tolist())  
  
Labels: [72100.0, 279600.0, 82700.0, 112500.0, 238300.0]
```

It works, although the predictions are not exactly accurate.

Let's measure the performance of our model using the RMSE metric.

```
In [100... from sklearn.metrics import mean_squared_error  
  
In [101... housing_predictions = lin_reg.predict(housing_prepared)  
  
In [102... lin_mse = mean_squared_error(housing_labels, housing_predictions)  
  
In [103... lin_rmse = np.sqrt(lin_mse)  
lin_rmse  
  
Out[103... 68627.87390018745
```

Most districts median housing values range between 120K to 265K, so an average error of 68K is not good.

This is an example of a model overfitting the data. When this happens, it can mean two things:

- The features do not provide enough information to make better predictions.
- The model is not powerful enough, meaning its hypothesis space is narrow.

The main ways to tackle underfitting:

- To feed the model better features.
- To select a more powerful model.
- To loosen the model's restrictions.

This model is not regularized, which rules out the last option. We could try to input more features, but let's start by testing a more powerful model.

Let's try out `DecisionTreeRegressor`, this is a powerful model, capable of finding non-linear relationships within the data:

```
In [104]: from sklearn.tree import DecisionTreeRegressor
```

```
In [105]: tree_reg = DecisionTreeRegressor()
```

```
In [106]: tree_reg.fit(X=housing_prepared, y=housing_labels)
```

```
Out[106]: DecisionTreeRegressor()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```
In [107]: housing_predictions = tree_reg.predict(housing_prepared)
```

```
In [108]: tree_mse = mean_squared_error(y_true=housing_labels, y_pred=housing_predictions)
```

```
In [109]: tree_rmse = np.sqrt(tree_mse)  
tree_rmse
```

```
Out[109]: 0.0
```

Better Evaluation using Cross-Validation

One way to evaluate our model is to use `train_test_split()` again on the training set, extract a validation set and evaluate our iterative models on it.

A great alternative is to use K-fold cross-validation. We randomly split the training data into 10 folds, we iteratively train the model on 9 folds and evaluate on 1, doing this 10 times.

We will end up with 10 metric scores:

```
In [110]: from sklearn.model_selection import cross_val_score
```

```
In [111]: scores = cross_val_score(estimator=tree_reg, X=housing_prepared,  
y=housing_labels, scoring='neg_mean_squared_error', cv=10)
```

```
In [112]: tree_rmse_scores = np.sqrt(-scores)
```

`scikit-learn`'s cross validation features expect a utility function (the greater the better) rather than a cost function (the lower the better). That's why we used `neg_mean_squared_error` and we negated it at RMSE evaluation.

```
In [113]: def display_scores(scores):
    print("Scores:", scores)
    print("Mean:", scores.mean())
    print("Standard Deviation:", scores.std())

In [114]: display_scores(tree_rmse_scores)

Scores: [73420.18119578 69564.42303171 68891.37403651 71450.13832167
96371.93163844 77144.32132592 70645.53949428 73310.3218479
68484.47299548 70726.35627711]
Mean: 71300.90601648012
Standard Deviation: 2528.456433119772
```

The decision tree seems to perform worse than the linear regression model!

We should notice that cross validation allows us to not only get an estimate of the performance of your model (mean), but how precise it is (std). We would not have this estimation if we used only one validation set. However, cross-validation comes at the cost of training the model several times, which is not always possible.

Let's compute the same scores for the linear regression model just to be sure:

```
In [115]: scores = cross_val_score(estimator=lin_reg, X=housing_prepared,
                               y=housing_labels, scoring='neg_mean_squared_error', cv=10)

In [116]: lin_rmse_scores = np.sqrt(-scores)

In [117]: display_scores(lin_rmse_scores)

Scores: [71762.76364394 64114.99166359 67771.17124356 68635.19072082
66846.14089488 72528.03725385 73997.08050233 68802.33629334
66443.28836884 70139.79923956]
Mean: 69104.07998247063
Standard Deviation: 2880.3282098180634
```

That's right! the decision tree model is overfitting so badly that it performs worse than the linear regression model.

Let's try one last model now, the random forest regressor. Random forests work by training many decision trees on random feature subsets then average out their predictions.

Building a model on top of many other models is called **Ensemble Learning**.

```
In [118]: from sklearn.ensemble import RandomForestRegressor

In [119]: forest_reg = RandomForestRegressor()

In [120]: forest_reg.fit(X=housing_prepared, y=housing_labels)

Out[120]: RandomForestRegressor()
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.
```

```
In [121]: forest_mse = mean_squared_error(y_true=housing_labels, y_pred=forest_reg.predict(X=housing_prepared))

In [122]: forest_rmse = np.sqrt(forest_mse)
forest_rmse

Out[122]: 18677.177813034952
```

```
In [ ]: scores = cross_val_score(estimator=forest_reg, X=housing_prepared,
                               y=housing_labels, scoring='neg_mean_squared_error', cv=10)

In [ ]: forest_rmse_scores = np.sqrt(-scores)

In [ ]: display_scores(scores=forest_rmse_scores)
```

This is much better, random forests seem very promising. We should notice, however, that the RMSE on the training set is still much lower than the validation RMSE, meaning the model overfitted, but not as badly as the decision tree model. Possible solutions to overfitting are:

- Getting more training data
- Simplifying the model
- Regularizing the model

We should save any model after training so that we can come back to it at any time you want. We make sure to save both the hyper-parameters and the parameters (weights) of the model. We can easily save scikit-learn models using Python's `joblib`:

```
In [ ]: import joblib  
In [ ]: joblib.dump(value=forest_reg, filename='models/01/forest_reg.m')  
In [ ]: # & Later  
       forest_reg = joblib.load(filename='models/01/forest_reg.m')
```

6. Fine-Tune Your Model

Grid Search

```
In [ ]: from sklearn.model_selection import GridSearchCV  
In [ ]: param_grid = [  
    {'n_estimators': [3, 10, 30], 'max_features': [2, 4, 6, 8]},  
    {'bootstrap': [False], 'n_estimators': [3, 10], 'max_features': [2, 3, 4]}]  
In [ ]: forest_reg = RandomForestRegressor()  
In [ ]: grid_search = GridSearchCV(estimator=forest_reg, param_grid=param_grid, scoring='neg_mean_squared_error', cv=5, return_train_score=True)  
In [ ]: grid_search.fit(X=housing_prepared, y=housing_labels)
```

If we can't guess an initial quality search grids, we can start with powers of 10 then zoom in once we have the best estimate.

The model will first explore 3×4 combinations of hyper-parameters, then jump to the 2nd hyper-parameter space and try $1 \times 2 \times 3$. For each combination, it will train 5 times using the cross validation strategy, all in all: It will train **90** different model variations.

```
In [ ]: grid_search.best_params_
```

We can also get the best estimator directly:

```
In [ ]: grid_search.best_estimator_
```

When `GridSearchCV` finds the best estimator, it will retrain it on the whole training set. This can be controlled by the parameter `refit=True` (by default)

```
In [ ]: cvres = grid_search.cv_results_
```

```
In [ ]: for mean_score, params in zip(cvres['mean_test_score'], cvres['params']):  
    print(np.sqrt(-mean_score), params)
```

In this example, the best hyper-parameter combination is: `50110.7370892457` `{'max_features': 6, 'n_estimators': 30}` with an average RMSE of **50110**. The model performs slightly better than a random forest with default hyper-parameters.

Randomized Search

The grid search is fine when you're exploring a few hyper-parameter combinations, but when the search space is big though, it is better to use `RandomizedSearchCV` instead. It works almost in the same way of a grid search, but it tries out a limited randomly selected number of hyper-parameters for each iteration. This approach has two main benefits:

- If we let this approach run for 1,000 iterations, it will explore 1,000 values for each hyper-parameters, instead of combining each unique value.
- By setting the number of iterations, we can control computing resources much more effectively than doing Grid search.

Ensemble Methods

Another way to fine-tune your model is to combine the models that work best. Usually, the ensemble model will perform better than any part of the model, especially if its models are producing different errors.

Analyze the best models & their errors

```
In [ ]: feature_importances = grid_search.best_estimator_.feature_importances_
(feature_importances*100).astype(int)

In [ ]: extra_attribs = ["rooms_per_hhold", "pop_per_hhold", "bedrooms_per_room"]

In [ ]: cat_encoder = full_pipeline.named_transformers_['cat']

In [ ]: cat_one_hot_attributes = cat_encoder.categories_[0].tolist()

In [ ]: attributes = num_attribs + extra_attribs + cat_one_hot_attributes

In [ ]: # sorted(zip(feature_importances, attributes), reverse=True)
dict(zip(feature_importances, attributes))
```

With this information, we might want to start dropping some of the attributes to simplify the model (ex. only one `ocean_proximity` value is important).

Evaluate your system on the test set

After tweaking the system for a while, we finally have a model that can be evaluated on the test set. There is nothing special about this process, we reproduce the same steps you used with training data to benchmark the model.

However, we should call `transform()`, and not `fit_transform()`.

```
In [ ]: final_model = grid_search.best_estimator_

In [ ]: X_test = strat_test_set.drop(labels='median_house_value', axis=1)
y_test = strat_test_set['median_house_value'].copy()

In [ ]: X_test_prepared = full_pipeline.transform(X=X_test)

In [ ]: final_predictions = final_model.predict(X=X_test_prepared)

In [ ]: final_mse = mean_squared_error(y_true=y_test, y_pred=final_predictions)

In [ ]: final_rmse = np.sqrt(final_mse)
final_rmse
```

In some cases, such a point estimate of the generalization error won't be enough for us to launch it in production. We might want to create a confidence interval of 95% around the metric.

In some cases, such a point estimate of the generalization error won't be enough for us to launch it in production. We might want to create a confidence interval of 95% around the metric.

For this, we use the individual predictions for each test set element.

```
In [ ]: from scipy import stats  
  
In [ ]: confidence = .95  
  
In [ ]: squared_errors = (y_test - final_predictions) ** 2  
  
In [ ]: np.sqrt(stats.t.interval(confidence, len(squared_errors) - 1, loc=squared_errors.mean(), scale=stats.sem(squared_errors)))
```

If we do a lot of hyper-parameter fine-tuning, we will end up with a slightly worse performance on the test set because we will sometimes overfit to the changing validation set. This didn't happen now, but when it happens, resist the temptation to go back and do more fine-tuning to have better results for the test set.

In our case with the California dataset, our system didn't actually beat the experts system (with 20% error). But management still decided to launch the service to free some time for its experts to work on other tasks.

7. Launch, Monitor, & Maintain your system

2.3 Experiment - 3

2.3.1 Question:

Use an appropriate data set for building the decision tree (ID3) and apply this knowledge to classify a new sample.

2.3.2 Code with Output:

```
In [1]: import numpy as np
import pandas as pd
eps = np.finfo(float).eps
from numpy import log2 as log

In [22]: df=pd.read_csv('/content/play_tennis.csv')
df = df.drop('day',axis=1)

In [23]: df.head(14)

Out[23]:   outlook temp humidity wind play
0   Sunny   Hot    High  Weak  No
1   Sunny   Hot    High Strong  No
2 Overcast   Hot    High  Weak Yes
3     Rain Mild    High  Weak Yes
4     Rain Cool   Normal Weak Yes
5     Rain Cool   Normal Strong  No
6 Overcast   Cool   Normal Strong Yes
7   Sunny Mild    High  Weak  No
8   Sunny Cool   Normal Weak Yes
9     Rain Mild   Normal Weak Yes
10  Sunny Mild   Normal Strong Yes
11 Overcast   Mild    High Strong Yes
12 Overcast   Hot    Normal Weak Yes
13     Rain Mild    High Strong  No

In [24]: print(f'Rows: {df.shape[0]}, Columns: {df.shape[1]}')

Rows: 14, Columns: 5

In [25]: print(df.columns)

Index(['outlook', 'temp', 'humidity', 'wind', 'play'], dtype='object')

In [26]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14 entries, 0 to 13
Data columns (total 5 columns):
 #   Column      Non-Null Count  Dtype  
--- 
 0   outlook      14 non-null    object 
 1   temp         14 non-null    object 
 2   humidity     14 non-null    object 
 3   wind         14 non-null    object 
 4   play         14 non-null    object 
dtypes: object(5)
memory usage: 688.0+ bytes
```

```
In [64]: df.describe()
```

```
Out[64]:    outlook temp humidity wind play
count      14     14      14     14     14
unique       3      3      2      2      2
top  Sunny   Mild    High  Weak   Yes
freq        5      6      7      8      9
```

```
In [63]: df.isnull()
```

```
Out[63]:    outlook temp humidity wind play
0    False  False    False  False  False
1    False  False    False  False  False
2    False  False    False  False  False
3    False  False    False  False  False
4    False  False    False  False  False
5    False  False    False  False  False
6    False  False    False  False  False
7    False  False    False  False  False
8    False  False    False  False  False
9    False  False    False  False  False
10   False  False    False  False  False
11   False  False    False  False  False
12   False  False    False  False  False
13   False  False    False  False  False
```

All values are FALSE for isnull(). Therefore no data cleaning is required.

