ex - 1a

October 31, 2025

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
import numpy as np

sns.set(style="whitegrid")

def load_job_data(csv_path=None):
    if csv_path:
        df = pd.read_csv(csv_path, parse_dates=['date_posted'])
        return df
    rng = pd.date_range(start='2015-01-01', end='2024-12-31', freq='D')
    years = rng.year
    base_by_year = {y: 50 + (y - 2015) * 60 for y in range(2015, 2025)}
    counts = [np.random.poisson(lam=max(1, base_by_year[y]/30)) for y in years]
    df = pd.DataFrame({'date_posted': rng, 'postings': counts})
    return df

def aggregate_by_year(df):
    df['date_posted'] = pd.to_datetime(df['date_posted'])
    df['year'] = df['date_posted'].dt.year
    if 'postings' in df.columns:
        yearly = df.groupby('year')['postings'].sum().
↪reset_index(name='num_postings')
    else:
        yearly = df.groupby('year').size().reset_index(name='num_postings')
    return yearly

def plot_trend(yearly_df, title="Data Science Job Postings by Year"):
    plt.figure(figsize=(10,5))
    ax = sns.lineplot(data=yearly_df, x='year', y='num_postings', marker='o')
    ax.set_title(title)
    ax.set_xlabel("Year")
    ax.set_ylabel("Number of Job Postings")
    plt.xticks(yearly_df['year'])
    plt.tight_layout()
```

```
    plt.show()

if _name_ == "_main_":
    df = load_job_data(csv_path=None)
    yearly = aggregate_by_year(df)
    print(yearly)
    plot_trend(yearly)
```

ex - 1b

October 31, 2025

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import re

sns.set(style="whitegrid")

ROLE_KEYWORDS = {
    'Data Scientist': ['data scientist', r'\bds\b', 'machine learning␣
↪scientist', 'ml scientist'],
    'Data Engineer': ['data engineer', 'etl engineer', 'pipeline engineer'],
    'Data Analyst': ['data analyst', 'business analyst', 'analyst', 'bi␣
↪analyst'],
    'Machine Learning Engineer': ['ml engineer', 'machine learning engineer',␣
↪'mle'],
    'BI Developer': ['bi developer', 'business intelligence', 'power bi',␣
↪'tableau developer'],
    'Research Scientist': ['research scientist', 'researcher'],
    'Other': []
}

def map_title_to_role(title):
    t = title.lower()
    for role, keys in ROLE_KEYWORDS.items():
        for key in keys:
            if re.search(r'\b' + re.escape(key) + r'\b', t) or key in t:
                return role
    return 'Other'

def categorize_roles(df, title_col='job_title'):
    df = df.copy()
    df[title_col] = df[title_col].astype(str)
    df['role'] = df[title_col].apply(map_title_to_role)
    return df

def plot_role_distribution(df, title_col='role'):
    counts = df[title_col].value_counts().reset_index()
```

```
    counts.columns = ['role', 'count']
    plt.figure(figsize=(10,5))
    sns.barplot(data=counts, x='role', y='count')
    plt.xticks(rotation=45, ha='right')
    plt.title("Distribution of Data Science Roles (bar)")
    plt.tight_layout()
    plt.show()

    plt.figure(figsize=(7,7))
    plt.pie(counts['count'], labels=counts['role'], autopct='%1.1f%%', startangle=140)
    plt.title("Distribution of Data Science Roles (pie)")
    plt.tight_layout()
    plt.show()

if _name_ == "_main_":
    sample_titles = [
        "Senior Data Scientist", "Junior Data Analyst", "Machine Learning Engineer",
        "Data Engineer", "BI Developer (Power BI)", "Business Analyst - Data",
        "Research Scientist, ML", "Data Scientist / ML", "Analyst", "ETL Engineer",
        "Data Scientist", "Data Analyst", "MLOps Engineer", "Data Engineer - Big Data"
    ]
    df = pd.DataFrame({'job_title': sample_titles})
    df = categorize_roles(df)
    print(df[['job_title','role']])
    plot_role_distribution(df, title_col='role')
```

ex - 1c

October 31, 2025

[ ]:
```python
import pandas as pd
import json
from xml.etree import ElementTree as ET

def structured_example():
    data = {
        'id': [1,2,3],
        'name': ['Alice','Bob','Carol'],
        'age': [29, 34, 23]
    }
    df = pd.DataFrame(data)
    print("Structured data (pandas DataFrame):")
    print(df)
    df.to_csv('structured_example.csv', index=False)
    print("Saved to structured_example.csv")

def unstructured_example():
    docs = [
        "Today I attended a data science meetup and learned about transformers.
 ↪",
        "Error: Connection refused at 2025-10-31 10:12:00 - service X failed.",
        "Image: binary data (not text) - e.g. photos, audio transcripts"
    ]
    print("\nUnstructured data (plain text documents):")
    for i, doc in enumerate(docs,1):
        print(f"Doc {i}: {doc}")
    with open('unstructured_example.txt','w',encoding='utf-8') as f:
        for d in docs:
            f.write(d + "\n")

def semi_structured_example():
    items = [
        {"id":1, "name":"Alice", "skills":["python","sql"]},
        {"id":2, "name":"Bob", "contact":{"email":"bob@example.com","phone":
 ↪"12345"}},
        {"id":3, "name":"Carol", "notes":"Prefers remote"}
    ]
```

```python
    print("\nSemi-structured data (JSON-like):")
    print(json.dumps(items, indent=2))
    with open('semi_structured_example.json','w',encoding='utf-8') as f:
        json.dump(items, f, indent=2)

def xml_example():
    root = ET.Element('employees')
    e1 = ET.SubElement(root,'employee', attrib={'id':'1'})
    ET.SubElement(e1, 'name').text = 'Alice'
    ET.SubElement(e1, 'role').text = 'Data Scientist'
    tree = ET.ElementTree(root)
    tree.write('semi_structured_example.xml', encoding='utf-8', xml_declaration=True)
    print("\nWrote semi_structured_example.xml (XML is semi-structured)")

if _name_ == "_main_":
    structured_example()
    unstructured_example()
    semi_structured_example()
    xml_example()

    print("\nCharacteristics summary:")
    print("- Structured: rigid schema, easy to query (e.g., SQL tables, CSV).")
    print("- Unstructured: no predefined schema (text, images), needs parsing/NLP/vision.")
    print("- Semi-structured: tags/keys but not rigid (JSON, XML, logs with key:value).")
```

ex - 1d

October 31, 2025

[ ]:
```
from cryptography.fernet import Fernet

def generate_key():
    return Fernet.generate_key()

def encrypt_message(key: bytes, plaintext: str) -> bytes:
    f = Fernet(key)
    token = f.encrypt(plaintext.encode('utf-8'))
    return token

def decrypt_message(key: bytes, token: bytes) -> str:
    f = Fernet(key)
    plaintext = f.decrypt(token)
    return plaintext.decode('utf-8')

if _name_ == "_main_":
    key = generate_key()
    print("Generated key (store securely):", key.decode())

    secret = "MyVerySensitivePassword123!"
    token = encrypt_message(key, secret)
    print("\nEncrypted token (bytes):", token)

    recovered = decrypt_message(key, token)
    print("\nDecrypted plaintext:", recovered)

    with open('secret.key','wb') as f:
        f.write(key)
    print("\nKey saved to secret.key (handle securely)")
```

ex - 2

October 31, 2025

[ ]:

```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
file_path='C:\sales_data.csv'
df = pd.read_csv(file_path)
print(df.head())
print(df.isnull().sum())
df['Sales'].fillna(df['Sales'].mean(), inplace=True)
df.dropna(subset=['Product', 'Quantity', 'Region'], inplace=True)
print(df.describe())
product_summary = df.groupby('Product').agg({
'Sales': 'sum',
'Quantity': 'sum'
}).reset_index()
print(product_summary)
plt.figure(figsize=(10, 6))
plt.bar(product_summary['Product'], product_summary['Sales'])
plt.xlabel('Product')
plt.ylabel('Total Sales')
plt.title('Total Sales by Product')
plt.show()
df['Date'] = pd.to_datetime(df['Date'])
sales_over_time = df.groupby('Date').agg({'Sales': 'sum'}).reset_index()
plt.figure(figsize=(10, 6))
plt.plot(sales_over_time['Date'],sales_over_time['Sales'])
plt.xlabel('Date')
plt.ylabel('Total Sales')
plt.title('SalesOver Time')
plt.show()
pivot_table = df.pivot_table(values='Sales', index='Region', columns='Product',
aggfunc=np.sum, fill_value=0)
print(pivot_table)
correlation_matrix = df.corr()
print(correlation_matrix)
import seaborn as sns
plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
```

```python
plt.title('Correlation Matrix')
plt.show()
```

ex - 3a

October 31, 2025

[ ]:
```python
import numpy as np
import pandas as pd
df = pd.read_csv("Hotel_Dataset.csv")
print("Original Data:")
print(df)
print("\nDuplicate rows:", df.duplicated().sum())
df.drop_duplicates(inplace=True)
print("\nAfter removing duplicates:")
print(df)
df.reset_index(drop=True, inplace=True)
print("\nAfter resetting index:")
print(df)
if 'Age_Group.1' in df.columns:
    df.drop(['Age_Group.1'], axis=1, inplace=True)
df.loc[df['CustomerID'] < 0, 'CustomerID'] = np.nan
df.loc[df['Bill'] < 0, 'Bill'] = np.nan
df.loc[df['EstimatedSalary'] < 0, 'EstimatedSalary'] = np.nan
df.loc[(df['NoOfPax'] < 1) | (df['NoOfPax'] > 20), 'NoOfPax'] = np.nan
df['Hotel'] = df['Hotel'].replace({'Ibys': 'Ibis'})
df['FoodPreference'] = df['FoodPreference'].replace(
    {'Vegetarian': 'Veg', 'veg': 'Veg', 'non-Veg': 'Non-Veg'}
)
df['EstimatedSalary'] = df['EstimatedSalary'].
 ↪fillna(round(df['EstimatedSalary'].mean()))
df['NoOfPax'] = df['NoOfPax'].fillna(round(df['NoOfPax'].median()))
df['Bill'] = df['Bill'].fillna(round(df['Bill'].mean()))
df.loc[(df['Rating(1-5)'] < 1) | (df['Rating(1-5)'] > 5), 'Rating(1-5)'] = np.
 ↪nan
df['Rating(1-5)'] = df['Rating(1-5)'].fillna(round(df['Rating(1-5)'].median()))
df = df.astype({
    'CustomerID': 'Int64',
    'NoOfPax': 'Int64',
    'Bill': 'Int64',
    'EstimatedSalary': 'Int64',
    'Rating(1-5)': 'Int64'
})
print("\nFinal Cleaned DataFrame:")
```

```python
print(df)
print("\nCleaned DataFrame Info:")
print(df.info())
```

ex - 3b

October 31, 2025

```
[ ]: import numpy as np
import pandas as pd
df = pd.read_csv("/content/pre_process_datasample (1).csv")
print("Original Dataset:\n", df)
df.info()
df.Country.fillna(df.Country.mode()[0], inplace=True)
df.Age.fillna(df.Age.median(), inplace=True)
df.Salary.fillna(round(df.Salary.mean()), inplace=True)
print("\nDataset after filling missing values:\n", df)
country_dummies = pd.get_dummies(df.Country)
updated_dataset = pd.concat([country_dummies, df.iloc[:, [1, 2, 3]]], axis=1)
updated_dataset.Purchased.replace(['No', 'Yes'], [0, 1], inplace=True)
print("\nFinal Processed Dataset:\n", updated_dataset)
```

exe-4

November 2, 2025

[1]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sn
import numpy as np
```

[2]:
```python
arr=np.random.randint(50,100,10)
```

[3]:
```python
arr
```

[3]:
```
array([59, 66, 67, 81, 61, 73, 88, 64, 52, 66], dtype=int32)
```

[4]:
```python
arr.mean()
```

[4]:
```
np.float64(67.7)
```

[5]:
```python
sorted(arr)
```

[5]:
```
[np.int32(52),
 np.int32(59),
 np.int32(61),
 np.int32(64),
 np.int32(66),
 np.int32(66),
 np.int32(67),
 np.int32(73),
 np.int32(81),
 np.int32(88)]
```

[6]:
```python
def out_detec(arr):
    q1,q3=np.percentile(arr,[25,75])
    qr=q3-q1
    n=q1-(1.5*qr)
    m=q3+(1.5*qr)
    return n,m
```

[7]:
```python
n,m=out_detec(arr)
```

[8]:
```
print(n)
print(m)
```