```
In [29]: # Entropy
```

```
def find_entropy(df):
    #target column
    target = df.keys()[-1]
    entropy = 0
    values = df[target].unique()
    #calc entropy
    for value in values:
        fraction = df[target].value_counts()[value]/len(df[target])
        entropy += -fraction*np.log2(fraction)
    return entropy
```

```
In [30]: # Average Information
```

```
def average_information(df,attribute):
    target = df.keys()[-1]    #target column
    target_variables = df[target].unique()  #This gives all 'Yes' and 'No'
    variables = df[attribute].unique()      #This gives different features in that attribute (like 'Hot','Cold' in Temperature)
    entropy2 = 0
    for variable in variables:
        entropy = 0
        for target_variable in target_variables:
            num = len(df[attribute][df[attribute]==variable][df[target] ==target_variable])
            den = len(df[attribute][df[attribute]==variable])
            fraction = num/(den+eps)
            entropy += -fraction*log(fraction+eps)
        fraction2 = den/len(df)
        entropy2 += -fraction2*entropy
    return abs(entropy2)
```

```
In [31]: # Information Gain

def find_winner(df):
    IG = []
    for key in df.keys()[:-1]:
        IG.append(find_entropy(df)-average_information(df,key))
    return df.keys()[:-1][np.argmax(IG)]
```

```
In [32]: def get_subtable(df, node,value):
    return df[df[node] == value].reset_index(drop=True)
```

```
In [33]: def buildTree(df,tree=None):
    target = df.keys()[-1]    #target column

    #Here we build our decision tree

    #Get attribute with maximum information gain
    node = find_winner(df)

    #Get distinct value of that attribute e.g Salary is node and Low,Med and High are values
    attValue = np.unique(df[node])

    #Create an empty dictionary to create tree
    if tree is None:
        tree={}
        tree[node] = {}

    #We make Loop to construct a tree by calling this function recursively.
    #In this we check if the subset is pure and stops if it is pure.

    for value in attValue:

        subtable = get_subtable(df,node,value)
        clValue,counts = np.unique(subtable[target],return_counts=True)

        if len(counts)==1:#Checking purity of subset
            tree[node][value] = clValue[0]
        else:
            tree[node][value] = buildTree(subtable) #Calling the function recursively

    return tree
```

```
In [34]: tree = buildTree(df)
```

```
In [35]: import pprint
pprint.pprint(tree)

{'outlook': {'Overcast': 'Yes',
             'Rain': {'wind': {'Strong': 'No', 'Weak': 'Yes'}},
             'Sunny': {'humidity': {'High': 'No', 'Normal': 'Yes'}}}}
```

2.4 Experiment - 4

2.4.1 Question:

Implement Linear and Multi-Linear Regression algorithm using appropriate dataset.

2.4.2 Code with Output:

Simple Linear Regression

Link - 1 (https://github.com/shuv50/Data-Science/blob/main/simple_Linear_Regression.ipynb)

```
▶ # Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from pandas.core.common import random_state
from sklearn.linear_model import LinearRegression
```

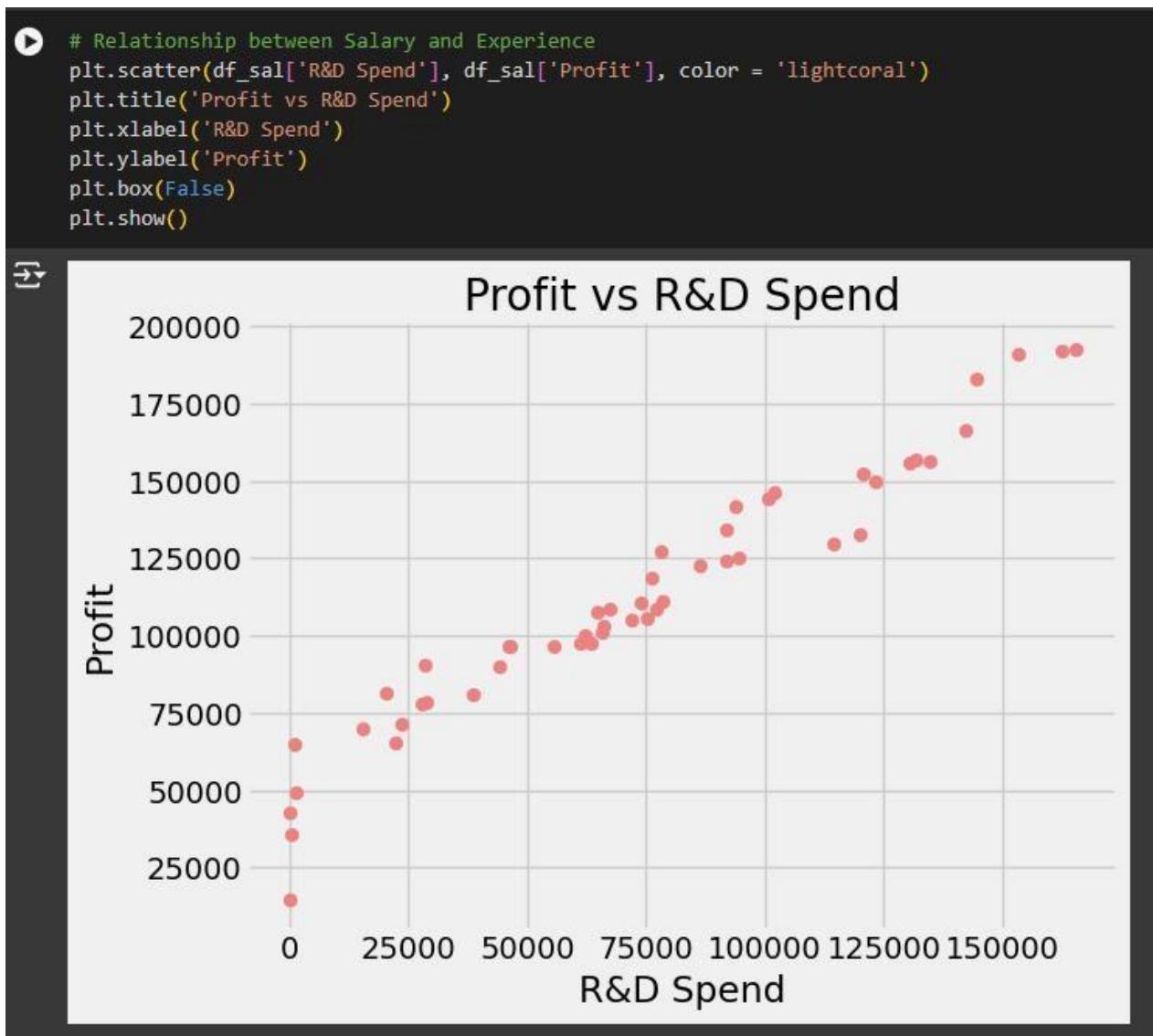
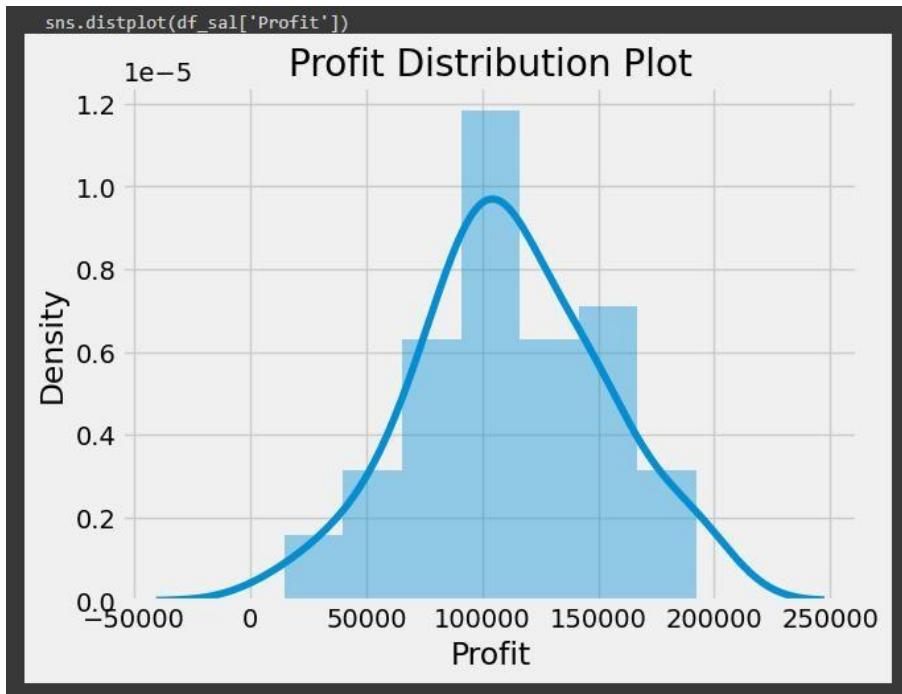
```
[ ] # Get dataset
df_sal = pd.read_csv('/content/50_Startups.csv')
df_sal.head()
```

| | R&D Spend | Administration | Marketing Spend | State | Profit |
|---|-----------|----------------|-----------------|------------|-----------|
| 0 | 165349.20 | 136897.80 | 471784.10 | New York | 192261.83 |
| 1 | 162597.70 | 151377.59 | 443898.53 | California | 191792.06 |
| 2 | 153441.51 | 101145.55 | 407934.54 | Florida | 191050.39 |
| 3 | 144372.41 | 118671.85 | 383199.62 | New York | 182901.99 |
| 4 | 142107.34 | 91391.77 | 366168.42 | Florida | 166187.94 |

```
[ ] # Describe data
df_sal.describe()
```

| | R&D Spend | Administration | Marketing Spend | Profit |
|-------|---------------|----------------|-----------------|---------------|
| count | 50.000000 | 50.000000 | 50.000000 | 50.000000 |
| mean | 73721.615600 | 121344.639600 | 211025.097800 | 112012.639200 |
| std | 45902.256482 | 28017.802755 | 122290.310726 | 40306.180338 |
| min | 0.000000 | 51283.140000 | 0.000000 | 14681.400000 |
| 25% | 39936.370000 | 103730.875000 | 129300.132500 | 90138.902500 |
| 50% | 73051.080000 | 122699.795000 | 212716.240000 | 107978.190000 |
| 75% | 101602.800000 | 144842.180000 | 299469.085000 | 139765.977500 |
| max | 165349.200000 | 182645.560000 | 471784.100000 | 192261.830000 |

```
▶ # Data distribution
plt.title('Profit Distribution Plot')
sns.distplot(df_sal['Profit'])
plt.show()
```



```
[ ] # Splitting variables
X = df_sal.iloc[:, :-1] # independent
y = df_sal.iloc[:, -1:] # dependent

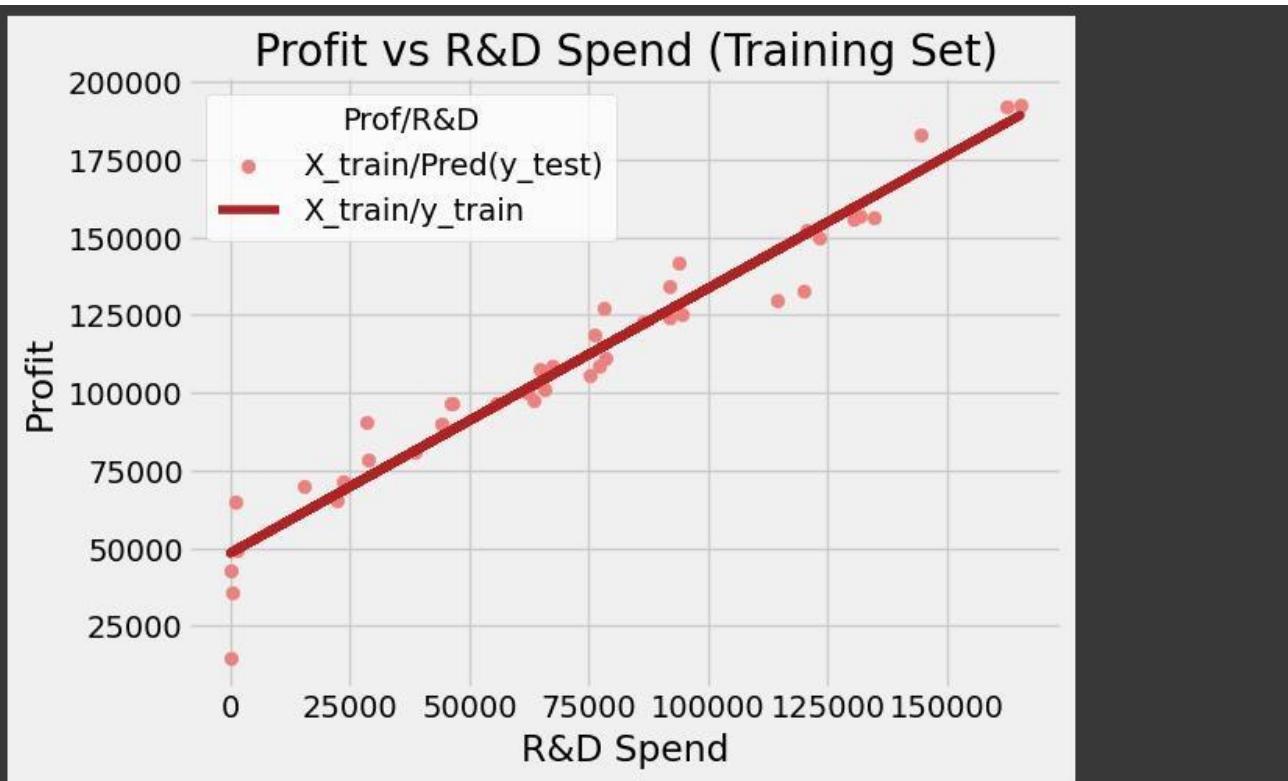
[ ] # Splitting dataset into test/train
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)