```
47.125
86.125
```

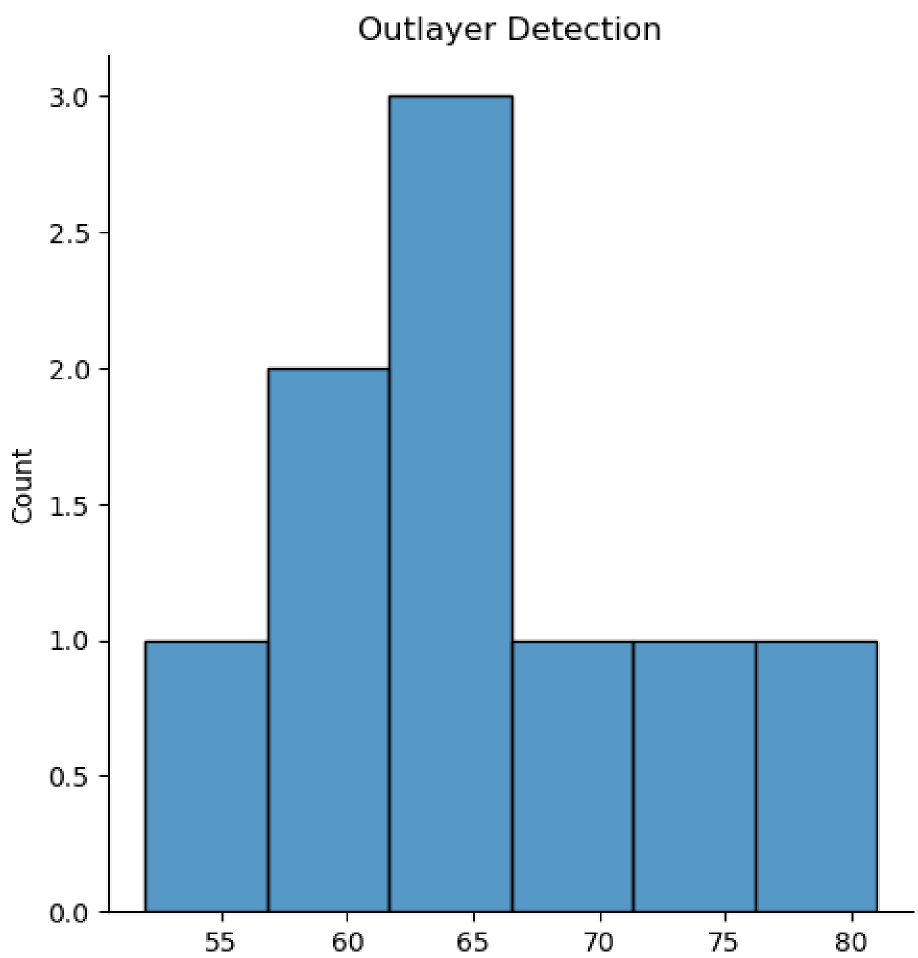
[9]:
```
arr1=arr[(arr>n) & (arr<m)]
```

[10]:
```
arr1
```

[10]:
```
array([59, 66, 67, 81, 61, 73, 64, 52, 66], dtype=int32)
```

[11]:
```
sn.displot(arr1)
plt.title("Outlayer Detection")
```

[11]:
```
Text(0.5, 1.0, 'Outlayer Detection')
```



[ ]:

```

```

Exercise5

November 2, 2025

[9]:
```
import pandas as pd
import numpy as np
df=pd.read_csv('pre_process_datasample_outlayers.csv')
```

[10]:
```
df.head()
```

[10]:
```
   Country   Age   Salary Purchased
0   France  44.0  72000.0        No
1    Spain  27.0  48000.0       Yes
2  Germany  30.0  54000.0        No
3    Spain  38.0  61000.0        No
4  Germany  40.0      NaN       Yes
```

[11]:
```
df['Country'] = df['Country'].fillna(df['Country'].mode()[0])
```

[12]:
```
val=df.iloc[:,:-1].values
val1=df.iloc[:,-1].values
from sklearn.impute import SimpleImputer
n=SimpleImputer(strategy="mean",missing_values=np.nan)
sa=SimpleImputer(strategy="mean",missing_values=np.nan)
n.fit(val[:,[1]])
```

[12]:
```
SimpleImputer()
```

[13]:
```
sa.fit(val[:,[2]])
```

[13]:
```
SimpleImputer()
```

[15]:
```
val[:,[1]]=n.transform(val[:,[1]])
val[:,[2]]=sa.transform(val[:,[2]])
val
```

[15]:
```
array([['France', 44.0, 72000.0],
       ['Spain', 27.0, 48000.0],
       ['Germany', 30.0, 54000.0],
       ['Spain', 38.0, 61000.0],
       ['Germany', 40.0, 63777.77777777778],
       ['France', 35.0, 58000.0],
```

```
       ['Spain', 38.77777777777778, 52000.0],
       ['France', 48.0, 79000.0],
       ['Germany', 50.0, 83000.0],
       ['France', 37.0, 67000.0]], dtype=object)
```

[16]:
```python
from sklearn.preprocessing import OneHotEncoder
m = OneHotEncoder(sparse_output=False)
m
```

[16]:
```
OneHotEncoder(sparse_output=False)
```

[17]:
```python
c=m.fit_transform(val[:,[0]])
c
```

[17]:
```
array([[1., 0., 0.],
       [0., 0., 1.],
       [0., 1., 0.],
       [0., 0., 1.],
       [0., 1., 0.],
       [1., 0., 0.],
       [0., 0., 1.],
       [1., 0., 0.],
       [0., 1., 0.],
       [1., 0., 0.]])
```

[18]:
```python
set_final=np.concatenate((c,val[:,[1,2]]),axis=1)
```

[19]:
```python
from sklearn.preprocessing import StandardScaler
```

[20]:
```python
sc=StandardScaler()
sc.fit(set_final)
feat_standard_scaler=sc.transform(set_final)
feat_standard_scaler
```

[20]:
```
array([[ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
         7.58874362e-01,  7.49473254e-01],
       [-8.16496581e-01, -6.54653671e-01,  1.52752523e+00,
        -1.71150388e+00, -1.43817841e+00],
       [-8.16496581e-01,  1.52752523e+00, -6.54653671e-01,
        -1.27555478e+00, -8.91265492e-01],
       [-8.16496581e-01, -6.54653671e-01,  1.52752523e+00,
        -1.13023841e-01, -2.53200424e-01],
       [-8.16496581e-01,  1.52752523e+00, -6.54653671e-01,
         1.77608893e-01,  6.63219199e-16],
       [ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
        -5.48972942e-01, -5.26656882e-01],
       [-8.16496581e-01, -6.54653671e-01,  1.52752523e+00,
         0.00000000e+00, -1.07356980e+00],
```

```
       [ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
         1.34013983e+00,  1.38753832e+00],
       [-8.16496581e-01,  1.52752523e+00, -6.54653671e-01,
         1.63077256e+00,  1.75214693e+00],
       [ 1.22474487e+00, -6.54653671e-01, -6.54653671e-01,
        -2.58340208e-01,  2.93712492e-01]])
```

[21]:
```
from sklearn.preprocessing import MinMaxScaler
mn1=MinMaxScaler(feature_range=(0,1))
mn1.fit(set_final)
f_min=mn1.transform(set_final)
f_min
```

[21]:
```
array([[1.        , 0.        , 0.        , 0.73913043, 0.68571429],
       [0.        , 0.        , 1.        , 0.        , 0.        ],
       [0.        , 1.        , 0.        , 0.13043478, 0.17142857],
       [0.        , 0.        , 1.        , 0.47826087, 0.37142857],
       [0.        , 1.        , 0.        , 0.56521739, 0.45079365],
       [1.        , 0.        , 0.        , 0.34782609, 0.28571429],
       [0.        , 0.        , 1.        , 0.51207729, 0.11428571],
       [1.        , 0.        , 0.        , 0.91304348, 0.88571429],
       [0.        , 1.        , 0.        , 1.        , 1.        ],
       [1.        , 0.        , 0.        , 0.43478261, 0.54285714]])
```

[ ]:

exercise6

November 2, 2025

[13]:
```
import pandas as pd
import numpy as np
import seaborn as sn
import pandas as pd
import matplotlib.pyplot as plt
```

[14]:
```
df=pd.read_csv('tips.csv')
```

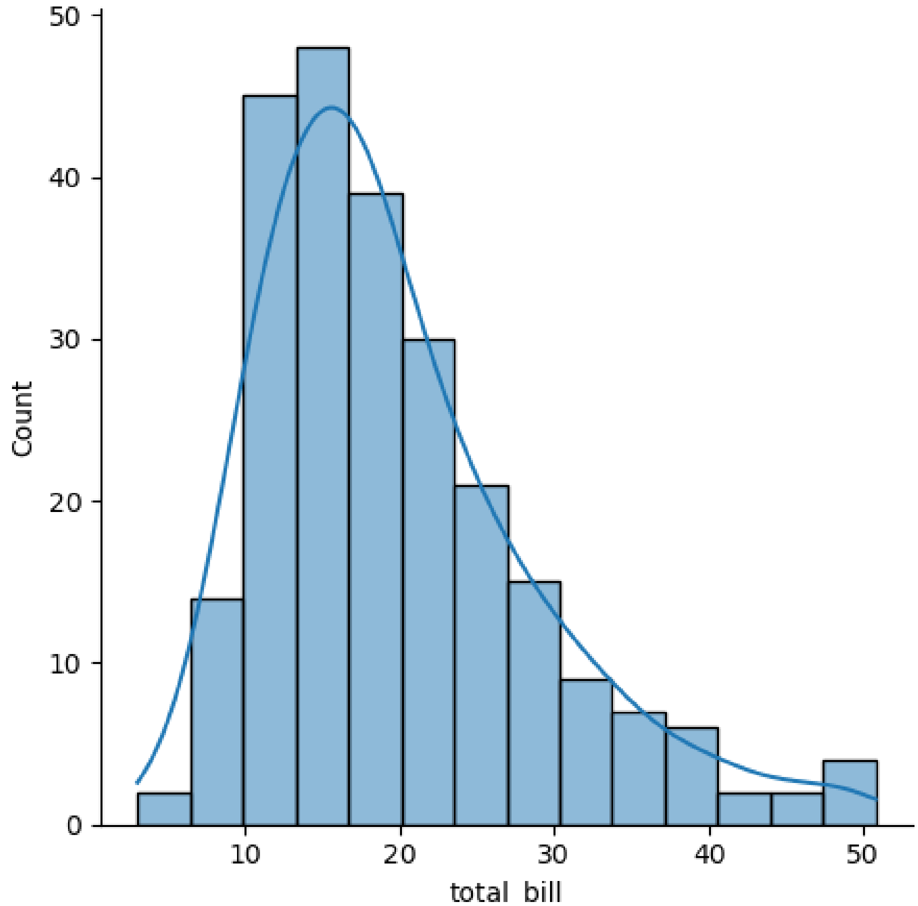
[15]:
```
df.head(10)
```

[15]:

	total_bill	tip	sex	smoker	day	time	size
0	16.99	1.01	Female	No	Sun	Dinner	2