[ ] # Regressor model
regressor = LinearRegression()
regressor.fit(X_train, y_train)

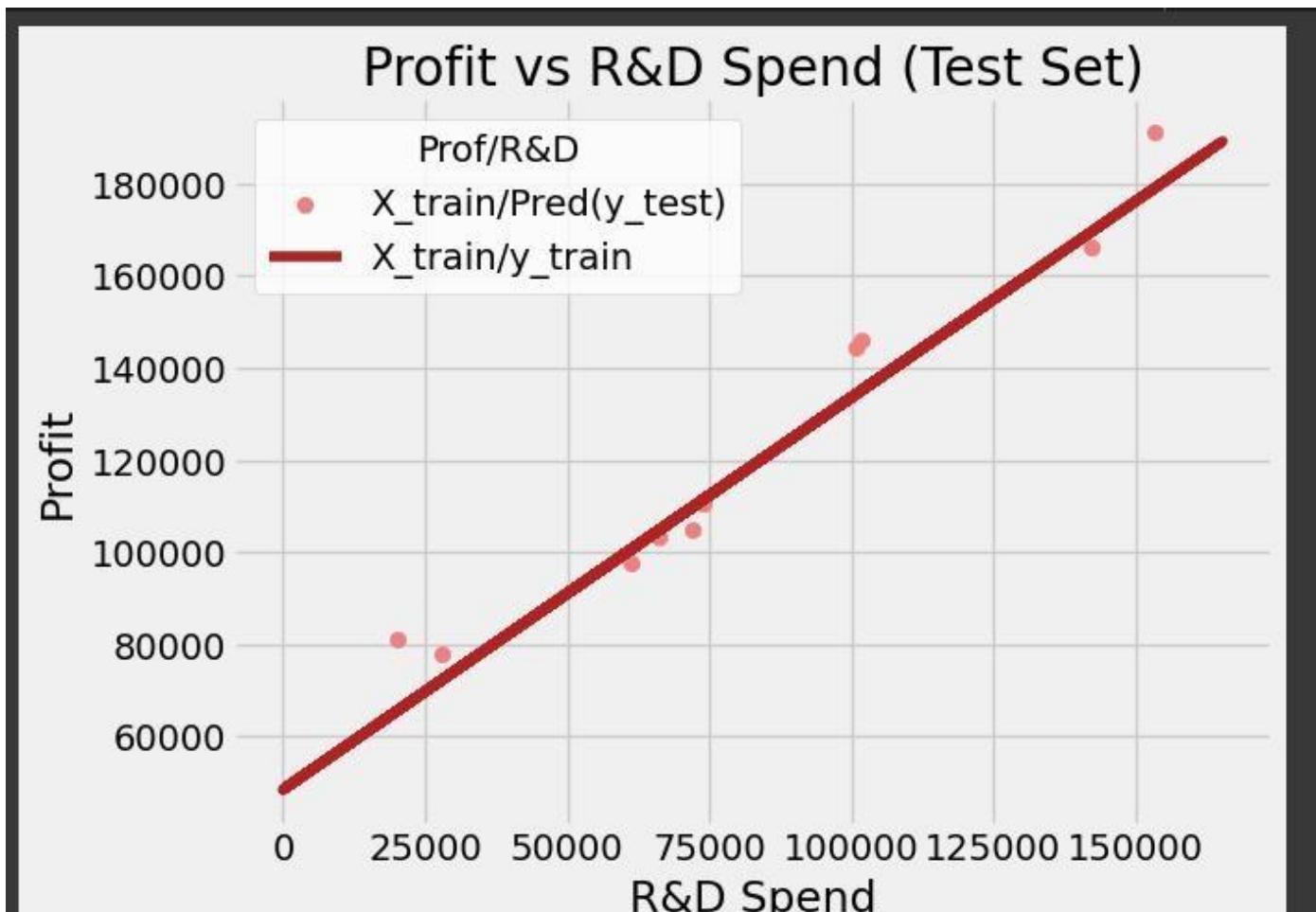
☞ LinearRegression
LinearRegression()
```

[] # Prediction result
`y_pred_test = regressor.predict(X_test) # predicted value of y_test
y_pred_train = regressor.predict(X_train) # predicted value of y_train`

▶ # Prediction on training set
`plt.scatter(X_train, y_train, color = 'lightcoral')
plt.plot(X_train, y_pred_train, color = 'firebrick')
plt.title('Profit vs R&D Spend (Training Set)')
plt.xlabel('R&D Spend')
plt.ylabel('Profit')
plt.legend(['X_train/Pred(y_test)', 'X_train/y_train'], title = 'Prof/R&D', loc='best', facecolor='white')
plt.box(False)
plt.show()`



```
# Prediction on test set
plt.scatter(X_test, y_test, color = 'lightcoral')
plt.plot(X_train, y_pred_train, color = 'firebrick')
plt.title('Profit vs R&D Spend (Test Set)')
plt.xlabel('R&D Spend')
plt.ylabel('Profit')
plt.legend(['X_train/Pred(y_test)', 'X_train/y_train'], title = 'Prof/R&D', loc='best', facecolor='white')
plt.box(False)
plt.show()
```



```
# Regressor coefficients and intercept
print(f'Coefficient: {regressor.coef_}')
print(f'Intercept: {regressor.intercept_}'')
```

```
Coefficient: [[0.8516228]]
Intercept: [48416.29766139]
```

▼ Multiple Linear Regression

Link - 2 (https://github.com/shuv50/Data-Science/blob/main/Multiple_Linear_Regression.ipynb)

```
[ ] # Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.linear_model import LinearRegression
```

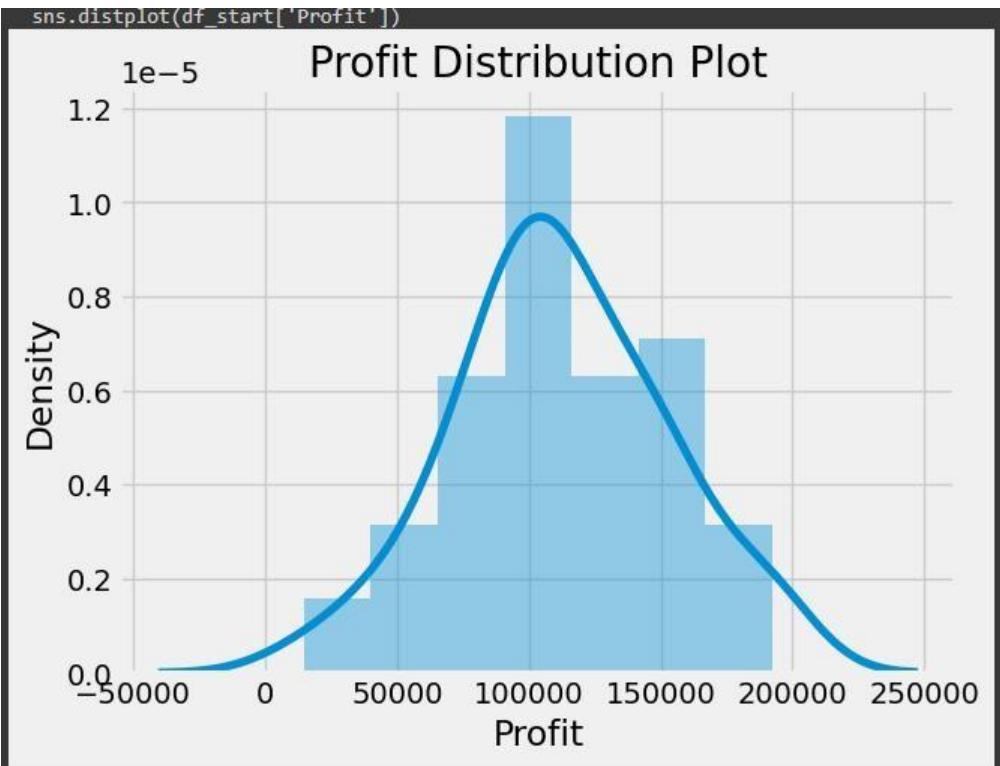
```
[ ] # Get dataset
df_start = pd.read_csv('/content/50_Startups.csv')
df_start.head()
```

| | R&D Spend | Administration | Marketing Spend | State | Profit |
|---|-----------|----------------|-----------------|------------|-----------|
| 0 | 165349.20 | 136897.80 | 471784.10 | New York | 192261.83 |
| 1 | 162597.70 | 151377.59 | 443898.53 | California | 191792.06 |
| 2 | 153441.51 | 101145.55 | 407934.54 | Florida | 191050.39 |
| 3 | 144372.41 | 118671.85 | 383199.62 | New York | 182901.99 |
| 4 | 142107.34 | 91391.77 | 366168.42 | Florida | 166187.94 |

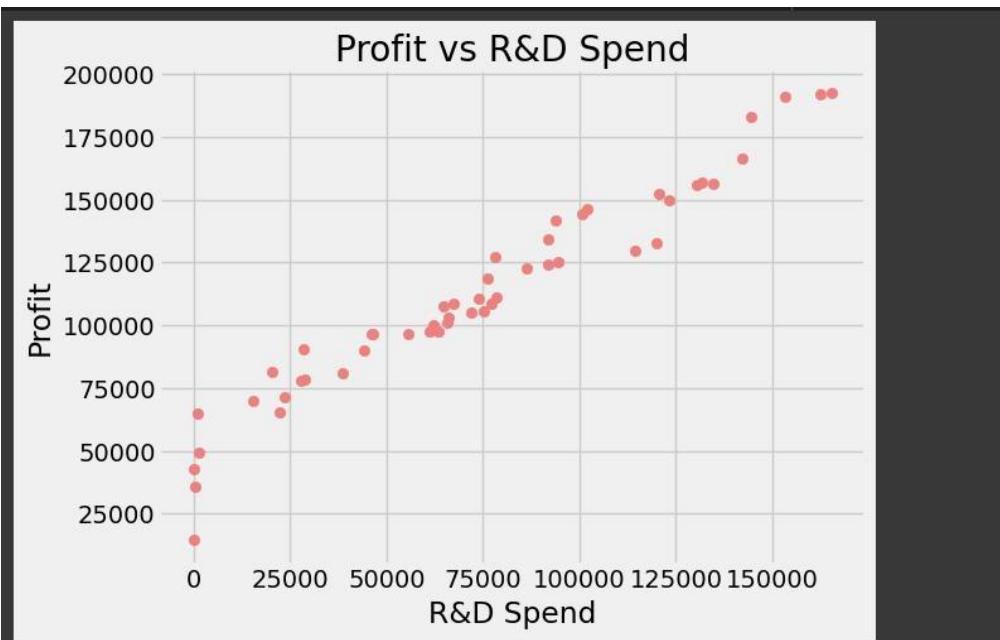
```
# Describe data
df_start.describe()
```

| | R&D Spend | Administration | Marketing Spend | Profit |
|-------|---------------|----------------|-----------------|---------------|
| count | 50.000000 | 50.000000 | 50.000000 | 50.000000 |
| mean | 73721.615600 | 121344.639600 | 211025.097800 | 112012.639200 |
| std | 45902.256482 | 28017.802755 | 122290.310726 | 40306.180338 |
| min | 0.000000 | 51283.140000 | 0.000000 | 14681.400000 |
| 25% | 39936.370000 | 103730.875000 | 129300.132500 | 90138.902500 |
| 50% | 73051.080000 | 122699.795000 | 212716.240000 | 107978.190000 |
| 75% | 101602.800000 | 144842.180000 | 299469.085000 | 139765.977500 |
| max | 165349.200000 | 182645.560000 | 471784.100000 | 192261.830000 |

```
# Data distribution
plt.title('Profit Distribution Plot')
sns.distplot(df_start['Profit'])
plt.show()
```



```
# Relationship between Profit and R&D Spend
plt.scatter(df_start['R&D Spend'], df_start['Profit'], color = 'lightcoral')
plt.title('Profit vs R&D Spend')
plt.xlabel('R&D Spend')
plt.ylabel('Profit')
plt.box(False)
plt.show()
```



```
# Split dataset in dependent/independent variables
X = df_start.iloc[:, :-1].values
y = df_start.iloc[:, -1].values