1	10.34	1.66	Male	No	Sun	Dinner	3
2	21.01	3.50	Male	No	Sun	Dinner	3
3	23.68	3.31	Male	No	Sun	Dinner	2
4	24.59	3.61	Female	No	Sun	Dinner	4
5	25.29	4.71	Male	No	Sun	Dinner	4
6	8.77	2.00	Male	No	Sun	Dinner	2
7	26.88	3.12	Male	No	Sun	Dinner	4
8	15.04	1.96	Male	No	Sun	Dinner	2
9	14.78	3.23	Male	No	Sun	Dinner	2

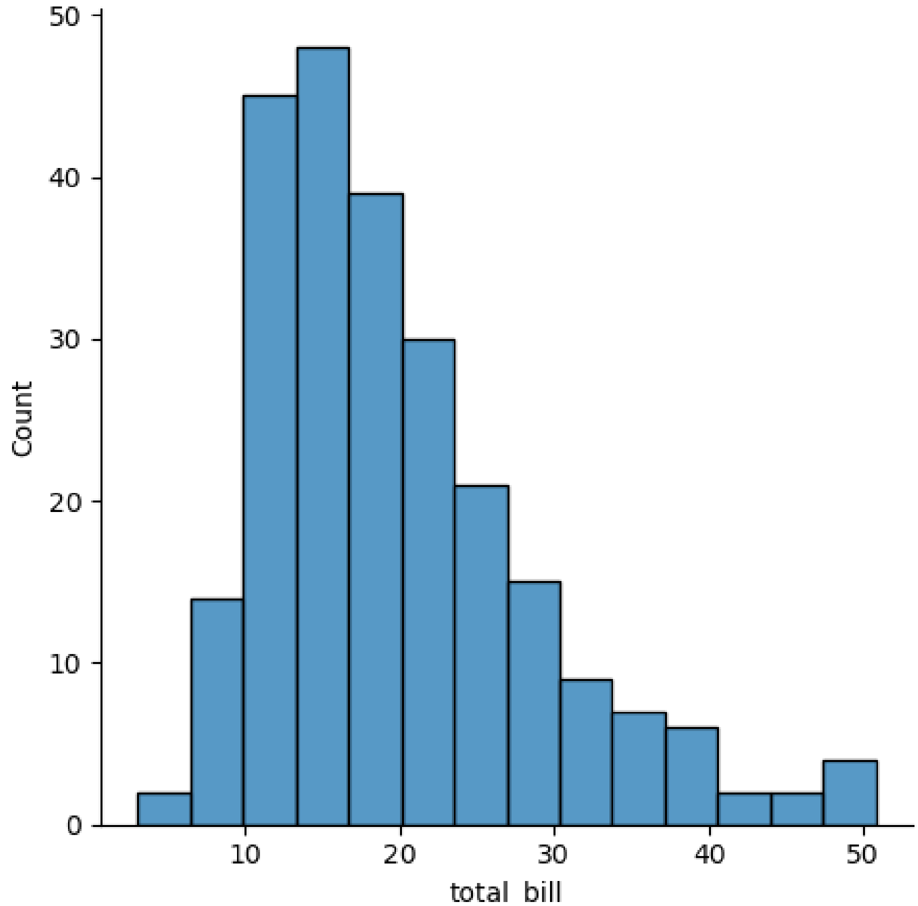
[16]:
```
sn.displot(df.total_bill,kde=True)
```

[16]:
```
<seaborn.axisgrid.FacetGrid at 0x19285a8a490>
```



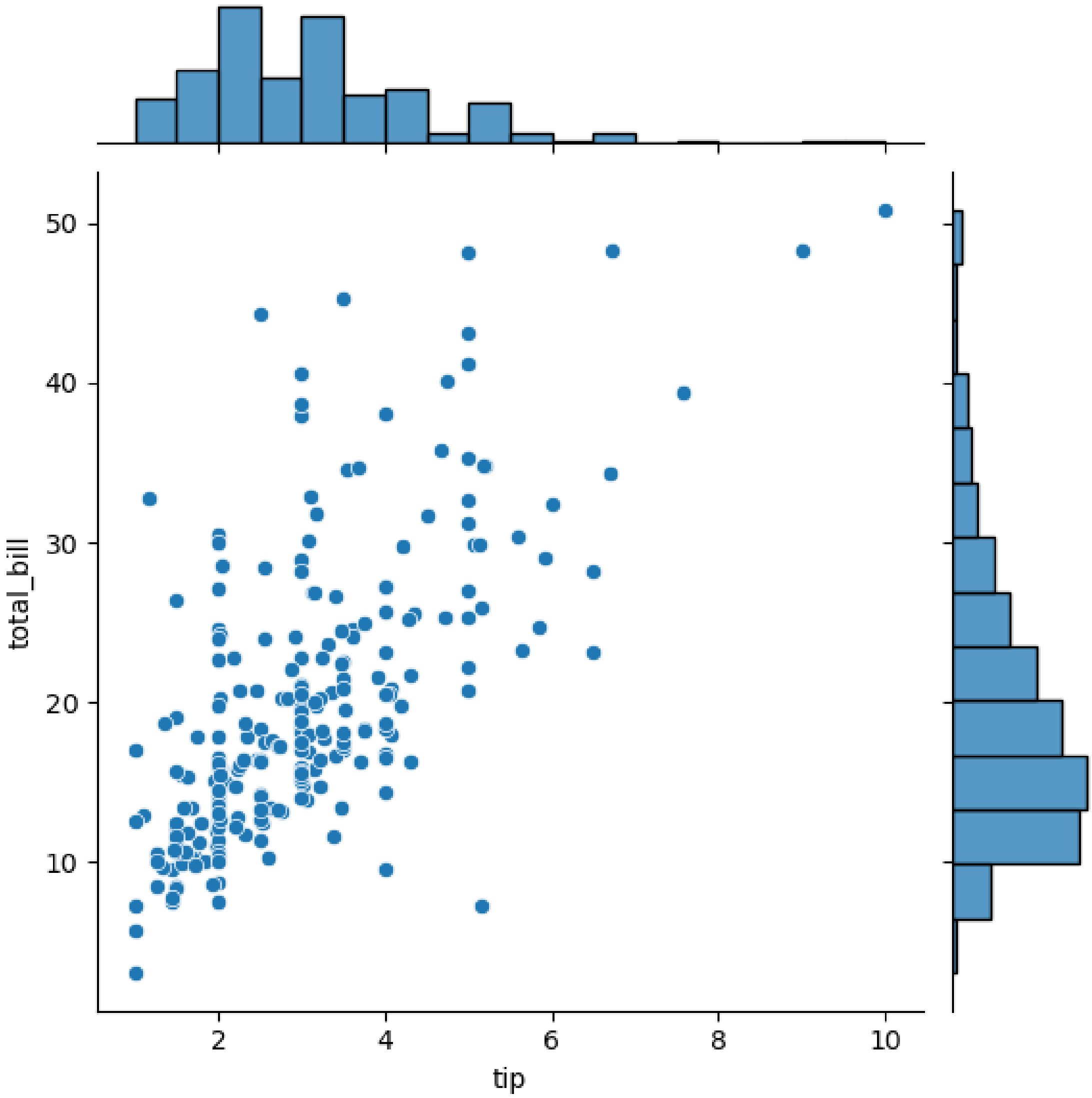
[17]:
```
sn.displot(df.total_bill,kde=False)
```

[17]: <seaborn.axisgrid.FacetGrid at 0x19285e2c7d0>



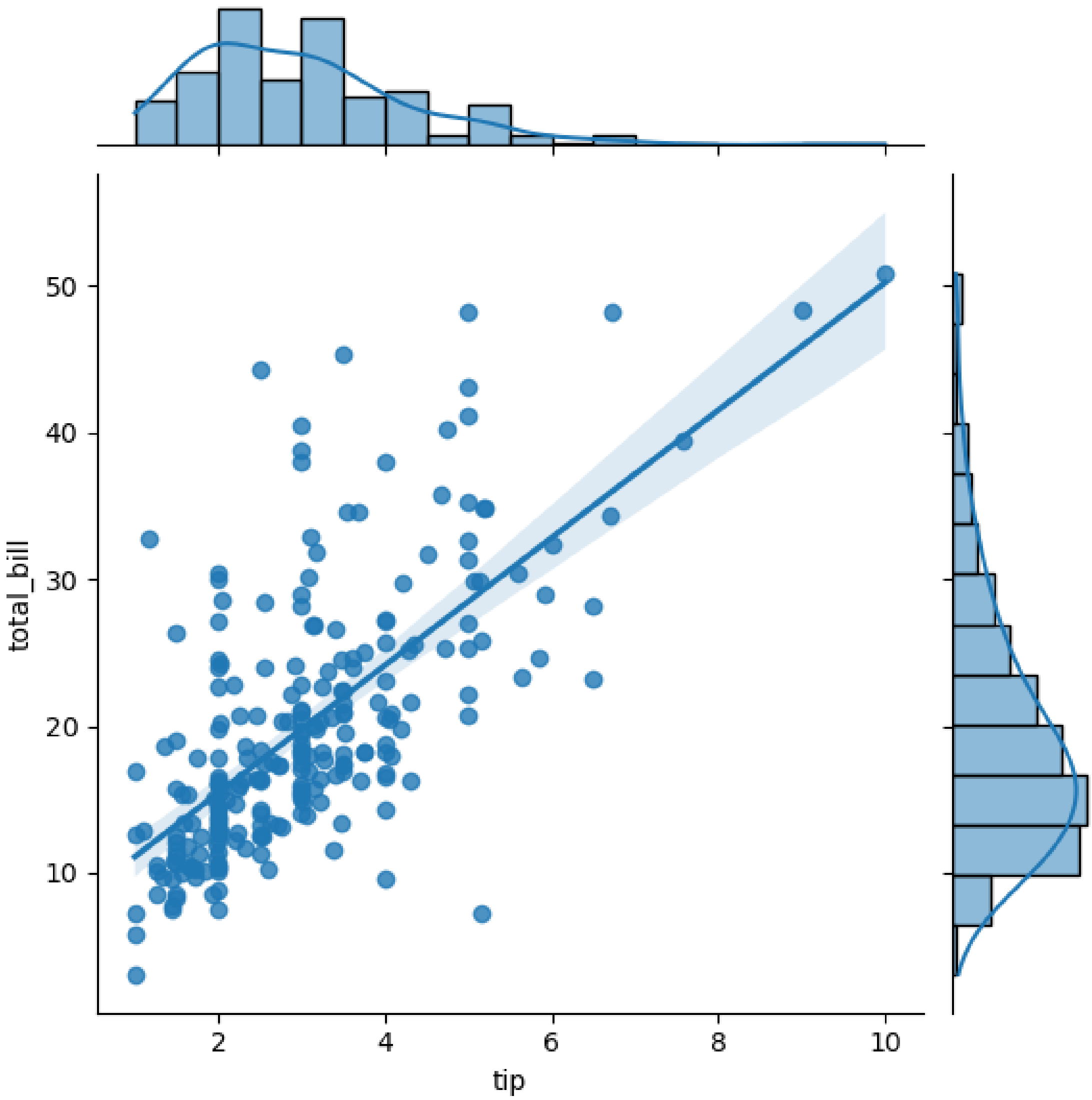
[21]:
```
#plt.scatter(x=df.tip,y=df.total_bill)
sn.jointplot(x=df.tip,y=df.total_bill)
```

[21]: <seaborn.axisgrid.JointGrid at 0x19285f33b10>



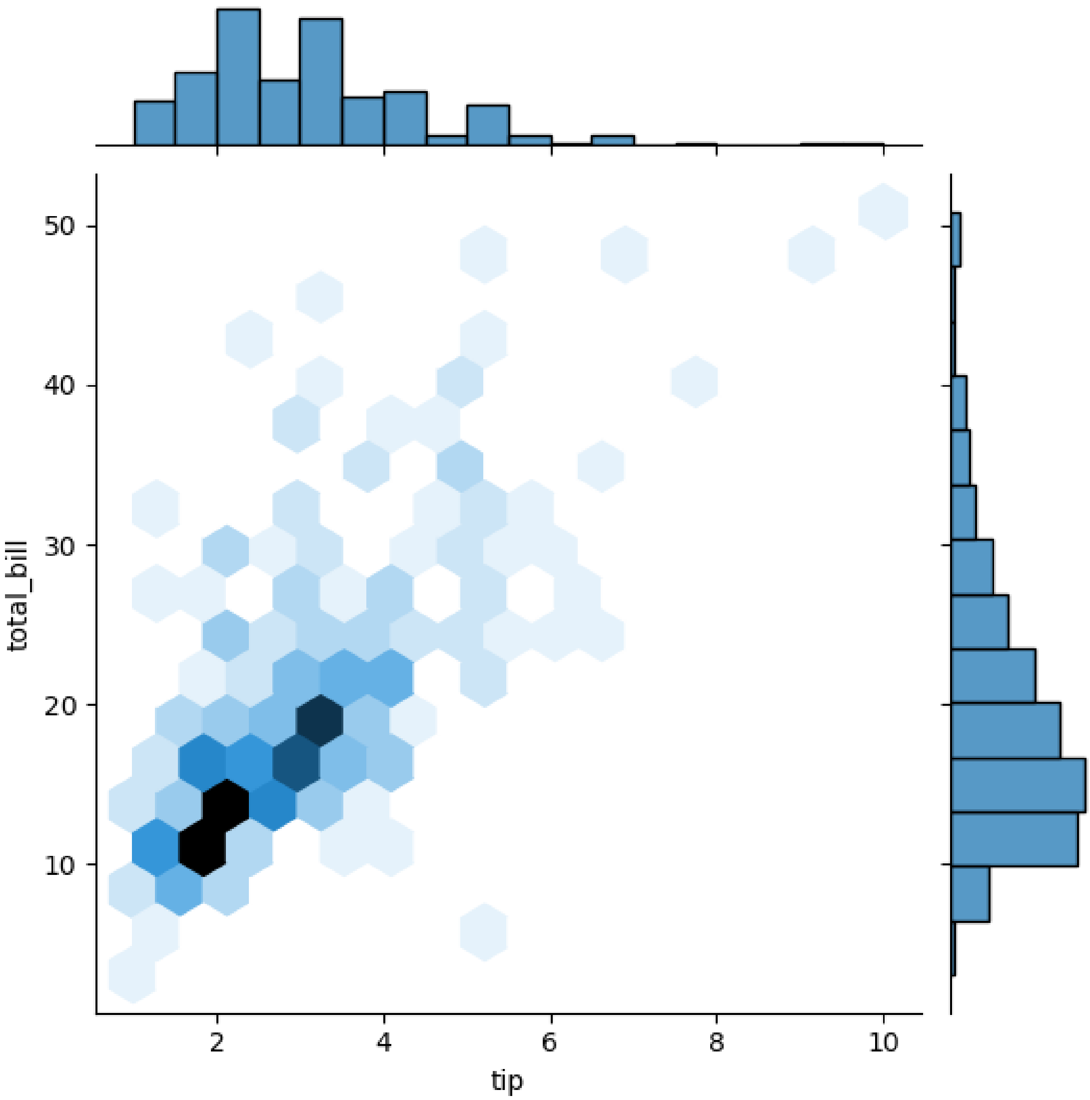
[22]:
```
sn.jointplot(x=df.tip,y=df.total_bill,kind="reg")
```

[22]: <seaborn.axisgrid.JointGrid at 0x1928606d1d0>



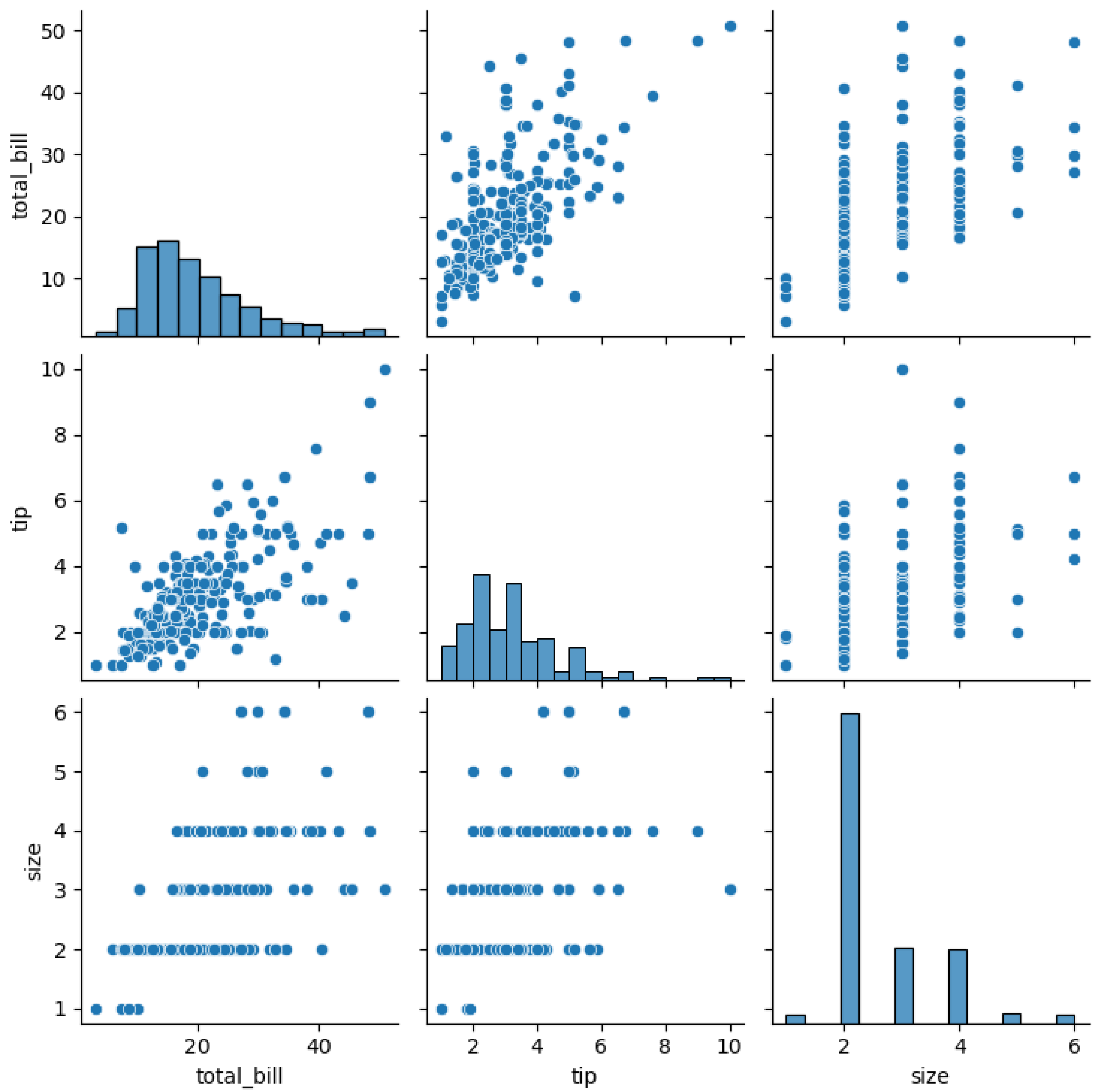
[25]:
```
sn.jointplot(x=df.tip,y=df.total_bill,kind="hex")
```

[25]: <seaborn.axisgrid.JointGrid at 0x19286a5c050>



[26]:
```
sn.pairplot(df)
```

[26]: <seaborn.axisgrid.PairGrid at 0x192fe45b4d0>

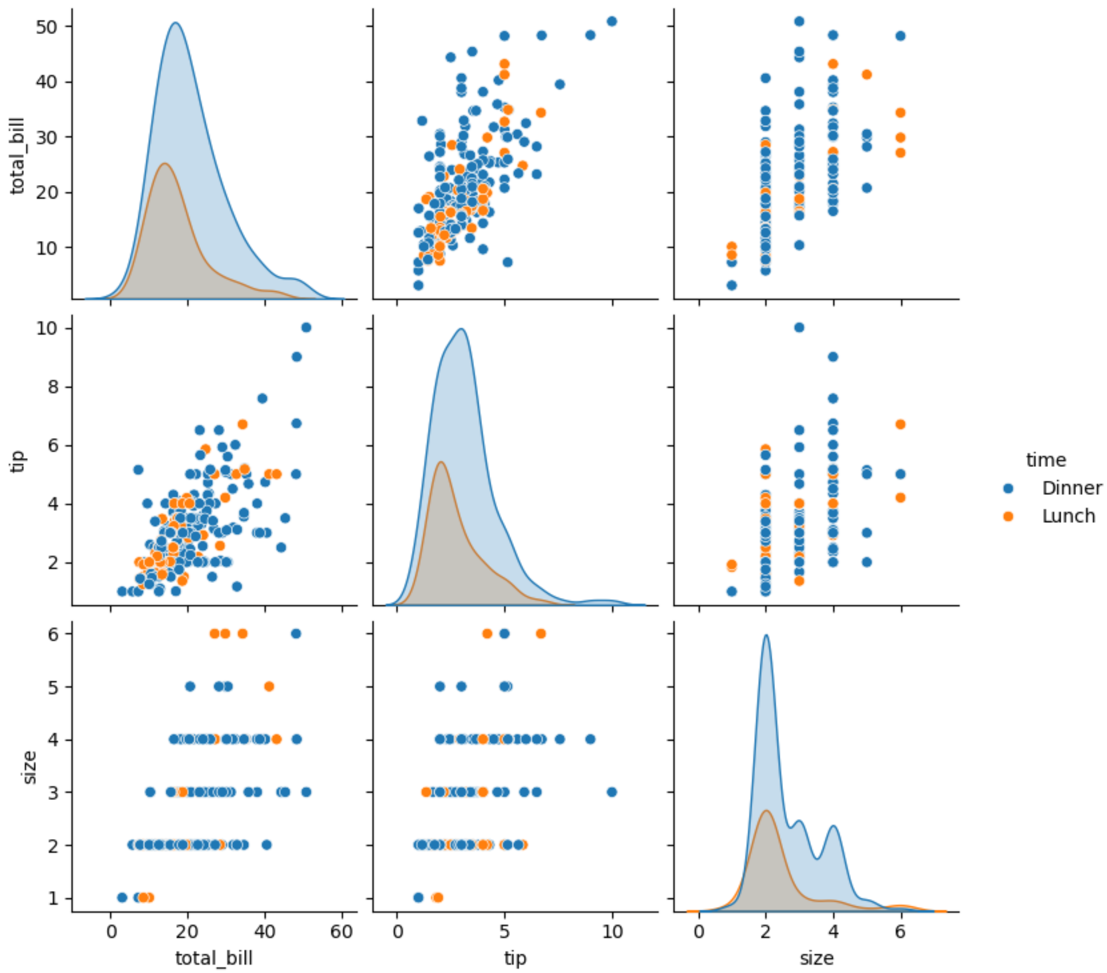


[29]:
```
#df.info()
df.time.value_counts()
```

[29]:
```
time
Dinner    176
Lunch      68
Name: count, dtype: int64
```

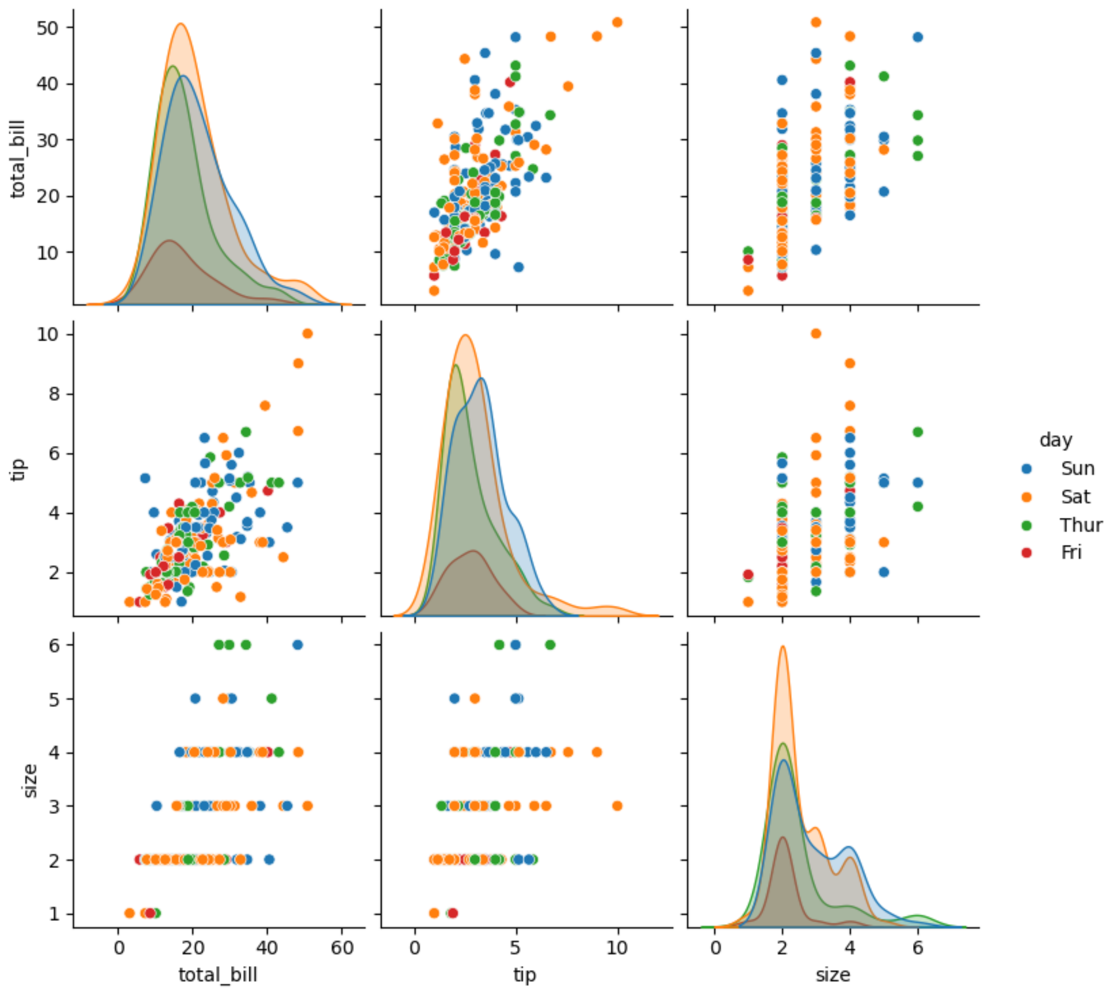
[30]:
```
sn.pairplot(df,hue='time')
```

[30]: <seaborn.axisgrid.PairGrid at 0x192885e7390>



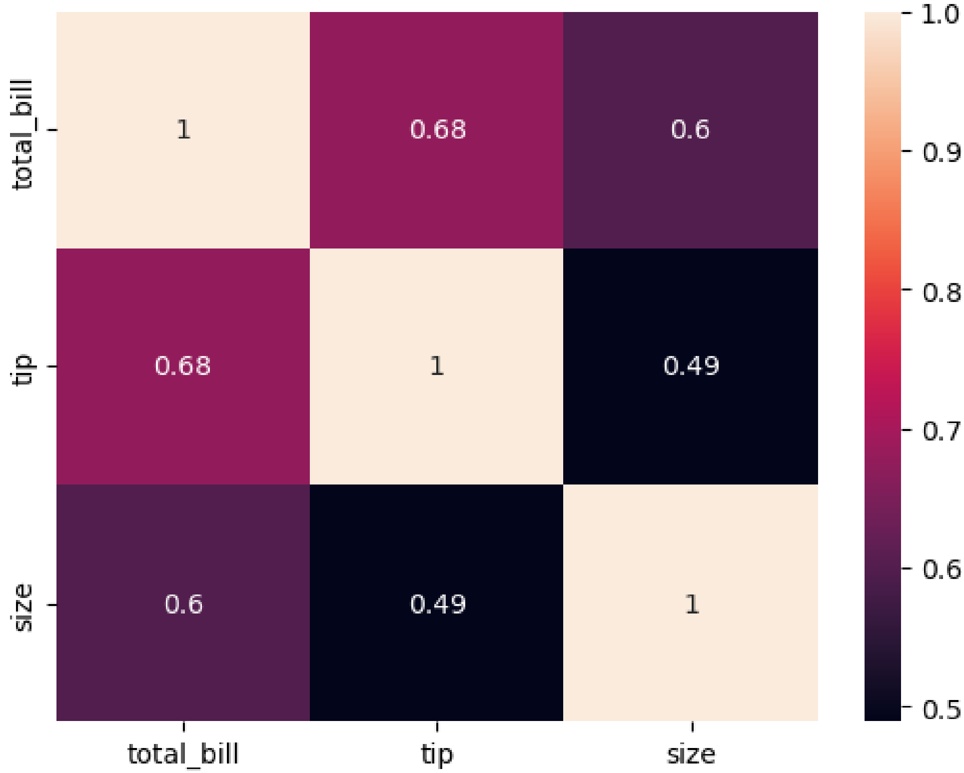

```
[31]: sn.pairplot(df,hue='day')
```

```
[31]: <seaborn.axisgrid.PairGrid at 0x1928939cf50>
```



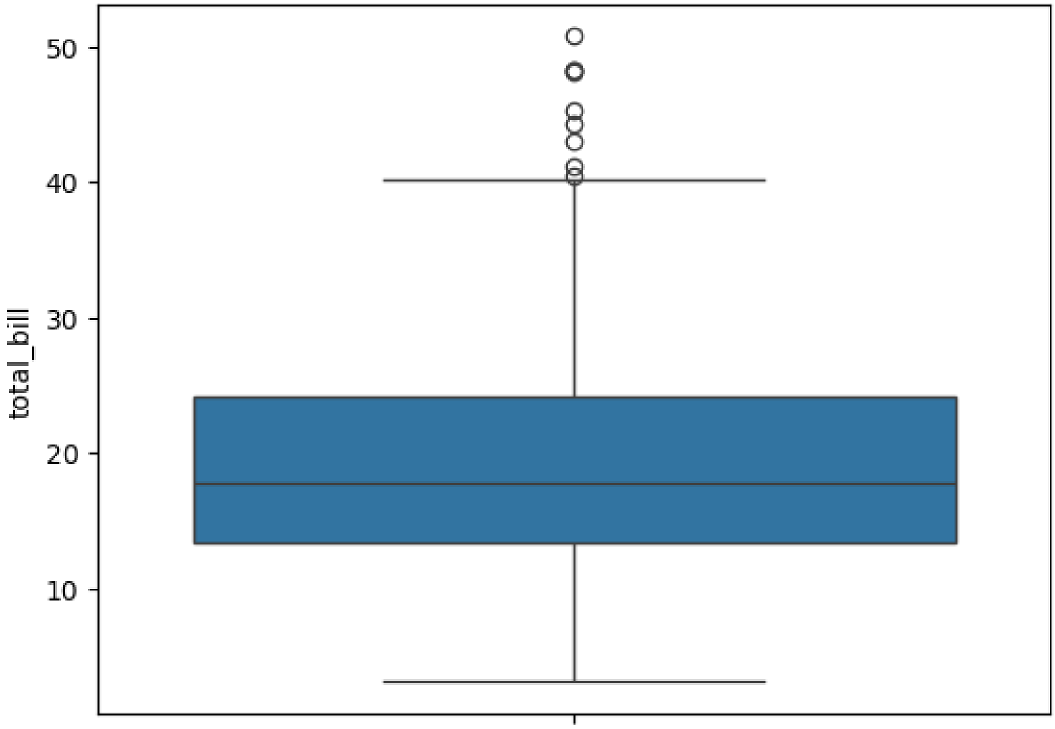
[32]:
```
sn.heatmap(df.corr(numeric_only=True),annot=True)
```

[32]: <Axes: >



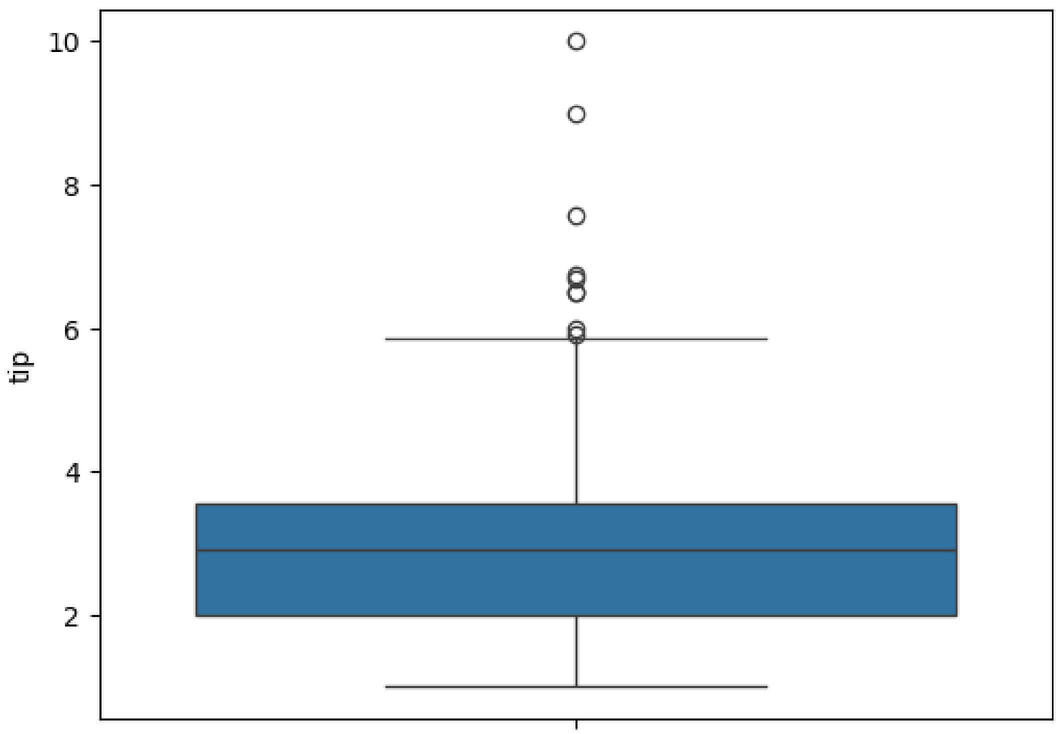
[34]:
```
sn.boxplot(df.total_bill)
```

[34]: `<Axes: ylabel='total_bill'>`



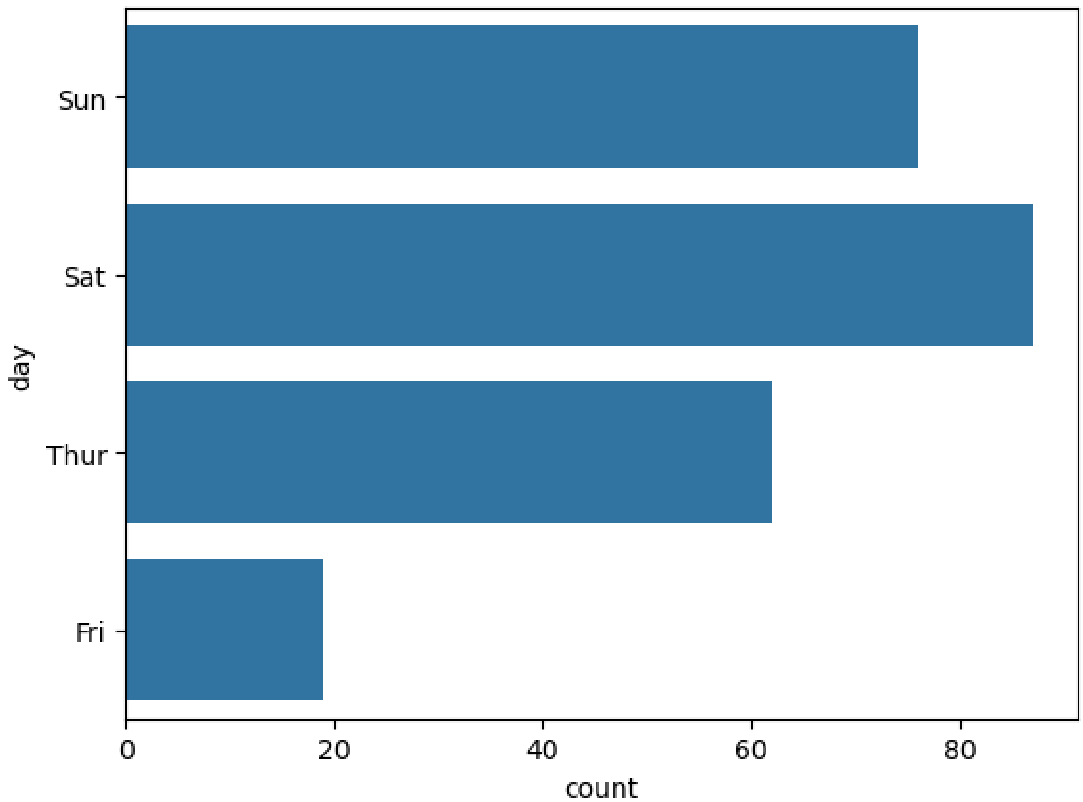
[36]:
```
sn.boxplot(df.tip)
```

[36]: <Axes: ylabel='tip'>



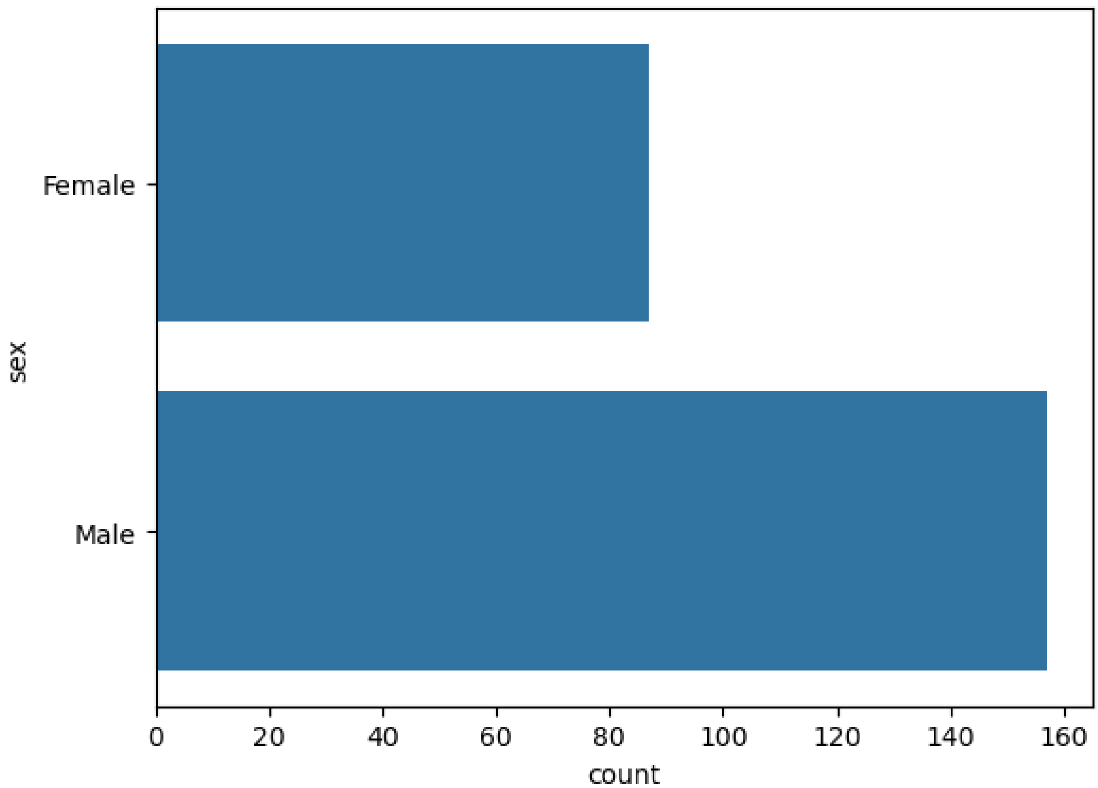
[37]:
```
sn.countplot(df.day)
```

[37]: <Axes: xlabel='count', ylabel='day'>



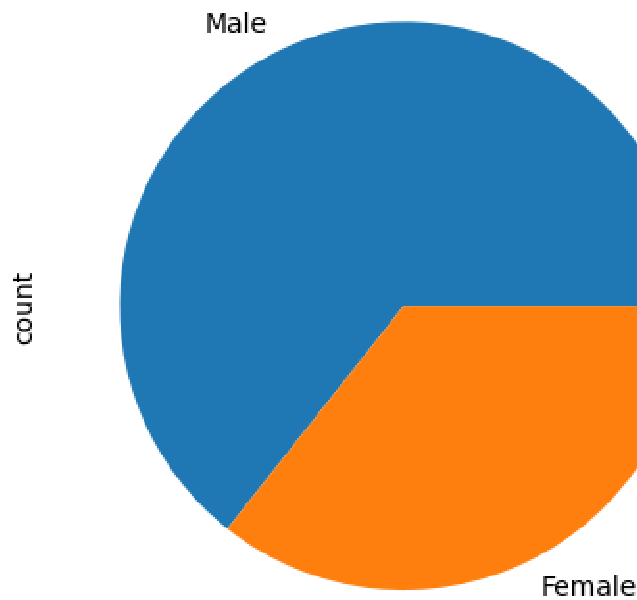
[38]:
```
sn.countplot(df.sex)
```

[38]: <Axes: xlabel='count', ylabel='sex'>



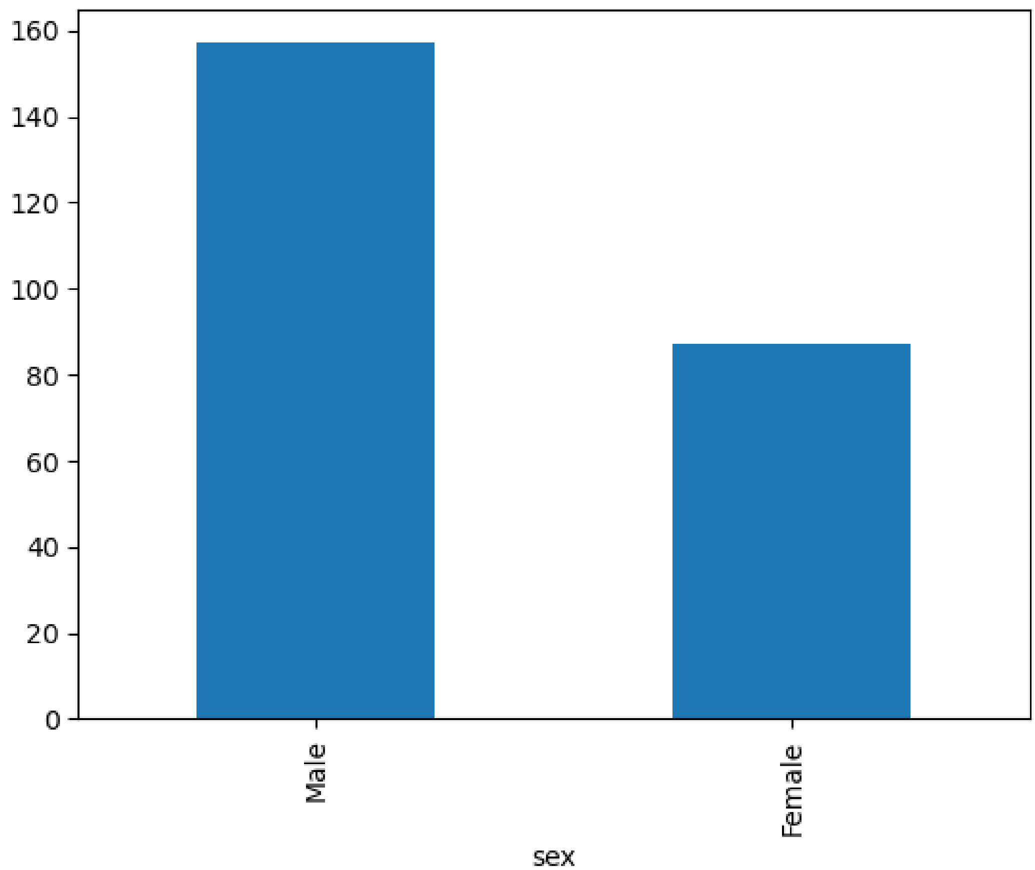
[39]:
```
df.sex.value_counts().plot(kind='pie')
```

[39]: <Axes: ylabel='count'>



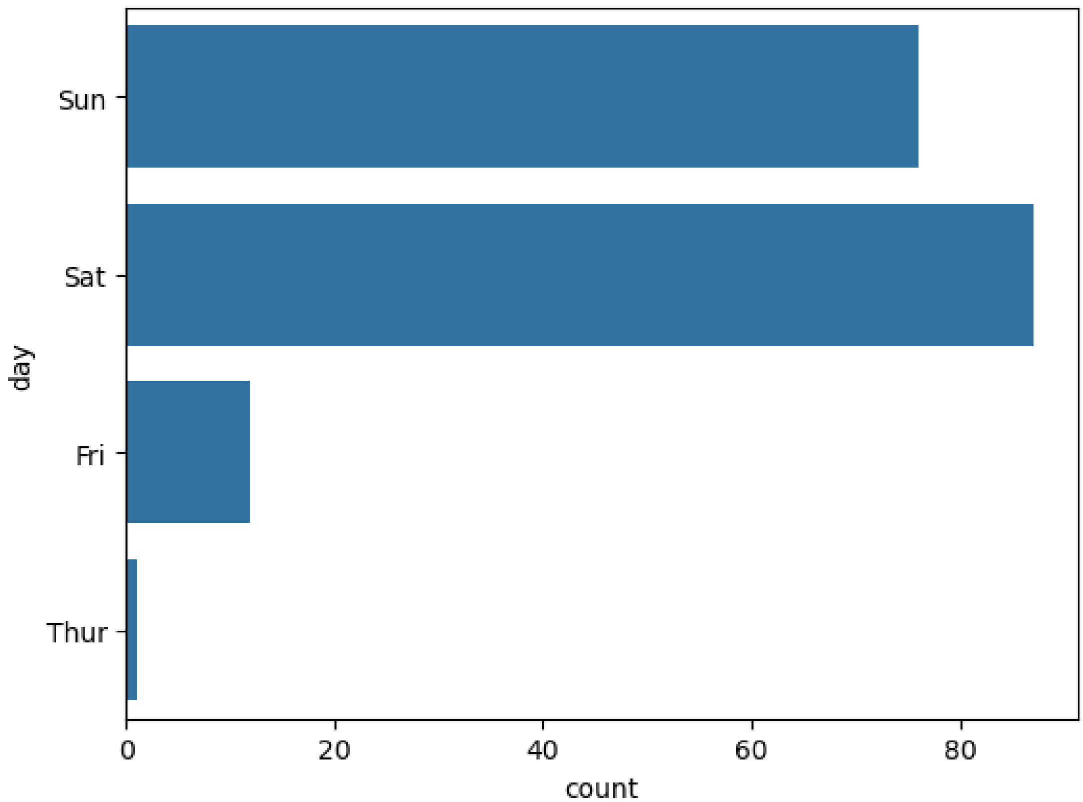
[40]:
```
df.sex.value_counts().plot(kind='bar')
```

[40]: <Axes: xlabel='sex'>



[41]:
```
sn.countplot(df[df.time=='Dinner']['day'])
```

[41]: <Axes: xlabel='count', ylabel='day'>


Sun
Sat
Fri
Thur
day
0
20
40
60
80
count