# One-hot encoding of categorical data
ct = ColumnTransformer(transformers = [('encoder', OneHotEncoder(), [3])], remainder = 'passthrough')
X = np.array(ct.fit_transform(X))
```

```
# Split dataset into test/train
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)

# Train multiple regression model
regressor = LinearRegression()
regressor.fit(X_train, y_train)

# Predict result
y_pred = regressor.predict(X_test)

# Compare predicted result with actual value
np.set_printoptions(precision = 2)
result = np.concatenate((y_pred.reshape(len(y_pred), 1), y_test.reshape(len(y_test), 1)), 1)
result

array([[103015.2 , 103282.38],
       [132582.28, 144259.4 ],
       [132447.74, 146121.95],
       [ 71976.1 ,  77798.83],
       [178537.48, 191050.39],
       [116161.24, 105008.31],
       [ 67851.69,  81229.06],
       [ 98791.73,  97483.56],
       [113969.44, 110352.25],
       [167921.07, 166187.94]])
```

2.5 Experiment - 5

2.5.1 Question:

Build Logistic Regression Model for a given dataset.

2.5.2 Code with Output:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import confusion_matrix
from sklearn.metrics import f1_score
```

```
df_net = pd.read_csv('/content/Social_Network_Ads.csv')
df_net.head()
```

| | User ID | Gender | Age | EstimatedSalary | Purchased |
|---|----------|--------|-----|-----------------|-----------|
| 0 | 15624510 | Male | 19 | 19000 | 0 |
| 1 | 15810944 | Male | 35 | 20000 | 0 |
| 2 | 15668575 | Female | 26 | 43000 | 0 |
| 3 | 15603246 | Female | 27 | 57000 | 0 |
| 4 | 15804002 | Male | 19 | 76000 | 0 |

```
df_net.drop(columns = ['User ID'], inplace=True)
df_net.head()
```

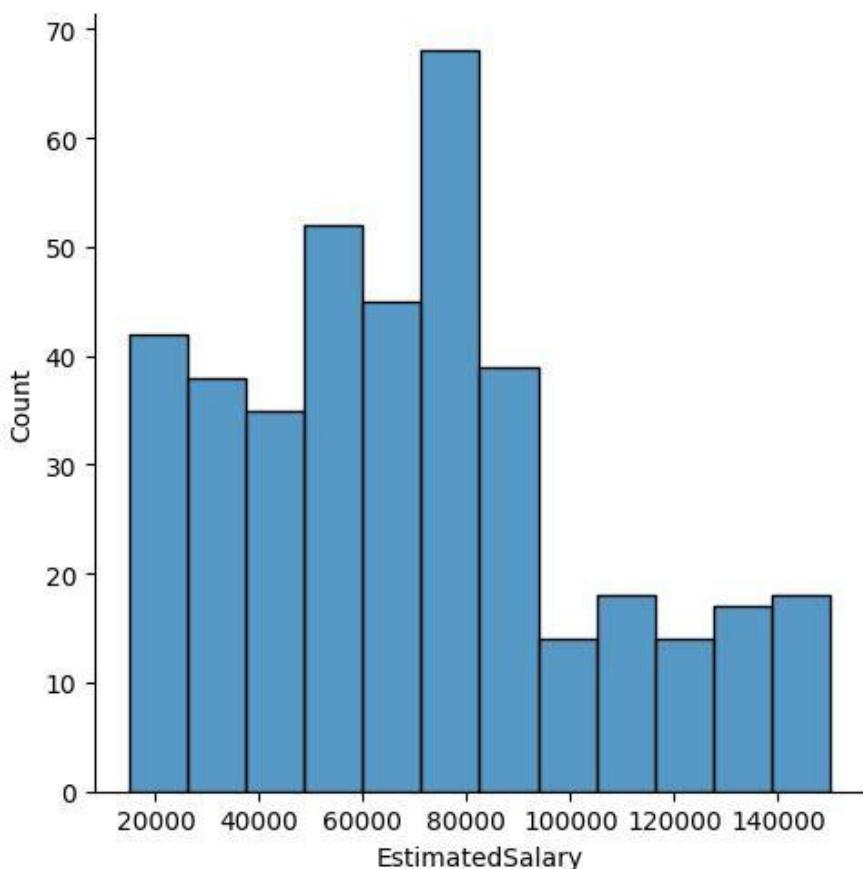
| | Gender | Age | EstimatedSalary | Purchased |
|---|--------|-----|-----------------|-----------|
| 0 | Male | 19 | 19000 | 0 |
| 1 | Male | 35 | 20000 | 0 |
| 2 | Female | 26 | 43000 | 0 |
| 3 | Female | 27 | 57000 | 0 |
| 4 | Male | 19 | 76000 | 0 |

```
df_net.describe()
```

| | Age | EstimatedSalary | Purchased |
|--------------|------------|-----------------|------------|
| count | 400.000000 | 400.000000 | 400.000000 |
| mean | 37.655000 | 69742.500000 | 0.357500 |
| std | 10.482877 | 34096.960282 | 0.479864 |
| min | 18.000000 | 15000.000000 | 0.000000 |
| 25% | 29.750000 | 43000.000000 | 0.000000 |
| 50% | 37.000000 | 70000.000000 | 0.000000 |
| 75% | 46.000000 | 88000.000000 | 1.000000 |
| max | 60.000000 | 150000.000000 | 1.000000 |

```
sns.distplot(df_net['EstimatedSalary'])
```

```
<seaborn.axisgrid.FacetGrid at 0x789c32189060>
```



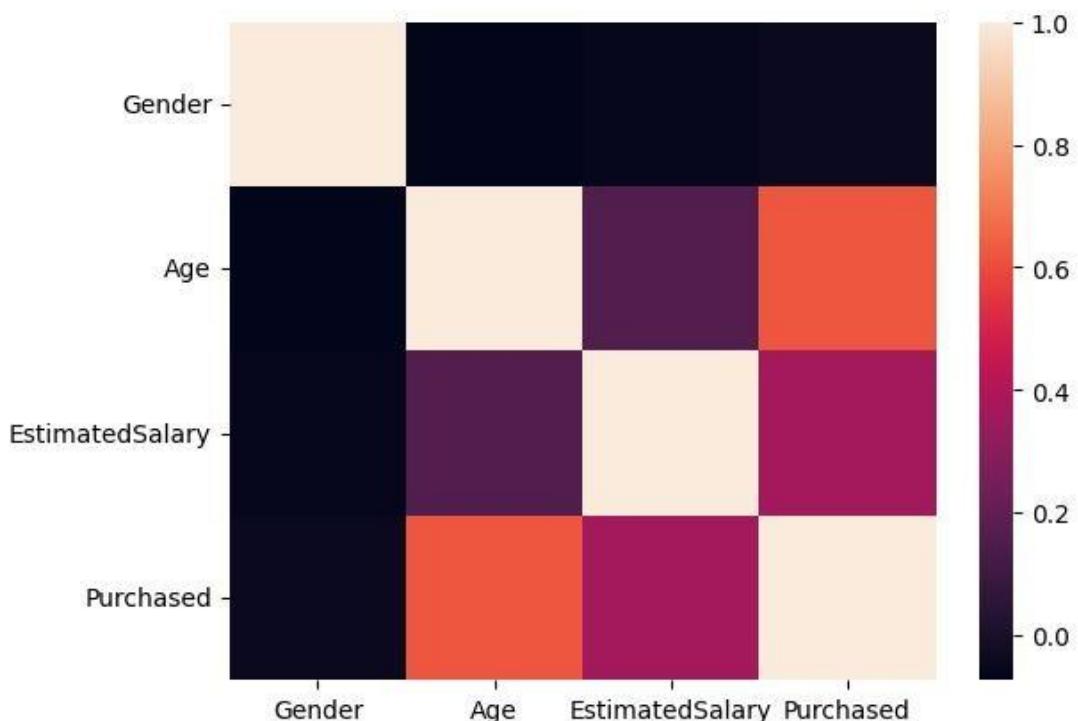
```
le = LabelEncoder()
df_net['Gender']= le.fit_transform(df_net['Gender'])
```

```
# Correlation matrix
df_net.corr()
```

| | Gender | Age | EstimatedSalary | Purchased |
|------------------------|---------------|------------|------------------------|------------------|
| Gender | 1.000000 | -0.073741 | -0.060435 | -0.042469 |
| Age | -0.073741 | 1.000000 | 0.155238 | 0.622454 |
| EstimatedSalary | -0.060435 | 0.155238 | 1.000000 | 0.362083 |
| Purchased | -0.042469 | 0.622454 | 0.362083 | 1.000000 |

```
sns.heatmap(df_net.corr())
```

<Axes: >

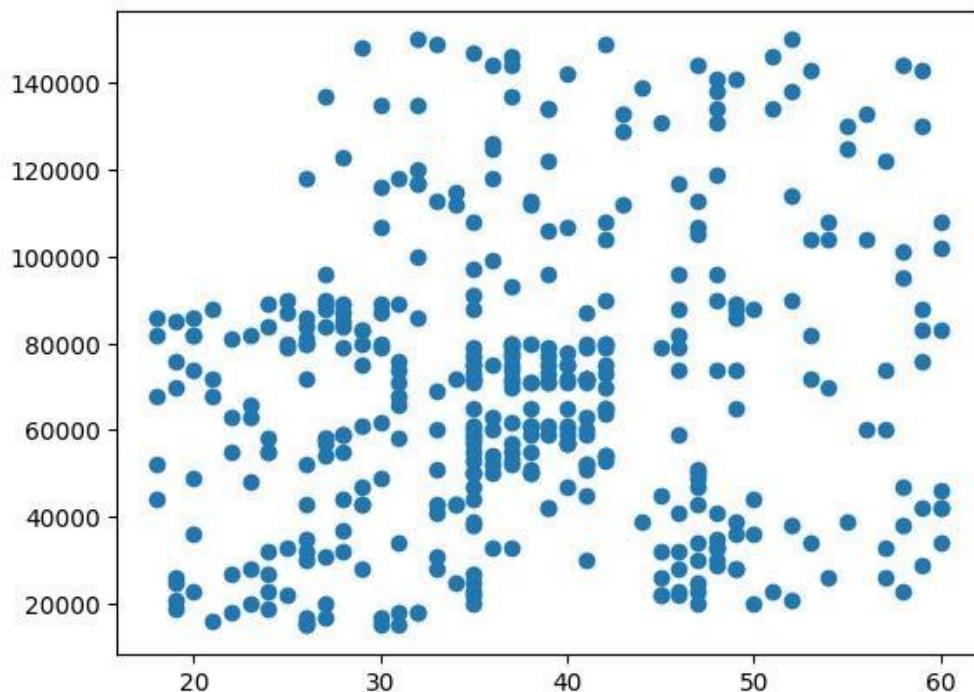


```
# Drop Gender column
df_net.drop(columns=['Gender'], inplace=True)
df_net.head()
```

| | Age | EstimatedSalary | Purchased |
|----------|------------|------------------------|------------------|
| 0 | 19 | 19000 | 0 |
| 1 | 35 | 20000 | 0 |
| 2 | 26 | 43000 | 0 |
| 3 | 27 | 57000 | 0 |
| 4 | 19 | 76000 | 0 |

```
# Relationship between Age and Salary
plt.scatter(df_net['Age'], df_net['EstimatedSalary'])
```

```
<matplotlib.collections.PathCollection at 0x789c2d4e0a90>
```



```
# Split data into dependent/independent variables  
X = df_net.iloc[:, :-1].values  
y = df_net.iloc[:, -1].values
```

```
# Split data into test/train set  
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = True)
```

```
# Scale dataset  
sc = StandardScaler()  
X_train = sc.fit_transform(X_train)  
X_test = sc.transform(X_test)
```

```
# Classifier  
classifier = LogisticRegression(random_state = 0)  
classifier.fit(X_train, y_train)
```

```
LogisticRegression(random_state=0)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```
# Prediction  
y_pred = classifier.predict(X_test)  
print(np.concatenate((y_pred.reshape(len(y_pred), 1), y_test.reshape(len(y_test), 1)), 1))
```

```
accuracy_score(y_test, y_pred)
```

```
0.83
```

```
# Classification report
print(f'Classification Report: \n{classification_report(y_test, y_pred)}')
```

```
Classification Report:
```

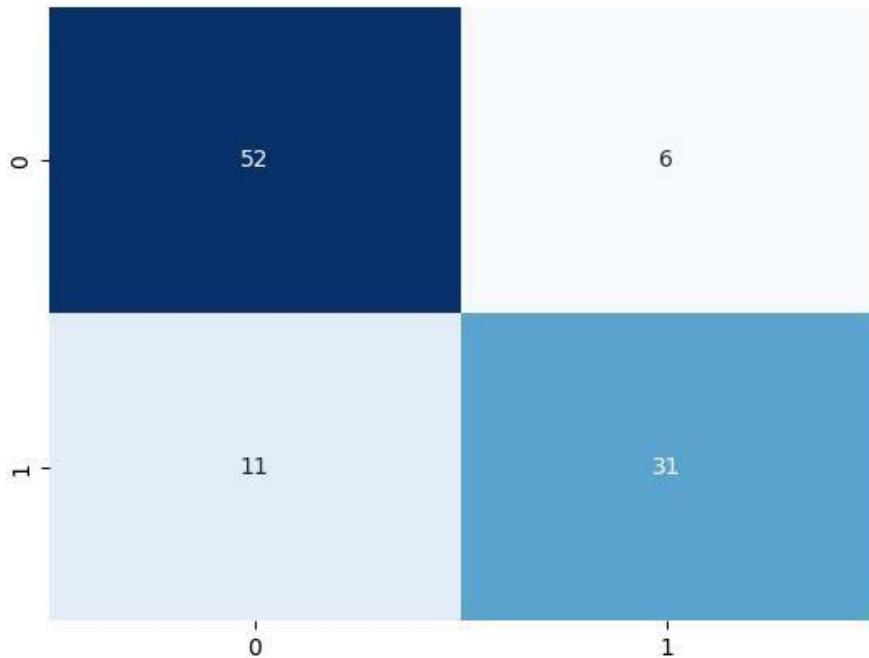
| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.83 | 0.90 | 0.86 | 58 |
| 1 | 0.84 | 0.74 | 0.78 | 42 |
| accuracy | | | 0.83 | 100 |
| macro avg | 0.83 | 0.82 | 0.82 | 100 |
| weighted avg | 0.83 | 0.83 | 0.83 | 100 |

```
print(f"F1 Score : {f1_score(y_test, y_pred)}")
```

```
F1 Score : 0.7848101265822786
```

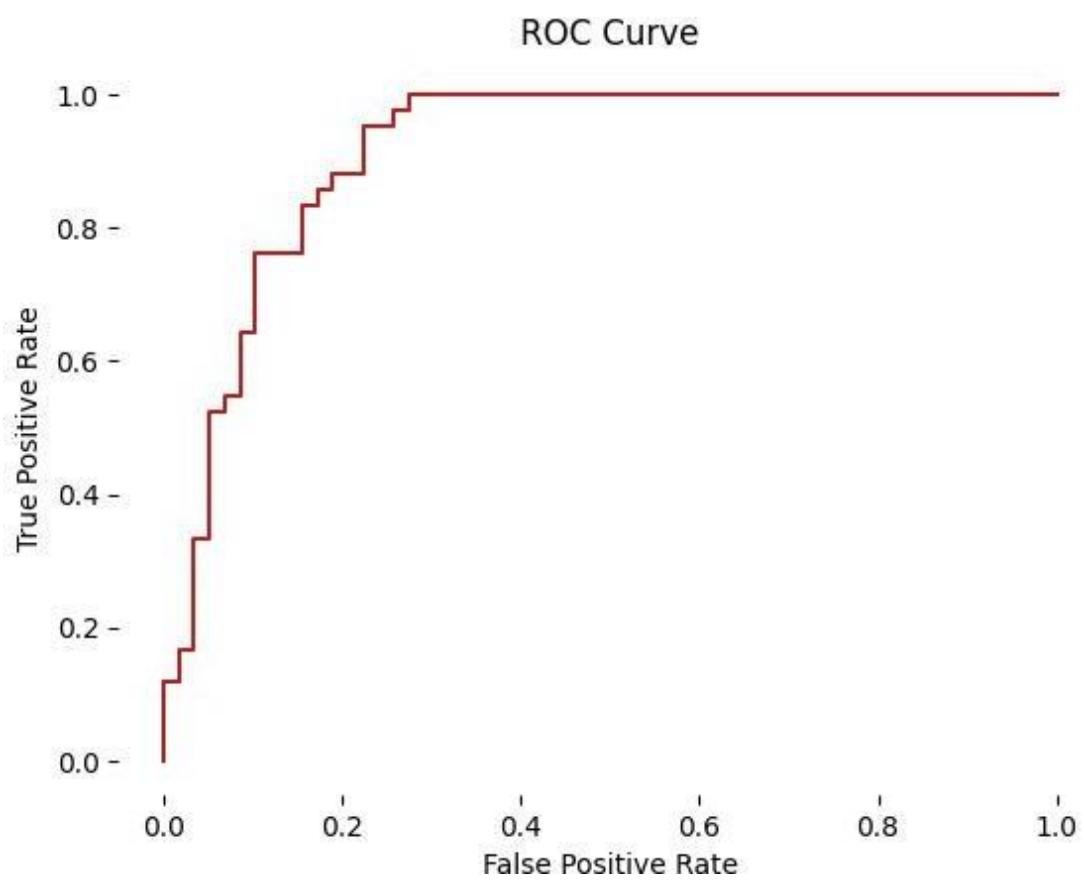
```
# Confusion matrix
cf_matrix = confusion_matrix(y_test, y_pred)
sns.heatmap(cf_matrix, annot=True, fmt='d', cmap='Blues', cbar=False)
```

```
<Axes: >
```



```
# Plot AUC/ROC curve
y_pred_proba = classifier.predict_proba(X_test)[:,1]
fpr, tpr, thresholds = metrics.roc_curve(y_test, y_pred_proba)

plt.plot(fpr, tpr, label='Logistic Regression', color = 'firebrick')
plt.title('ROC Curve')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.box(False)
plt.show()
```



2.6 Experiment - 6

2.6.1 Question:

Build KNN Classification model for a given dataset.

2.6.2 Code with Output:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split

df = pd.read_csv("prostate.csv")
df.head()

scaler = StandardScaler()
scaler.fit(df.drop('Target', axis=1))
scaled_features = scaler.transform(df.drop('Target', axis=1))

df_feat = pd.DataFrame(scaled_features, columns=df.columns[:-1])

X_train, X_test, y_train, y_test = train_test_split(scaled_features, df['Target'], test_size=0.30)

# FIRST A QUICK COMPARISON TO OUR ORIGINAL K = 1
knn = KNeighborsClassifier(n_neighbors=1)
knn.fit(X_train, y_train)
pred = knn.predict(X_test)

print('WITH K = 1')
print('Confusion Matrix')
print(confusion_matrix(y_test, pred))
print('Classification Report')
print(classification_report(y_test, pred))

# NOW WITH K = 10
knn = KNeighborsClassifier(n_neighbors=10)

knn.fit(X_train, y_train)
pred = knn.predict(X_test)

print('WITH K = 10')
print('Confusion Matrix')
print(confusion_matrix(y_test, pred))
print('Classification Report')
print(classification_report(y_test, pred))
```

```
WITH K = 1
Confusion Matrix
[[22  5]
 [ 1  2]]
Classification Report
precision    recall   f1-score   support
0            0.96    0.81      0.88     27
1            0.29    0.67      0.40      3
accuracy                           0.80      30
macro avg       0.62    0.74      0.64     30
weighted avg    0.89    0.80      0.83     30
```

```
WITH K = 10
Confusion Matrix
[[24  3]
 [ 1  2]]
Classification Report
precision    recall   f1-score   support
0            0.96    0.89      0.92     27
1            0.40    0.67      0.50      3
accuracy                           0.87      30
macro avg       0.68    0.78      0.71     30
weighted avg    0.90    0.87      0.88     30
```

2.7 Experiment - 7

2.7.1 Question:

Build Support vector machine model for a given dataset.

2.7.2 Code with Output:

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

```
import warnings
warnings.filterwarnings('ignore')
```

```
data = '/content/pulsar_stars.csv'
df = pd.read_csv(data)
```

```
df.shape
```

```
(17898, 9)
```

```
df.head()
```

| | Mean of the integrated profile | Standard deviation of the integrated profile | Excess kurtosis of the integrated profile | Skewness of the integrated profile | Mean of the DM-SNR curve | Standard deviation of the DM-SNR curve | Excess kurtosis of the DM-SNR curve | Skewness of the DM-SNR curve | target_class |
|---|--------------------------------|--|---|------------------------------------|--------------------------|--|-------------------------------------|------------------------------|--------------|
| 0 | 140.562500 | 55.683782 | -0.234571 | -0.699648 | 3.199833 | 19.110426 | 7.975532 | 74.242225 | 0 |
| 1 | 102.507812 | 58.882430 | 0.465318 | -0.515088 | 1.677258 | 14.860146 | 10.576487 | 127.393580 | 0 |
| 2 | 103.015625 | 39.341649 | 0.323328 | 1.051164 | 3.121237 | 21.744669 | 7.735822 | 63.171909 | 0 |
| 3 | 136.750000 | 57.178449 | -0.068415 | -0.636238 | 3.642977 | 20.959280 | 6.896499 | 53.593661 | 0 |
| 4 | 88.726562 | 40.672225 | 0.600866 | 1.123492 | 1.178930 | 11.468720 | 14.269573 | 252.567306 | 0 |

```
col_names = df.columns
col_names
```

```
Index(['Mean of the integrated profile',
       'Standard deviation of the integrated profile',
       'Excess kurtosis of the integrated profile',
       'Skewness of the integrated profile', 'Mean of the DM-SNR curve',
       'Standard deviation of the DM-SNR curve',
       'Excess kurtosis of the DM-SNR curve', 'Skewness of the DM-SNR curve',
       'target_class'],
      dtype='object')
```

```
df.columns = df.columns.str.strip()
```

```
# view column names again
df.columns
```

```
Index(['Mean of the integrated profile',
       'Standard deviation of the integrated profile',
       'Excess kurtosis of the integrated profile',
       'Skewness of the integrated profile', 'Mean of the DM-SNR curve',
       'Standard deviation of the DM-SNR curve',
       'Excess kurtosis of the DM-SNR curve', 'Skewness of the DM-SNR curve',
       'target_class'],
      dtype='object')
```

```
df.columns = ['IP Mean', 'IP Sd', 'IP Kurtosis', 'IP Skewness', 'DM-SNR Mean', 'DM-SNR Sd', 'DM-SNR Kurtosis', 'DM-SNR Skewness']
```

```
df.columns
```

```
Index(['IP Mean', 'IP Sd', 'IP Kurtosis', 'IP Skewness', 'DM-SNR Mean',  
       'DM-SNR Sd', 'DM-SNR Kurtosis', 'DM-SNR Skewness', 'target_class'],  
      dtype='object')
```

```
df['target_class'].value_counts()
```

```
target_class  
0    16259  
1    1639  
Name: count, dtype: int64
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 17898 entries, 0 to 17897  
Data columns (total 9 columns):  
 #   Column           Non-Null Count  Dtype     
---  --  
 0   IP Mean          17898 non-null   float64  
 1   IP Sd            17898 non-null   float64  
 2   IP Kurtosis       17898 non-null   float64  
 3   IP Skewness        17898 non-null   float64  
 4   DM-SNR Mean       17898 non-null   float64  
 5   DM-SNR Sd          17898 non-null   float64  
 6   DM-SNR Kurtosis    17898 non-null   float64  
 7   DM-SNR Skewness     17898 non-null   float64  
 8   target_class       17898 non-null   int64  
dtypes: float64(8), int64(1)  
memory usage: 1.2 MB
```

```
# check for missing values in variables  
df.isnull().sum()
```

```
IP Mean          0  
IP Sd            0  
IP Kurtosis       0  
IP Skewness        0  
DM-SNR Mean       0  
DM-SNR Sd          0  
DM-SNR Kurtosis    0  
DM-SNR Skewness     0  
target_class       0  
dtype: int64
```

```
# view summary statistics in numerical variables  
round(df.describe(),2)
```

| | IP Mean | IP Sd | IP Kurtosis | IP Skewness | DM-SNR Mean | DM-SNR Sd | DM-SNR Kurtosis | DM-SNR Skewness | target_class |
|-------|----------|----------|-------------|-------------|-------------|-----------|-----------------|-----------------|--------------|
| count | 17898.00 | 17898.00 | 17898.00 | 17898.00 | 17898.00 | 17898.00 | 17898.00 | 17898.00 | 17898.00 |
| mean | 111.08 | 46.55 | 0.48 | 1.77 | 12.61 | 26.33 | 8.30 | 104.86 | 0.09 |
| std | 25.65 | 6.84 | 1.06 | 6.17 | 29.47 | 19.47 | 4.51 | 106.51 | 0.29 |
| min | 5.81 | 24.77 | -1.88 | -1.79 | 0.21 | 7.37 | -3.14 | -1.98 | 0.00 |
| 25% | 100.93 | 42.38 | 0.03 | -0.19 | 1.92 | 14.44 | 5.78 | 34.96 | 0.00 |
| 50% | 115.08 | 46.95 | 0.22 | 0.20 | 2.80 | 18.46 | 8.43 | 83.06 | 0.00 |
| 75% | 127.09 | 51.02 | 0.47 | 0.93 | 5.46 | 28.43 | 10.70 | 139.31 | 0.00 |
| max | 192.62 | 98.78 | 8.07 | 68.10 | 223.39 | 110.64 | 34.54 | 1191.00 | 1.00 |

```
X = df.drop(['target_class'], axis=1)  
y = df['target_class']
```

```
# split X and y into training and testing sets
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)
```

```
X_train.shape, X_test.shape
```

```
((14318, 8), (3580, 8))
```

```
cols = X_train.columns
```

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