```
[ ]:
```

regression_and_exercise_7

November 2, 2025

[1]:
```
import pandas as pd
df=pd.read_csv('Salary_data.csv')
```

[2]:
```
df.head(5)
```

[2]:

	YearsExperience	Salary
0	1.1	39343
1	1.3	46205
2	1.5	37731
3	2.0	43525
4	2.2	39891

[3]:
```
df.dropna()
```

[3]:

	YearsExperience	Salary
0	1.1	39343
1	1.3	46205
2	1.5	37731
3	2.0	43525
4	2.2	39891
5	2.9	56642
6	3.0	60150
7	3.2	54445
8	3.2	64445
9	3.7	57189
10	3.9	63218
11	4.0	55794
12	4.0	56957
13	4.1	57081
14	4.5	61111
15	4.9	67938
16	5.1	66029
17	5.3	83088
18	5.9	81363
19	6.0	93940
20	6.8	91738
21	7.1	98273
22	7.9	101302

```
23              8.2  113812
24              8.7  109431
25              9.0  105582
26              9.5  116969
27              9.6  112635
28             10.3  122391
29             10.5  121872
```

[4]:
```
x=df.iloc[:,[0]].values
y=df.iloc[:,[1]].values
```

[5]:
```
from sklearn.model_selection import train_test_split
```

[6]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=0)
```

[7]:
```
from sklearn.linear_model import LinearRegression
```

[8]:
```
model=LinearRegression()#this is the stage where i create a model which has no␣
↪data an empty model with no knowledge
```

[9]:
```
model
```

[9]:
```
LinearRegression()
```

[10]:
```
model.fit(x_train,y_train)#model is trained with the data of x and y
```

[10]:
```
LinearRegression()
```

[11]:
```
model.predict([[5]])
```

[11]:
```
array([[73342.97478427]])
```

[12]:
```
y_pred=model.predict(x_test)
```

[13]:
```
y_pred
```

[13]:
```
array([[ 40748.96184072],
       [122699.62295594],
       [ 64961.65717022],
       [ 63099.14214487],
       [115249.56285456],
       [107799.50275317]])
```

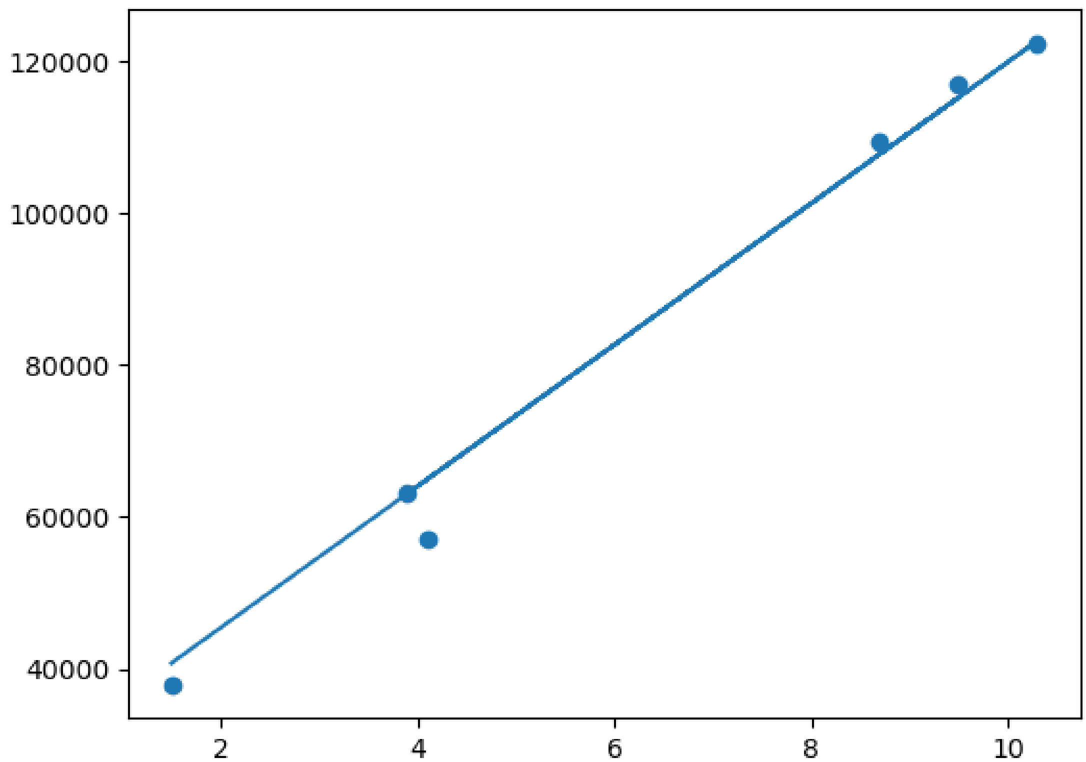
[14]:
```
errors=y_pred-y_test
errors
```

[14]:
```
array([[ 3017.96184072],
       [  308.62295594],
```

```
       [ 7880.65717022],
       [ -118.85785513],
       [-1719.43714544],
       [-1631.49724683]])
```

[15]:
```python
import matplotlib.pyplot as plt
plt.scatter(x_test,y_test)
plt.plot(x_test,y_pred)
```

[15]:
```
[<matplotlib.lines.Line2D at 0x26ea0de2fd0>]
```



[16]:
```python
from sklearn.metrics import r2_score
accuracy=r2_score(y_test,y_pred)
```

[17]:
```python
accuracy
```

[17]:
```
0.988169515729126
```

[18]:
```python
model.predict([[44]])
```

[18]:
```
array([[436533.40472671]])
```

[19]:
```
model.score(x_train,y_train)#This tells how the model regression fits this model
```

[19]: 0.9411949620562126

[20]:
```
model.score(x_test,y_test)
```

[20]: 0.988169515729126

[21]:
```
model.coef_#the coefficient is the slope of the best-fit line.
```

[21]: array([[9312.57512673]])

[22]:
```
model.intercept_
```

[22]: array([26780.09915063])

[23]:
```
model.predict([[55]])
```

[23]: array([[538971.73112073]])