```
X_train = pd.DataFrame(X_train, columns=[cols])
```

```
X_test = pd.DataFrame(X_test, columns=[cols])
```

```
X_train.describe()
```

| | IP Mean | IP Sd | IP Kurtosis | IP Skewness | DM-SNR Mean | DM-SNR Sd | DM-SNR Kurtosis | DM-SNR Skewness |
|-------|---------------|---------------|---------------|---------------|---------------|---------------|-----------------|-----------------|
| count | 1.431800e+04 | 1.431800e+04 |
| mean | 1.908113e-16 | -6.550610e-16 | 1.042143e-17 | 3.870815e-17 | -8.734147e-17 | -1.617802e-16 | -1.513588e-17 | 1.122785e-16 |
| std | 1.000035e+00 | 1.000035e+00 |
| min | -4.035499e+00 | -3.181033e+00 | -2.185946e+00 | -5.744051e-01 | -4.239001e-01 | -9.733707e-01 | -2.455649e+00 | -1.003411e+00 |
| 25% | -3.896291e-01 | -6.069473e-01 | -4.256221e-01 | -3.188054e-01 | -3.664918e-01 | -6.125457e-01 | -5.641035e-01 | -6.627590e-01 |
| 50% | 1.587461e-01 | 5.846646e-02 | -2.453172e-01 | -2.578142e-01 | -3.372294e-01 | -4.067482e-01 | 3.170446e-02 | -2.059136e-01 |
| 75% | 6.267059e-01 | 6.501017e-01 | -1.001238e-02 | -1.419621e-01 | -2.463724e-01 | 1.078934e-01 | 5.362759e-01 | 3.256217e-01 |
| max | 3.151882e+00 | 7.621116e+00 | 7.008906e+00 | 1.054430e+01 | 7.025568e+00 | 4.292181e+00 | 5.818557e+00 | 1.024613e+01 |

SVM with default hyperparameters

```
# Default hyperparameter means C=1.0, kernel=rbf and gamma=auto among other parameters
# import SVC classifier
from sklearn.svm import SVC

# import metrics to compute accuracy
from sklearn.metrics import accuracy_score

# instantiate classifier with default hyperparameters
svc=SVC()

# fit classifier to training set
svc.fit(X_train,y_train)

# make predictions on test set
y_pred=svc.predict(X_test)

# compute and print accuracy score
print('Model accuracy score with default hyperparameters: {:.4f}'.format(accuracy_score(y_test, y_pred)))
```

```
Model accuracy score with default hyperparameters: 0.9827
```

```
# SVM with rbf kernel and C=100.0
# instantiate classifier with rbf kernel and C=100
svc=SVC(C=100.0)

# fit classifier to training set
svc.fit(X_train,y_train)

# make predictions on test set
y_pred=svc.predict(X_test)

# compute and print accuracy score
print('Model accuracy score with rbf kernel and C=100.0 : {0:0.4f}'.format(accuracy_score(y_test, y_pred)))

Model accuracy score with rbf kernel and C=100.0 : 0.9832
```

```
# SVM with rbf kernel and C=1000.0
# instantiate classifier with rbf kernel and C=1000
svc=SVC(C=1000.0)

# fit classifier to training set
svc.fit(X_train,y_train)

# make predictions on test set
y_pred=svc.predict(X_test)

# compute and print accuracy score
print('Model accuracy score with rbf kernel and C=1000.0 : {0:0.4f}'.format(accuracy_score(y_test, y_pred)))

Model accuracy score with rbf kernel and C=1000.0 : 0.9816
```

SVM with linear kernel

```
# Run SVM with Linear kernel and C=1.0
# instantiate classifier with Linear kernel and C=1.0
linear_svc=SVC(kernel='linear', C=1.0)

# fit classifier to training set
linear_svc.fit(X_train,y_train)

# make predictions on test set
y_pred_test=linear_svc.predict(X_test)

# compute and print accuracy score
print('Model accuracy score with linear kernel and C=1.0 : {0:0.4f}'.format(accuracy_score(y_test, y_pred_test)))

Model accuracy score with linear kernel and C=1.0 : 0.9830
```

```
# Run SVM with Linear kernel and C=100.0
# instantiate classifier with linear kernel and C=100.0
linear_svc100=SVC(kernel='linear', C=100.0)

# fit classifier to training set
linear_svc100.fit(X_train, y_train)

# make predictions on test set
y_pred=linear_svc100.predict(X_test)

# compute and print accuracy score
print('Model accuracy score with linear kernel and C=100.0 : {0:0.4f}'.format(accuracy_score(y_test, y_pred)))

Model accuracy score with linear kernel and C=100.0 : 0.9832
```

```
# Run SVM with linear kernel and C=1000.0
# instantiate classifier with linear kernel and C=1000.0
linear_svc1000=SVC(kernel='linear', C=1000.0)

# fit classifier to training set
linear_svc1000.fit(X_train, y_train)

# make predictions on test set
y_pred=linear_svc1000.predict(X_test)

# compute and print accuracy score
print('Model accuracy score with linear kernel and C=1000.0 : {0:.4f}'.format(accuracy_score(y_test, y_pred)))

Model accuracy score with linear kernel and C=1000.0 : 0.9832
```

Compare the train-set and test-set accuracy

```
y_pred_train = linear_svc.predict(X_train)
y_pred_train

array([0, 0, 1, ..., 0, 0, 0])

print('Training-set accuracy score: {0:.4f}'.format(accuracy_score(y_train, y_pred_train)))
```

Training-set accuracy score: 0.9783

Check for overfitting and underfitting

```
# print the scores on training and test set
print('Training set score: {:.4f}'.format(linear_svc.score(X_train, y_train)))
print('Test set score: {:.4f}'.format(linear_svc.score(X_test, y_test)))
```

Training set score: 0.9783

Test set score: 0.9830

Classification metrics

```
# Print the Confusion Matrix and slice it into four pieces

from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test, y_pred_test)

print('Confusion matrix\n\n', cm)

print('\nTrue Positives(TP) = ', cm[0,0])

print('\nTrue Negatives(TN) = ', cm[1,1])

print('\nFalse Positives(FP) = ', cm[0,1])

print('\nFalse Negatives(FN) = ', cm[1,0])
```

Confusion matrix

```
[[3289  17]
 [ 44 230]]
```

```
True Positives(TP) = 3289
```

```
True Negatives(TN) = 230
```

```
False Positives(FP) = 17
```

```
False Negatives(FN) = 44
```

```
[1]: from sklearn.metrics import classification_report  
print(classification_report(y_test, y_pred_test))
```

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.99 | 0.99 | 0.99 | 3306 |
| 1 | 0.93 | 0.84 | 0.88 | 274 |
| accuracy | | | 0.98 | 3580 |
| macro avg | 0.96 | 0.92 | 0.94 | 3580 |
| weighted avg | 0.98 | 0.98 | 0.98 | 3580 |

```
[2]: # Classification accuracy  
TP = cm[0,0]  
TN = cm[1,1]  
FP = cm[0,1]  
FN = cm[1,0]  
  
# print classification accuracy  
classification_accuracy = (TP + TN) / float(TP + TN + FP + FN)  
print('Classification accuracy : {0:0.4f}'.format(classification_accuracy))
```

```
Classification accuracy : 0.9830
```

```
[3]: # Classification error  
classification_error = (FP + FN) / float(TP + TN + FP + FN)  
print('Classification error : {0:0.4f}'.format(classification_error))
```

```
Classification error : 0.0170
```

```
# Precision score  
precision = TP / float(TP + FP)  
print('Precision : {0:0.4f}'.format(precision))  
  
Precision : 0.9949
```

```
# Recall  
recall = TP / float(TP + FN)  
print('Recall or Sensitivity : {0:0.4f}'.format(recall))
```

```
Recall or Sensitivity : 0.9868
```

2.8 Experiment - 8

2.8.1 Question:

- a) Implement Random forest ensemble method on a given dataset.
- b) Implement Boosting ensemble method on a given dataset.

2.8.2 Code with Output:

a) Random Forest:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
sns.set_style("whitegrid")
plt.style.use("fivethirtyeight")
```



```
df = pd.read_csv("/content/diabetes.csv")
df.head()
```

| | Pregnancies | Glucose | BloodPressure | SkinThickness | Insulin | BMI | DiabetesPedigreeFunction | Age | Outcome | |
|---|-------------|---------|---------------|---------------|---------|------|--------------------------|-------|---------|---|
| 0 | 6 | 148 | 72 | 35 | 0 | 33.6 | | 0.627 | 50 | 1 |
| 1 | 1 | 85 | 66 | 29 | 0 | 26.6 | | 0.351 | 31 | 0 |
| 2 | 8 | 183 | 64 | 0 | 0 | 23.3 | | 0.672 | 32 | 1 |
| 3 | 1 | 89 | 66 | 23 | 94 | 28.1 | | 0.167 | 21 | 0 |
| 4 | 0 | 137 | 40 | 35 | 168 | 43.1 | | 2.288 | 33 | 1 |

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column           Non-Null Count  Dtype  
 --- 
 0   Pregnancies      768 non-null    int64  
 1   Glucose          768 non-null    int64  
 2   BloodPressure    768 non-null    int64  
 3   SkinThickness    768 non-null    int64  
 4   Insulin          768 non-null    int64  
 5   BMI              768 non-null    float64 
 6   DiabetesPedigreeFunction 768 non-null    float64 
 7   Age              768 non-null    int64  
 8   Outcome          768 non-null    int64  
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

```
pd.set_option('display.float_format', '{:.2f}'.format)
df.describe()
```

| | Pregnancies | Glucose | BloodPressure | SkinThickness | Insulin | BMI | DiabetesPedigreeFunction | Age | Outcome | |
|-------|-------------|---------|---------------|---------------|---------|--------|--------------------------|--------|---------|--------|
| count | 768.00 | 768.00 | 768.00 | 768.00 | 768.00 | 768.00 | | 768.00 | 768.00 | 768.00 |
| mean | 3.85 | 120.89 | 69.11 | 20.54 | 79.80 | 31.99 | | 0.47 | 33.24 | 0.35 |
| std | 3.37 | 31.97 | 19.36 | 15.95 | 115.24 | 7.88 | | 0.33 | 11.76 | 0.48 |
| min | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | | 0.08 | 21.00 | 0.00 |
| 25% | 1.00 | 99.00 | 62.00 | 0.00 | 0.00 | 27.30 | | 0.24 | 24.00 | 0.00 |
| 50% | 3.00 | 117.00 | 72.00 | 23.00 | 30.50 | 32.00 | | 0.37 | 29.00 | 0.00 |
| 75% | 6.00 | 140.25 | 80.00 | 32.00 | 127.25 | 36.60 | | 0.63 | 41.00 | 1.00 |
| max | 17.00 | 199.00 | 122.00 | 99.00 | 846.00 | 67.10 | | 2.42 | 81.00 | 1.00 |

```

categorical_val = []
continous_val = []
for column in df.columns:
#     print('=====')
#     print(f'{column} : {df[column].unique()}')
    if len(df[column].unique()) <= 10:
        categorical_val.append(column)
    else:
        continous_val.append(column)

# How many missing zeros are missing in each feature
feature_columns = [
    'Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness',
    'Insulin', 'BMI', 'DiabetesPedigreeFunction', 'Age'
]

for column in feature_columns:
    print("====")
    print(f'{column} ==> Missing zeros : {len(df.loc[df[column] == 0])}')
    print("====")

Pregnancies ==> Missing zeros : 111
=====
Glucose ==> Missing zeros : 5
=====
BloodPressure ==> Missing zeros : 35
=====
SkinThickness ==> Missing zeros : 227
=====
Insulin ==> Missing zeros : 374
=====
BMI ==> Missing zeros : 11
=====
DiabetesPedigreeFunction ==> Missing zeros : 0
=====
Age ==> Missing zeros : 0

from sklearn.impute import SimpleImputer

fill_values = SimpleImputer(missing_values=0, strategy="mean", copy=False)
df[feature_columns] = fill_values.fit_transform(df[feature_columns])

for column in feature_columns:
    print("====")
    print(f'{column} ==> Missing zeros : {len(df.loc[df[column] == 0])}')
    print("====")

Pregnancies ==> Missing zeros : 0
=====
Glucose ==> Missing zeros : 0
=====
BloodPressure ==> Missing zeros : 0
=====
SkinThickness ==> Missing zeros : 0
=====
Insulin ==> Missing zeros : 0
=====
BMI ==> Missing zeros : 0
=====
DiabetesPedigreeFunction ==> Missing zeros : 0
=====
Age ==> Missing zeros : 0

```

```

from sklearn.model_selection import train_test_split

X = df[feature_columns]
y = df.Outcome

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

from sklearn.metrics import confusion_matrix, accuracy_score, classification_report

def evaluate(model, X_train, X_test, y_train, y_test):
    y_test_pred = model.predict(X_test)
    y_train_pred = model.predict(X_train)

    print("TRAINING RESULTS: \n====")
    clf_report = pd.DataFrame(classification_report(y_train, y_train_pred, output_dict=True))
    print(f"CONFUSION MATRIX:\n{confusion_matrix(y_train, y_train_pred)}")
    print(f"ACCURACY SCORE:\n{accuracy_score(y_train, y_train_pred):.4f}")
    print(f"CLASSIFICATION REPORT:\n{clf_report}")

    print("TESTING RESULTS: \n====")
    clf_report = pd.DataFrame(classification_report(y_test, y_test_pred, output_dict=True))
    print(f"CONFUSION MATRIX:\n{confusion_matrix(y_test, y_test_pred)}")
    print(f"ACCURACY SCORE:\n{accuracy_score(y_test, y_test_pred):.4f}")
    print(f"CLASSIFICATION REPORT:\n{clf_report}")

```

```

from sklearn.ensemble import RandomForestClassifier

rf_clf = RandomForestClassifier(random_state=42, n_estimators=1000)
rf_clf.fit(X_train, y_train)
evaluate(rf_clf, X_train, X_test, y_train, y_test)

```

TRAINIG RESULTS:

=====

CONFUSION MATRIX:

| |
|-----------|
| [[349 0] |
| [0 188]] |

ACCURACY SCORE:

1.0000

CLASSIFICATION REPORT:

| | 0 | 1 | accuracy | macro avg | weighted avg |
|-----------|--------|--------|----------|-----------|--------------|
| precision | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| recall | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| f1-score | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| support | 349.00 | 188.00 | 1.00 | 537.00 | 537.00 |

TESTING RESULTS:

=====

CONFUSION MATRIX:

| |
|------------|
| [[123 28] |
| [29 51]] |

ACCURACY SCORE:

0.7532

CLASSIFICATION REPORT:

| | 0 | 1 | accuracy | macro avg | weighted avg |
|-----------|--------|-------|----------|-----------|--------------|
| precision | 0.81 | 0.65 | 0.75 | 0.73 | 0.75 |
| recall | 0.81 | 0.64 | 0.75 | 0.73 | 0.75 |
| f1-score | 0.81 | 0.64 | 0.75 | 0.73 | 0.75 |
| support | 151.00 | 80.00 | 0.75 | 231.00 | 231.00 |

b) Boosting Ensemble:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
sns.set_style("whitegrid")
plt.style.use("fivethirtyeight")
```

```
df = pd.read_csv("/content/diabetes.csv")
df.head()
```

| | Pregnancies | Glucose | BloodPressure | SkinThickness | Insulin | BMI | DiabetesPedigreeFunction | Age | Outcome | |
|---|-------------|---------|---------------|---------------|---------|------|--------------------------|-------|---------|---|
| 0 | 6 | 148 | 72 | 35 | 0 | 33.6 | | 0.627 | 50 | 1 |
| 1 | 1 | 85 | 66 | 29 | 0 | 26.6 | | 0.351 | 31 | 0 |
| 2 | 8 | 183 | 64 | 0 | 0 | 23.3 | | 0.672 | 32 | 1 |
| 3 | 1 | 89 | 66 | 23 | 94 | 28.1 | | 0.167 | 21 | 0 |
| 4 | 0 | 137 | 40 | 35 | 168 | 43.1 | | 2.288 | 33 | 1 |

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column            Non-Null Count  Dtype  
--- 
 0   Pregnancies      768 non-null    int64  
 1   Glucose          768 non-null    int64  
 2   BloodPressure    768 non-null    int64  
 3   SkinThickness    768 non-null    int64  
 4   Insulin          768 non-null    int64  
 5   BMI              768 non-null    float64 
 6   DiabetesPedigreeFunction 768 non-null    float64 
 7   Age              768 non-null    int64  
 8   Outcome          768 non-null    int64  
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

```
pd.set_option('display.float_format', '{:.2f}'.format)
df.describe()
```

| | Pregnancies | Glucose | BloodPressure | SkinThickness | Insulin | BMI | DiabetesPedigreeFunction | Age | Outcome |
|-------|-------------|---------|---------------|---------------|---------|--------|--------------------------|--------|---------|
| count | 768.00 | 768.00 | 768.00 | 768.00 | 768.00 | 768.00 | 768.00 | 768.00 | 768.00 |
| mean | 3.85 | 120.89 | 69.11 | 20.54 | 79.80 | 31.99 | | 33.24 | 0.35 |
| std | 3.37 | 31.97 | 19.36 | 15.95 | 115.24 | 7.88 | | 11.76 | 0.48 |
| min | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | | 21.00 | 0.00 |
| 25% | 1.00 | 99.00 | 62.00 | 0.00 | 0.00 | 27.30 | | 24.00 | 0.00 |
| 50% | 3.00 | 117.00 | 72.00 | 23.00 | 30.50 | 32.00 | | 29.00 | 0.00 |
| 75% | 6.00 | 140.25 | 80.00 | 32.00 | 127.25 | 36.60 | | 41.00 | 1.00 |
| max | 17.00 | 199.00 | 122.00 | 99.00 | 846.00 | 67.10 | | 81.00 | 1.00 |

```

categorical_val = []
continous_val = []
for column in df.columns:
#     print('=====')
#     print(f'{column} : {df[column].unique()}')
    if len(df[column].unique()) <= 10:
        categorical_val.append(column)
    else:
        continous_val.append(column)

# How many missing zeros are mising in each feature
feature_columns = [
    'Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness',
    'Insulin', 'BMI', 'DiabetesPedigreeFunction', 'Age'
]

for column in feature_columns:
    print("====")
    print(f'{column} ==> Missing zeros : {len(df.loc[df[column] == 0])}')

```

```

=====
Pregnancies ==> Missing zeros : 111
=====
Glucose ==> Missing zeros : 5
=====
BloodPressure ==> Missing zeros : 35
=====
SkinThickness ==> Missing zeros : 227
=====
Insulin ==> Missing zeros : 374
=====
BMI ==> Missing zeros : 11
=====
DiabetesPedigreeFunction ==> Missing zeros : 0
=====
Age ==> Missing zeros : 0

```

```

from sklearn.impute import SimpleImputer

fill_values = SimpleImputer(missing_values=0, strategy="mean", copy=False)
df[feature_columns] = fill_values.fit_transform(df[feature_columns])

for column in feature_columns:
    print("====")
    print(f'{column} ==> Missing zeros : {len(df.loc[df[column] == 0])}')

=====
Pregnancies ==> Missing zeros : 0
=====
Glucose ==> Missing zeros : 0
=====
BloodPressure ==> Missing zeros : 0
=====
SkinThickness ==> Missing zeros : 0
=====
Insulin ==> Missing zeros : 0
=====
BMI ==> Missing zeros : 0
=====
DiabetesPedigreeFunction ==> Missing zeros : 0
=====
Age ==> Missing zeros : 0

```

```

from sklearn.model_selection import train_test_split

X = df[feature_columns]
y = df['Outcome']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

from sklearn.metrics import confusion_matrix, accuracy_score, classification_report

def evaluate(model, X_train, X_test, y_train, y_test):
    y_test_pred = model.predict(X_test)
    y_train_pred = model.predict(X_train)

    print("TRAINING RESULTS: \n====")
    clf_report = pd.DataFrame(classification_report(y_train, y_train_pred, output_dict=True))
    print(f"CONFUSION MATRIX:\n{confusion_matrix(y_train, y_train_pred)}")
    print(f"ACCURACY SCORE:\n{accuracy_score(y_train, y_train_pred):.4f}")
    print(f"CLASSIFICATION REPORT:\n{clf_report}")

    print("TESTING RESULTS: \n====")
    clf_report = pd.DataFrame(classification_report(y_test, y_test_pred, output_dict=True))
    print(f"CONFUSION MATRIX:\n{confusion_matrix(y_test, y_test_pred)}")
    print(f"ACCURACY SCORE:\n{accuracy_score(y_test, y_test_pred):.4f}")
    print(f"CLASSIFICATION REPORT:\n{clf_report}")

from sklearn.ensemble import AdaBoostClassifier

ada_boost_clf = AdaBoostClassifier(n_estimators=30)
ada_boost_clf.fit(X_train, y_train)
evaluate(ada_boost_clf, X_train, X_test, y_train, y_test)

```

TRAINING RESULTS:

=====

CONFUSION MATRIX:

| |
|------------|
| [[310 39] |
| [51 137]] |

ACCURACY SCORE:

0.8324

CLASSIFICATION REPORT:

| | 0 | 1 | accuracy | macro avg | weighted avg |
|-----------|--------|--------|----------|-----------|--------------|
| precision | 0.86 | 0.78 | 0.83 | 0.82 | 0.83 |
| recall | 0.89 | 0.73 | 0.83 | 0.81 | 0.83 |
| f1-score | 0.87 | 0.75 | 0.83 | 0.81 | 0.83 |
| support | 349.00 | 188.00 | 0.83 | 537.00 | 537.00 |

TESTING RESULTS:

=====

CONFUSION MATRIX:

| |
|-----------|
| [[123 28] |
| [27 53]] |

ACCURACY SCORE:

0.7619

CLASSIFICATION REPORT:

| | 0 | 1 | accuracy | macro avg | weighted avg |
|-----------|--------|-------|----------|-----------|--------------|
| precision | 0.82 | 0.65 | 0.76 | 0.74 | 0.76 |
| recall | 0.81 | 0.66 | 0.76 | 0.74 | 0.76 |
| f1-score | 0.82 | 0.66 | 0.76 | 0.74 | 0.76 |
| support | 151.00 | 80.00 | 0.76 | 231.00 | 231.00 |

2.9 Experiment - 9

2.9.1 Question:

Build k-Means algorithm to cluster a set of data stored in a .CSV file.

2.9.2 Code with Output:

```
import pandas as pd
```

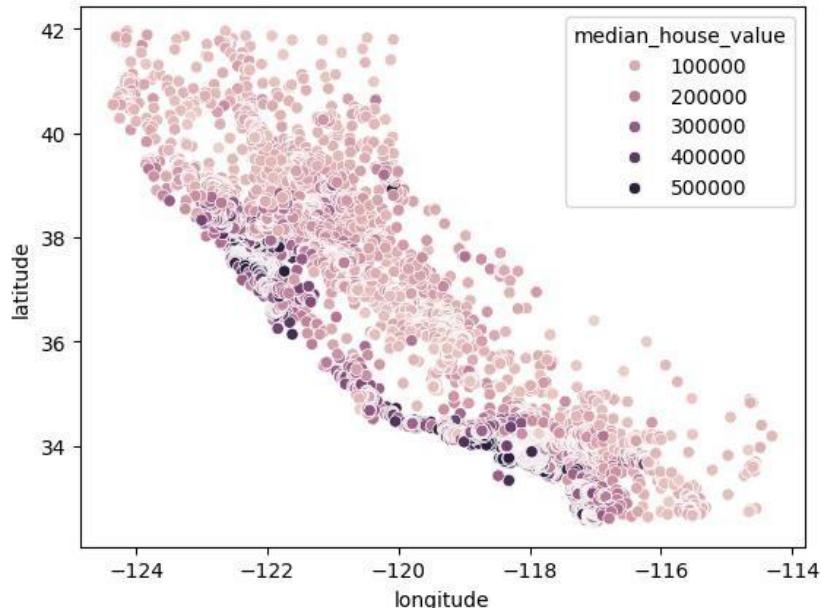
```
home_data = pd.read_csv('/content/housing.csv', usecols = ['longitude', 'latitude', 'median_house_value'])  
home_data.head()
```

| | longitude | latitude | median_house_value |
|---|-----------|----------|--------------------|
| 0 | -122.23 | 37.88 | 452600.0 |
| 1 | -122.22 | 37.86 | 358500.0 |
| 2 | -122.24 | 37.85 | 352100.0 |
| 3 | -122.25 | 37.85 | 341300.0 |
| 4 | -122.25 | 37.85 | 342200.0 |

```
import seaborn as sns
```

```
sns.scatterplot(data = home_data, x = 'longitude', y = 'latitude', hue = 'median_house_value')
```

```
<Axes: xlabel='longitude', ylabel='latitude'>
```



```
from sklearn.model_selection import train_test_split
```

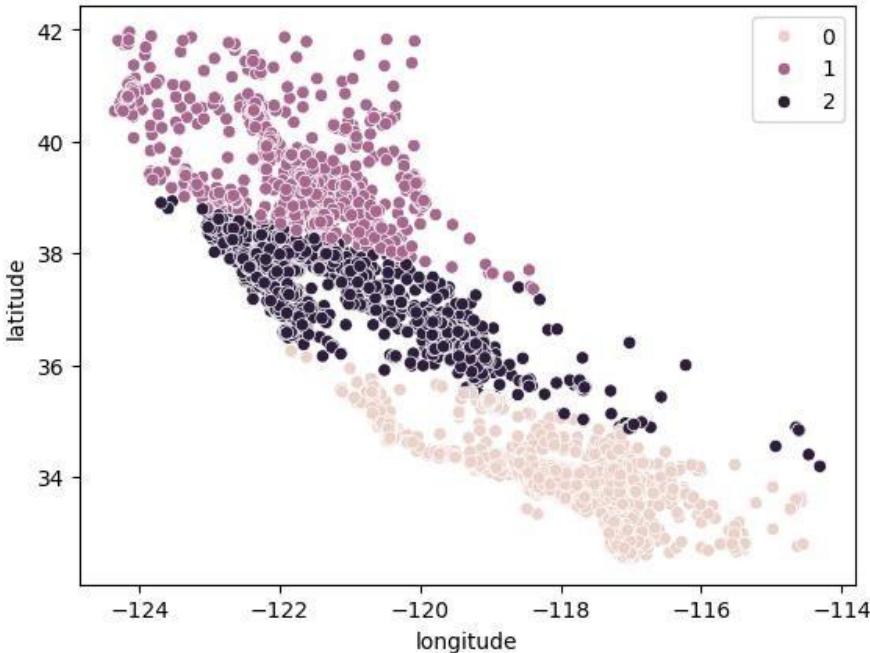
```
X_train, X_test, y_train, y_test = train_test_split(home_data[['latitude', 'longitude']], home_data[['median_house_value']])
```