[ ]:
```

```

Exercise8

November 2, 2025

[1]:
```python
import pandas as pd
df=pd.read_csv('Iris (1).csv')
```

[8]:
```python
df.head(5)
```

[8]:

	sepal.length	sepal.width	petal.length	petal.width	variety
0	5.1	3.5	1.4	0.2	Setosa
1	4.9	3.0	1.4	0.2	Setosa
2	4.7	3.2	1.3	0.2	Setosa
3	4.6	3.1	1.5	0.2	Setosa
4	5.0	3.6	1.4	0.2	Setosa

[9]:
```python
df.variety.value_counts()
```

[9]:
```
variety
Setosa        50
Versicolor    50
Virginica     50
Name: count, dtype: int64
```

[10]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   sepal.length  150 non-null    float64
 1   sepal.width   150 non-null    float64
 2   petal.length  150 non-null    float64
 3   petal.width   150 non-null    float64
 4   variety       150 non-null    object
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

[16]:
```python
df["output"] = 0
```

[42]:
```python
df.loc[:49, "output"] = 1
```

[43]:
```
df.loc[50:99,"output"]=2
```

[44]:
```
df.loc[100:149,"output"]=3
```

[45]:
```
df.head(5)
```

[45]:

	sepal.length	sepal.width	petal.length	petal.width	variety	output
0	5.1	3.5	1.4	0.2	Setosa	1
1	4.9	3.0	1.4	0.2	Setosa	1
2	4.7	3.2	1.3	0.2	Setosa	1
3	4.6	3.1	1.5	0.2	Setosa	1
4	5.0	3.6	1.4	0.2	Setosa	1

[46]:
```
df.tail(5)
```

[46]:

	sepal.length	sepal.width	petal.length	petal.width	variety	output
145	6.7	3.0	5.2	2.3	Virginica	3
146	6.3	2.5	5.0	1.9	Virginica	3
147	6.5	3.0	5.2	2.0	Virginica	3
148	6.2	3.4	5.4	2.3	Virginica	3
149	5.9	3.0	5.1	1.8	Virginica	3

[47]:
```
from sklearn.model_selection import train_test_split
```

[48]:
```
feature=df
label=df
```

[56]:
```
feature=df.drop("output",axis=1)
for col in feature.columns:
    if feature[col].dtype == 'object':
        le = LabelEncoder()
        feature[col] = le.fit_transform(feature[col])
label=df["output"]
```

[57]:
```
feature
```

[57]:

	sepal.length	sepal.width	petal.length	petal.width	variety
0	5.1	3.5	1.4	0.2	0
1	4.9	3.0	1.4	0.2	0
2	4.7	3.2	1.3	0.2	0
3	4.6	3.1	1.5	0.2	0
4	5.0	3.6	1.4	0.2	0
..	…	…	…	…	…
145	6.7	3.0	5.2	2.3	2
146	6.3	2.5	5.0	1.9	2
147	6.5	3.0	5.2	2.0	2
148	6.2	3.4	5.4	2.3	2
149	5.9	3.0	5.1	1.8	2

```
[150 rows x 5 columns]
```

[58]:
```python
label
```

[58]:
```
0      1
1      1
2      1
3      1
4      1
      ..
145    3
146    3
147    3
148    3
149    3
Name: output, Length: 150, dtype: int64
```

[59]:
```python
X_train,X_test,Y_train,y_test=train_test_split(feature,label,test_size=0.
 ↪2,random_state=1)
```

[60]:
```python
from sklearn.neighbors import KNeighborsClassifier
```

[61]:
```python
op=KNeighborsClassifier(n_neighbors=5)
```

[62]:
```python
op.fit(X_train,Y_train)
```

[62]:
```
KNeighborsClassifier()
```

[64]:
```python
print(op.score(X_test,y_test))
```

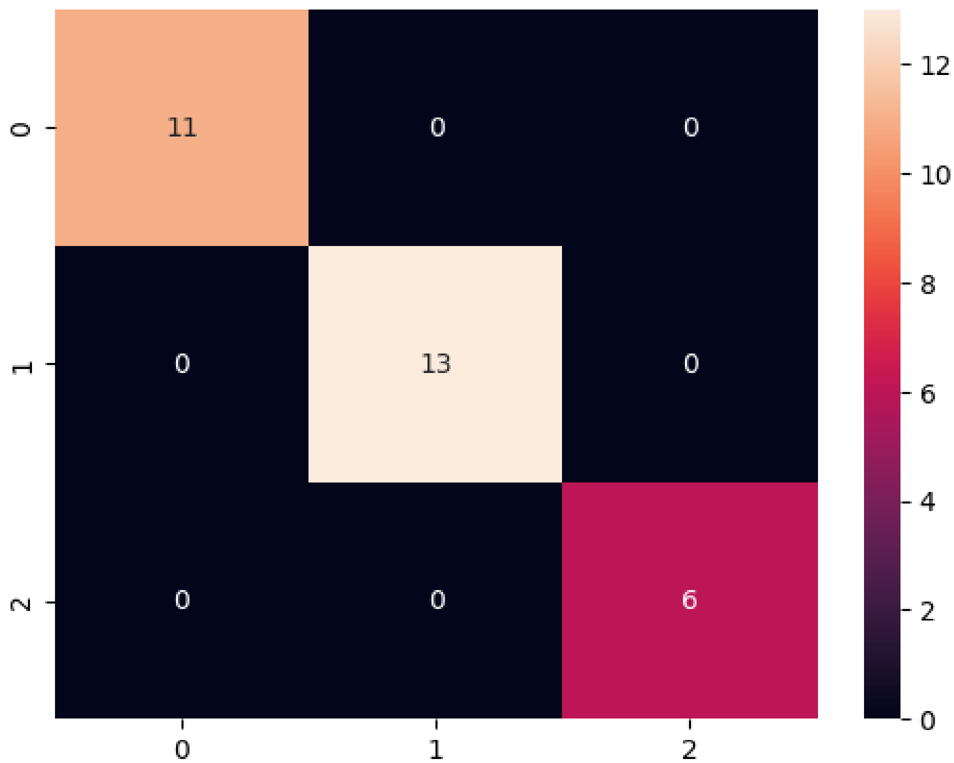
```
1.0
```

[65]:
```python
from sklearn.metrics import confusion_matrix
y_pred=op.predict(X_test)
```

[69]:
```python
c_n_m=confusion_matrix(y_test,y_pred)
```

[70]:
```python
import seaborn as sn
sn.heatmap(c_n_m,annot=True)
```

[70]:
```
<Axes: >
```



[72]:
```python
from sklearn.metrics import classification_report
print(classification_report(label,op.predict(feature)))
```

```
              precision    recall  f1-score   support

           1       1.00      1.00      1.00        50
           2       1.00      1.00      1.00        50
           3       1.00      1.00      1.00        50

    accuracy                           1.00       150
   macro avg       1.00      1.00      1.00       150
weighted avg       1.00      1.00      1.00       150
```

[ ]:

Exercise-9

November 2, 2025

[1]:
```python
import pandas as pd
df=pd.read_csv('Social_Network_Ads.csv')
```

[3]:
```python
import numpy as np
import pandas as pd
```

[4]:
```python
features=df.iloc[:,[2,3]].values
label=df.iloc[:,4].values
features
```

[4]:
```
array([[    19,  19000],
       [    35,  20000],
       [    26,  43000],
       [    27,  57000],
       [    19,  76000],
       [    27,  58000],
       [    27,  84000],
       [    32, 150000],
       [    25,  33000],
       [    35,  65000],
       [    26,  80000],
       [    26,  52000],
       [    20,  86000],
       [    32,  18000],
       [    18,  82000],
       [    29,  80000],
       [    47,  25000],
       [    45,  26000],
       [    46,  28000],
       [    48,  29000],
       [    45,  22000],
       [    47,  49000],
       [    48,  41000],
       [    45,  22000],
       [    46,  23000],
       [    47,  20000],
       [    49,  28000],
       [    47,  30000],
```

```
[    29,  43000],
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[    28,  44000],
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[    33,  28000],
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[    27,  17000],
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[    32,  18000],
```

```
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[    41,  59000],
[    36,  75000],
[    37,  72000],
```

```
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[     30,  87000],
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[     28,  55000],
[     23,  63000],
[     20,  82000],
[     30, 107000],
[     28,  59000],
[     19,  25000],
[     19,  85000],
[     18,  68000],
[     35,  59000],
[     30,  89000],
[     34,  25000],
[     24,  89000],
[     27,  96000],
[     41,  30000],
[     29,  61000],
[     20,  74000],
[     26,  15000],
[     41,  45000],
[     31,  76000],
[     36,  50000],
[     40,  47000],
[     31,  15000],
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[     29,  75000],
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[     32, 100000],
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[     37,  33000],
[     35,  38000],
[     33,  69000],
[     18,  86000],
[     22,  55000],
[     35,  71000],
[     29, 148000],
```

```
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[     28,  89000],
[     34,  43000],
[     30,  79000],
[     20,  36000],
[     26,  80000],
[     35,  22000],
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[     47,  43000],
[     60, 108000],
```

```
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```

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```

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[    38,  50000],
[    49, 141000],
[    39,  79000],
[    39,  75000],
[    54, 104000],
[    35,  55000],
[    45,  32000],
[    36,  60000],
[    52, 138000],
[    53,  82000],
[    41,  52000],
[    48,  30000],
[    48, 131000],
[    41,  60000],
[    41,  72000],
[    42,  75000],
[    36, 118000],
[    47, 107000],
[    38,  51000],
[    48, 119000],
[    42,  65000],
[    40,  65000],
[    57,  60000],
[    36,  54000],
[    58, 144000],
[    35,  79000],
[    38,  55000],
[    39, 122000],
[    53, 104000],
[    35,  75000],
[    38,  65000],
[    47,  51000],
[    47, 105000],
[    41,  63000],
[    53,  72000],
[    54, 108000],
[    39,  77000],
[    38,  61000],
[    38, 113000],
[    37,  75000],
[    42,  90000],
[    37,  57000],
[    36,  99000],
[    60,  34000],
[    54,  70000],
```

```
        [    41,  72000],
        [    40,  71000],
        [    42,  54000],
        [    43, 129000],
        [    53,  34000],
        [    47,  50000],
        [    42,  79000],
        [    42, 104000],
        [    59,  29000],
        [    58,  47000],
        [    46,  88000],
        [    38,  71000],
        [    54,  26000],
        [    60,  46000],
        [    60,  83000],
        [    39,  73000],
        [    59, 130000],
        [    37,  80000],
        [    46,  32000],
        [    46,  74000],
        [    42,  53000],
        [    41,  87000],
        [    58,  23000],
        [    42,  64000],
        [    48,  33000],
        [    44, 139000],
        [    49,  28000],
        [    57,  33000],
        [    56,  60000],
        [    49,  39000],
        [    39,  71000],
        [    47,  34000],
        [    48,  35000],
        [    48,  33000],
        [    47,  23000],
        [    45,  45000],
        [    60,  42000],
        [    39,  59000],
        [    46,  41000],
        [    51,  23000],
        [    50,  20000],
        [    36,  33000],
        [    49,  36000]])
```

[5]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
```

[6]:
```python
for i in range(1, 401):
    x_train, x_test, y_train, y_test = train_test_split(features, label,␣
↪test_size=0.2, random_state=i)

    model = LogisticRegression()
    model.fit(x_train, y_train)

    train_score = model.score(x_train, y_train)
    test_score = model.score(x_test, y_test)

    if test_score > train_score:
        print("Test {:.3f} Train {:.3f} Random State {}".format(test_score,␣
↪train_score, i))
```

```
Test 0.900 Train 0.841 Random State 4
Test 0.863 Train 0.850 Random State 5
Test 0.863 Train 0.859 Random State 6
Test 0.887 Train 0.838 Random State 7
Test 0.863 Train 0.838 Random State 9
Test 0.900 Train 0.841 Random State 10
Test 0.863 Train 0.856 Random State 14
Test 0.850 Train 0.844 Random State 15
Test 0.863 Train 0.856 Random State 16
Test 0.875 Train 0.834 Random State 18
Test 0.850 Train 0.844 Random State 19
Test 0.875 Train 0.844 Random State 20
Test 0.863 Train 0.834 Random State 21
Test 0.875 Train 0.841 Random State 22
Test 0.875 Train 0.841 Random State 24
Test 0.850 Train 0.834 Random State 26
Test 0.850 Train 0.841 Random State 27
Test 0.863 Train 0.834 Random State 30
Test 0.863 Train 0.856 Random State 31
Test 0.875 Train 0.853 Random State 32
Test 0.863 Train 0.844 Random State 33
Test 0.875 Train 0.831 Random State 35
Test 0.863 Train 0.853 Random State 36
Test 0.887 Train 0.841 Random State 38
Test 0.875 Train 0.838 Random State 39
Test 0.887 Train 0.838 Random State 42
Test 0.875 Train 0.847 Random State 46
Test 0.912 Train 0.831 Random State 47
Test 0.875 Train 0.831 Random State 51
Test 0.900 Train 0.844 Random State 54
Test 0.850 Train 0.844 Random State 57
Test 0.875 Train 0.844 Random State 58
Test 0.925 Train 0.838 Random State 61
Test 0.887 Train 0.834 Random State 65
```