```
from sklearn import preprocessing
```

```
X_train_norm = preprocessing.normalize(X_train)  
X_test_norm = preprocessing.normalize(X_test)
```

```
from sklearn.cluster import KMeans  
  
kmeans = KMeans(n_clusters = 3, random_state = 0, n_init='auto')  
kmeans.fit(X_train_norm)  
  
KMeans(n_clusters=3, n_init='auto', random_state=0)  
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.  
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.
```

```
sns.scatterplot(data = X_train, x = 'longitude', y = 'latitude', hue = kmeans.labels_)
```



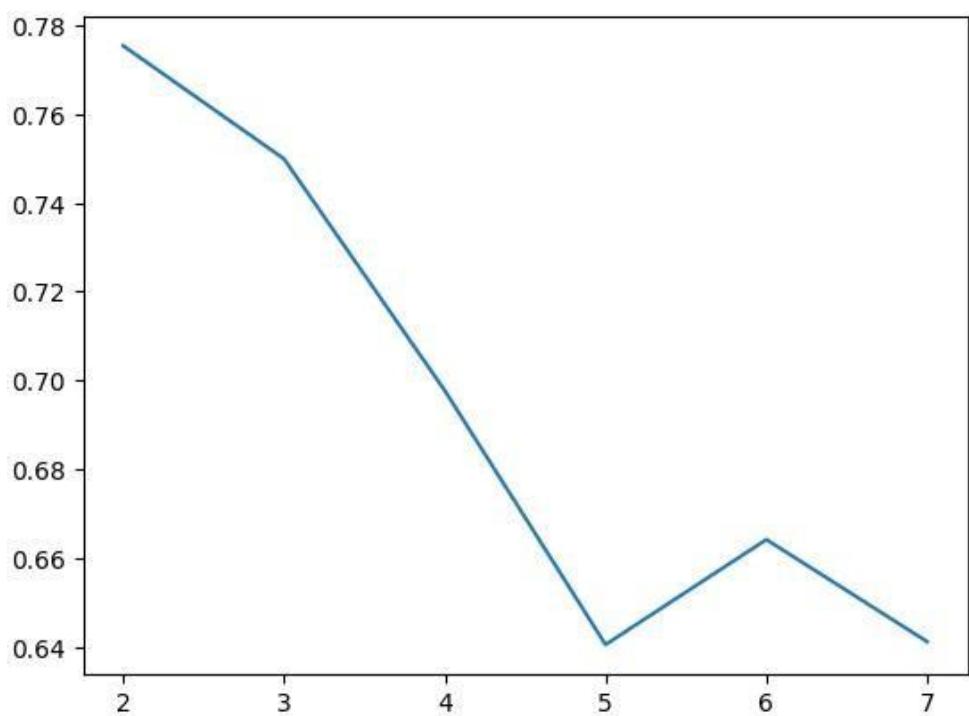
```
from sklearn.metrics import silhouette_score  
silhouette_score(X_train_norm, kmeans.labels_, metric='euclidean')
```

```
0.7499371920703546
```

```
K = range(2, 8)  
fits = []  
score = []  
  
for k in K:  
    # train the model for current value of k on training data  
    model = KMeans(n_clusters = k, random_state = 0, n_init='auto').fit(X_train_norm)  
  
    # append the model to fits  
    fits.append(model)  
  
    # Append the silhouette score to scores  
    score.append(silhouette_score(X_train_norm, model.labels_, metric='euclidean'))
```

```
sns.lineplot(x = K, y = score)
```

<Axes: >



2.10 Experiment - 10

2.10.1 Question:

Implement Dimensionality reduction using Principle Component Analysis (PCA) method.

2.10.2 Code with Output:

```
: from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
import pandas as pd
import seaborn as sns
from sklearn import datasets

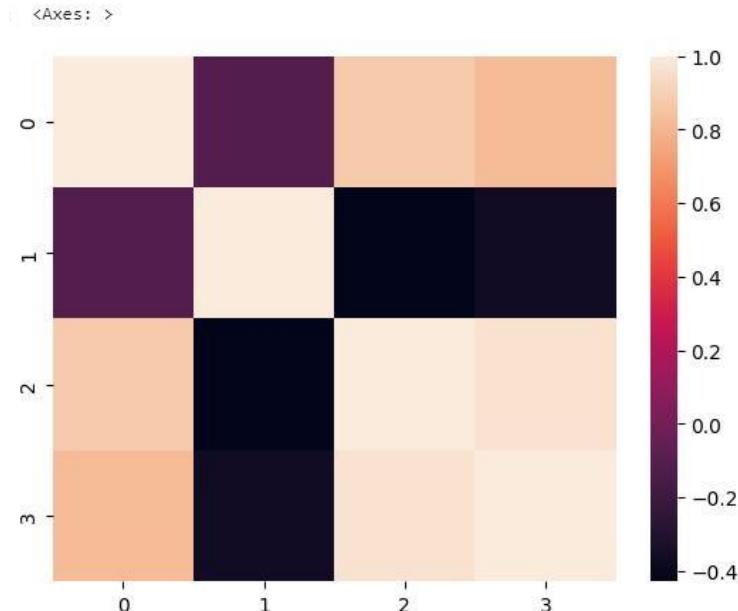
: iris = datasets.load_iris()
df = pd.DataFrame(iris['data'], columns= iris['feature_names'])
df.head()

:      sepal length (cm)  sepal width (cm)  petal length (cm)  petal width (cm)
: 0           5.1          3.5            1.4            0.2
: 1           4.9          3.0            1.4            0.2
: 2           4.7          3.2            1.3            0.2
: 3           4.6          3.1            1.5            0.2
: 4           5.0          3.6            1.4            0.2

: scaler = StandardScaler()
scaled_data = pd.DataFrame(scaler.fit_transform(df))
scaled_data.head()

:      0         1         2         3
: 0 -0.900681  1.019004 -1.340227 -1.315444
: 1 -1.143017 -0.131979 -1.340227 -1.315444
: 2 -1.385353  0.328414 -1.397064 -1.315444
: 3 -1.506521  0.098217 -1.283389 -1.315444
: 4 -1.021849  1.249201 -1.340227 -1.315444

: sns.heatmap(scaled_data.corr())
```

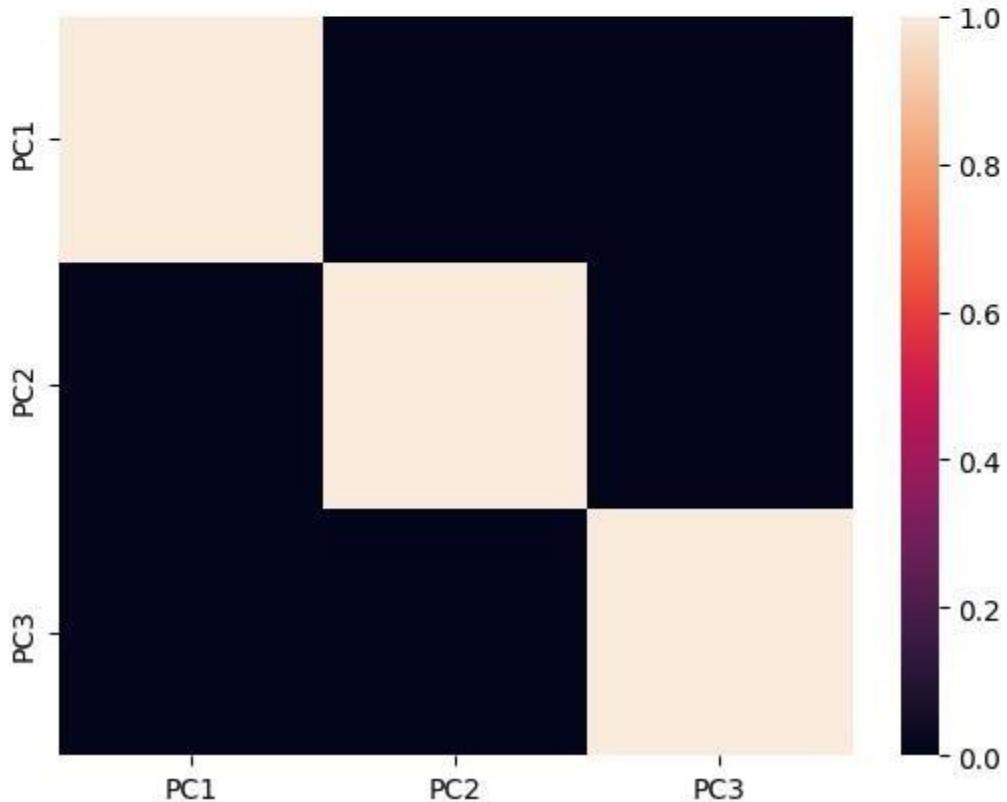


```
data_pca = pd.DataFrame(data_pca, columns=['PC1', 'PC2', 'PC3'])
data_pca.head()
```

| | PC1 | PC2 | PC3 |
|---|-----------|-----------|-----------|
| 0 | -2.264703 | 0.480027 | -0.127706 |
| 1 | -2.080961 | -0.674134 | -0.234609 |
| 2 | -2.364229 | -0.341908 | 0.044201 |
| 3 | -2.299384 | -0.597395 | 0.091290 |
| 4 | -2.389842 | 0.646835 | 0.015738 |

```
sns.heatmap(data_pca.corr())
```

```
<Axes: >
```



2.11 Experiment - 11

2.11.1 Question:

Build Artificial Neural Network model with back propagation on a given dataset.

2.11.2 Code with Output:

```
import numpy as np

# Define input (X) and output (Y) arrays
X = np.array(([2, 9], [1, 5], [3, 6]), dtype=float) # two inputs [sleep, study]
Y = np.array(([92], [86], [89]), dtype=float) # one output (Expected & in Exams)

# Normalize the data
X = X / np.amax(X, axis=0) # maximum of X array longitudinally
Y = Y / 100 # max test score is 100

# Set parameters
epoch = 5000
lr = 0.1
inputlayer_neurons = X.shape[1] # number of features in data set
hiddenlayer_neurons = 3 # number of hidden layer neurons
output_neurons = 1 # number of neurons at output layer

# Weight and bias initialization
wh = np.random.uniform(size=(inputlayer_neurons, hiddenlayer_neurons)) # weights for the input layer to hidden layer
bh = np.random.uniform(size=(1, hiddenlayer_neurons)) # bias for the hidden layer
wout = np.random.uniform(size=(hiddenlayer_neurons, output_neurons)) # weights for the hidden layer to output layer
bout = np.random.uniform(size=(1, output_neurons)) # bias for the output layer
```

```
# Activation function
def sigmoid(x):
    return 1 / (1 + np.exp(-x))

# Derivative of sigmoid function
def derivatives_sigmoid(x):
    return x * (1 - x)

# Training algorithm
for i in range(epoch):
    # Forward Propagation
    hinp1 = np.dot(X, wh)
    hinp = hinp1 + bh
    hlayer_act = sigmoid(hinp)
    outinp1 = np.dot(hlayer_act, wout)
    outinp = outinp1 + bout
    output = sigmoid(outinp)

    # Backpropagation
    EO = Y - output # error at output
    outgrad = derivatives_sigmoid(output)
    d_output = EO * outgrad
    EH = d_output.dot(wout.T) # error at hidden layer
    hiddengrad = derivatives_sigmoid(hlayer_act) # derivative of sigmoid function
    d_hiddenlayer = EH * hiddengrad
```

```
# Updating weights and biases
wout += hlayer_act.T.dot(d_output) * lr
bout += np.sum(d_output, axis=0, keepdims=True) * lr
wh += X.T.dot(d_hiddenlayer) * lr
bh += np.sum(d_hiddenlayer, axis=0, keepdims=True) * lr

# Output after training
print("Input: \n" + str(X))
print("Actual Output: \n" + str(Y))
print("Predicted Output: \n", output)
```

Input:

```
[[0.66666667 1.          ]
 [0.33333333 0.55555556]
 [1.          0.66666667]]
```

Actual Output:

```
[[0.92]
 [0.86]
 [0.89]]
```

Predicted Output:

```
[[0.89526104]
 [0.87867405]
 [0.89490822]]
```