```
Test 0.887 Train 0.841 Random State 68
Test 0.900 Train 0.831 Random State 72
Test 0.887 Train 0.838 Random State 75
Test 0.925 Train 0.825 Random State 76
Test 0.863 Train 0.841 Random State 77
Test 0.863 Train 0.859 Random State 81
Test 0.875 Train 0.838 Random State 82
Test 0.887 Train 0.838 Random State 83
Test 0.863 Train 0.853 Random State 84
Test 0.863 Train 0.841 Random State 85
Test 0.863 Train 0.841 Random State 87
Test 0.875 Train 0.847 Random State 88
Test 0.912 Train 0.838 Random State 90
Test 0.863 Train 0.850 Random State 95
Test 0.875 Train 0.850 Random State 99
Test 0.850 Train 0.841 Random State 101
Test 0.850 Train 0.841 Random State 102
Test 0.900 Train 0.825 Random State 106
Test 0.863 Train 0.841 Random State 107
Test 0.850 Train 0.834 Random State 109
Test 0.850 Train 0.841 Random State 111
Test 0.912 Train 0.841 Random State 112
Test 0.863 Train 0.850 Random State 115
Test 0.863 Train 0.841 Random State 116
Test 0.875 Train 0.834 Random State 119
Test 0.912 Train 0.828 Random State 120
Test 0.863 Train 0.859 Random State 125
Test 0.850 Train 0.847 Random State 128
Test 0.875 Train 0.850 Random State 130
Test 0.900 Train 0.844 Random State 133
Test 0.925 Train 0.834 Random State 134
Test 0.863 Train 0.850 Random State 135
Test 0.875 Train 0.831 Random State 138
Test 0.863 Train 0.850 Random State 141
Test 0.850 Train 0.847 Random State 143
Test 0.850 Train 0.847 Random State 146
Test 0.850 Train 0.844 Random State 147
Test 0.863 Train 0.850 Random State 148
Test 0.875 Train 0.838 Random State 150
Test 0.887 Train 0.831 Random State 151
Test 0.925 Train 0.844 Random State 152
Test 0.850 Train 0.841 Random State 153
Test 0.900 Train 0.844 Random State 154
Test 0.900 Train 0.841 Random State 155
Test 0.887 Train 0.847 Random State 156
Test 0.887 Train 0.834 Random State 158
Test 0.875 Train 0.828 Random State 159
Test 0.900 Train 0.831 Random State 161
```

```
Test 0.850 Train 0.838 Random State 163
Test 0.875 Train 0.831 Random State 164
Test 0.863 Train 0.850 Random State 169
Test 0.875 Train 0.841 Random State 171
Test 0.850 Train 0.841 Random State 172
Test 0.900 Train 0.825 Random State 180
Test 0.850 Train 0.834 Random State 184
Test 0.925 Train 0.822 Random State 186
Test 0.900 Train 0.831 Random State 193
Test 0.863 Train 0.850 Random State 195
Test 0.863 Train 0.841 Random State 196
Test 0.863 Train 0.838 Random State 197
Test 0.875 Train 0.841 Random State 198
Test 0.887 Train 0.838 Random State 199
Test 0.887 Train 0.844 Random State 200
Test 0.863 Train 0.838 Random State 202
Test 0.863 Train 0.841 Random State 203
Test 0.887 Train 0.831 Random State 206
Test 0.863 Train 0.834 Random State 211
Test 0.850 Train 0.844 Random State 212
Test 0.863 Train 0.834 Random State 214
Test 0.875 Train 0.831 Random State 217
Test 0.963 Train 0.819 Random State 220
Test 0.875 Train 0.844 Random State 221
Test 0.850 Train 0.841 Random State 222
Test 0.900 Train 0.844 Random State 223
Test 0.863 Train 0.853 Random State 227
Test 0.863 Train 0.834 Random State 228
Test 0.900 Train 0.841 Random State 229
Test 0.850 Train 0.844 Random State 232
Test 0.875 Train 0.847 Random State 233
Test 0.912 Train 0.841 Random State 234
Test 0.863 Train 0.841 Random State 235
Test 0.850 Train 0.847 Random State 236
Test 0.875 Train 0.847 Random State 239
Test 0.850 Train 0.844 Random State 241
Test 0.887 Train 0.850 Random State 242
Test 0.887 Train 0.825 Random State 243
Test 0.875 Train 0.847 Random State 244
Test 0.875 Train 0.841 Random State 245
Test 0.875 Train 0.847 Random State 246
Test 0.863 Train 0.859 Random State 247
Test 0.887 Train 0.844 Random State 248
Test 0.863 Train 0.850 Random State 250
Test 0.875 Train 0.831 Random State 251
Test 0.887 Train 0.844 Random State 252
Test 0.863 Train 0.847 Random State 255
Test 0.900 Train 0.841 Random State 257
```

```
Test 0.863 Train 0.856 Random State 260
Test 0.863 Train 0.841 Random State 266
Test 0.863 Train 0.838 Random State 268
Test 0.875 Train 0.841 Random State 275
Test 0.863 Train 0.850 Random State 276
Test 0.925 Train 0.838 Random State 277
Test 0.875 Train 0.847 Random State 282
Test 0.850 Train 0.847 Random State 283
Test 0.850 Train 0.844 Random State 285
Test 0.912 Train 0.834 Random State 286
Test 0.850 Train 0.841 Random State 290
Test 0.850 Train 0.841 Random State 291
Test 0.850 Train 0.847 Random State 292
Test 0.863 Train 0.838 Random State 294
Test 0.887 Train 0.828 Random State 297
Test 0.863 Train 0.834 Random State 300
Test 0.863 Train 0.850 Random State 301
Test 0.887 Train 0.850 Random State 302
Test 0.875 Train 0.847 Random State 303
Test 0.863 Train 0.834 Random State 305
Test 0.912 Train 0.838 Random State 306
Test 0.875 Train 0.847 Random State 308
Test 0.900 Train 0.844 Random State 311
Test 0.863 Train 0.834 Random State 313
Test 0.912 Train 0.834 Random State 314
Test 0.875 Train 0.838 Random State 315
Test 0.900 Train 0.847 Random State 317
Test 0.912 Train 0.822 Random State 319
Test 0.863 Train 0.850 Random State 321
Test 0.912 Train 0.828 Random State 322
Test 0.850 Train 0.847 Random State 328
Test 0.850 Train 0.838 Random State 332
Test 0.887 Train 0.853 Random State 336
Test 0.850 Train 0.838 Random State 337
Test 0.875 Train 0.841 Random State 343
Test 0.863 Train 0.844 Random State 346
Test 0.887 Train 0.831 Random State 351
Test 0.863 Train 0.850 Random State 352
Test 0.950 Train 0.819 Random State 354
Test 0.863 Train 0.850 Random State 356
Test 0.912 Train 0.841 Random State 357
Test 0.863 Train 0.838 Random State 358
Test 0.850 Train 0.841 Random State 362
Test 0.900 Train 0.844 Random State 363
Test 0.863 Train 0.853 Random State 364
Test 0.938 Train 0.822 Random State 366
Test 0.912 Train 0.841 Random State 369
Test 0.863 Train 0.853 Random State 371
```

```
Test 0.925 Train 0.834 Random State 376
Test 0.912 Train 0.828 Random State 377
Test 0.887 Train 0.850 Random State 378
Test 0.887 Train 0.850 Random State 379
Test 0.863 Train 0.841 Random State 382
Test 0.863 Train 0.859 Random State 386
Test 0.850 Train 0.838 Random State 387
Test 0.875 Train 0.828 Random State 388
Test 0.850 Train 0.844 Random State 394
Test 0.863 Train 0.838 Random State 395
Test 0.900 Train 0.844 Random State 397
Test 0.863 Train 0.844 Random State 400
```

[7]:
```
x_train, x_test, y_train, y_test = train_test_split(features, label,␣
 ↪test_size=0.2, random_state=42)
finalModel = LogisticRegression()
finalModel.fit(x_train, y_train)
```

[7]:
```
LogisticRegression()
```

[8]:
```
print(finalModel.score(x_train,y_train))
print(finalModel.score(x_test,y_test))
```

```
0.8375
0.8875
```

[9]:
```
from sklearn.metrics import classification_report
print(classification_report(label,finalModel.predict(features)))
```

```
              precision    recall  f1-score   support

           0       0.85      0.93      0.89       257
           1       0.85      0.70      0.77       143

    accuracy                           0.85       400
   macro avg       0.85      0.81      0.83       400
weighted avg       0.85      0.85      0.84       400
```

[ ]:

Experiment-10

November 2, 2025

[34]:
```
import pandas as pd
df=pd.read_csv('Mall_Customers.csv')
```

[35]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

[36]:
```
feature=df.iloc[:,[3,4]].values
```

[37]:
```
feature
```

[37]:
```
array([[ 15,  39],
       [ 15,  81],
       [ 16,   6],
       [ 16,  77],
       [ 17,  40],
       [ 17,  76],
       [ 18,   6],
       [ 18,  94],
       [ 19,   3],
       [ 19,  72],
       [ 19,  14],
       [ 19,  99],
       [ 20,  15],
       [ 20,  77],
       [ 20,  13],
       [ 20,  79],
       [ 21,  35],
       [ 21,  66],
       [ 23,  29],
       [ 23,  98],
       [ 24,  35],
       [ 24,  73],
       [ 25,   5],
       [ 25,  73],
       [ 28,  14],
```

```
[ 28,  82],
[ 28,  32],
[ 28,  61],
[ 29,  31],
[ 29,  87],
[ 30,   4],
[ 30,  73],
[ 33,   4],
[ 33,  92],
[ 33,  14],
[ 33,  81],
[ 34,  17],
[ 34,  73],
[ 37,  26],
[ 37,  75],
[ 38,  35],
[ 38,  92],
[ 39,  36],
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[ 48,  51],
[ 48,  59],
[ 48,  50],
[ 48,  48],
[ 48,  59],
[ 48,  47],
[ 49,  55],
[ 49,  42],
```

```
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[ 54,  47],
[ 54,  54],
[ 54,  53],
[ 54,  48],
[ 54,  52],
[ 54,  42],
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[ 60,  42],
[ 60,  52],
[ 60,  47],
[ 60,  50],
[ 61,  42],
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[ 62,  59],
[ 62,  55],
[ 62,  56],
[ 62,  42],
[ 63,  50],
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[ 63,  54],
[ 64,  42],
[ 64,  46],
[ 65,  48],
[ 65,  50],
[ 65,  43],
[ 65,  59],
[ 67,  43],
```

```
[ 67,  57],
[ 67,  56],
[ 67,  40],
[ 69,  58],
[ 69,  91],
[ 70,  29],
[ 70,  77],
[ 71,  35],
[ 71,  95],
[ 71,  11],
[ 71,  75],
[ 71,   9],
[ 71,  75],
[ 72,  34],
[ 72,  71],
[ 73,   5],
[ 73,  88],
[ 73,   7],
[ 73,  73],
[ 74,  10],
[ 74,  72],
[ 75,   5],
[ 75,  93],
[ 76,  40],
[ 76,  87],
[ 77,  12],
[ 77,  97],
[ 77,  36],
[ 77,  74],
[ 78,  22],
[ 78,  90],
[ 78,  17],
[ 78,  88],
[ 78,  20],
[ 78,  76],
[ 78,  16],
[ 78,  89],
[ 78,   1],
[ 78,  78],
[ 78,   1],
[ 78,  73],
[ 79,  35],
[ 79,  83],
[ 81,   5],
[ 81,  93],
[ 85,  26],
[ 85,  75],
```

```
       [ 86,  20],
       [ 86,  95],
       [ 87,  27],
       [ 87,  63],
       [ 87,  13],
       [ 87,  75],
       [ 87,  10],
       [ 87,  92],
       [ 88,  13],
       [ 88,  86],
       [ 88,  15],
       [ 88,  69],
       [ 93,  14],
       [ 93,  90],
       [ 97,  32],
       [ 97,  86],
       [ 98,  15],
       [ 98,  88],
       [ 99,  39],
       [ 99,  97],
       [101,  24],
       [101,  68],
       [103,  17],
       [103,  85],
       [103,  23],
       [103,  69],
       [113,   8],
       [113,  91],
       [120,  16],
       [120,  79],
       [126,  28],
       [126,  74],
       [137,  18],
       [137,  83]])
```

[38]:
```python
import os
os.environ["OMP_NUM_THREADS"] = "1"
```

[39]:
```python
from sklearn.cluster import KMeans
model=KMeans(n_clusters=5)
model.fit(feature)
KMeans(n_clusters=5)
```

```
D:\Ashvanthan\anaconda3\python\Lib\site-
packages\sklearn\cluster\_kmeans.py:1419: UserWarning: KMeans is known to have a
memory leak on Windows with MKL, when there are less chunks than available
threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```

[39]: KMeans(n_clusters=5)

[40]:
```
Final=df.iloc[:,[3,4]]
Final['label']=model.predict(feature)
Final
```

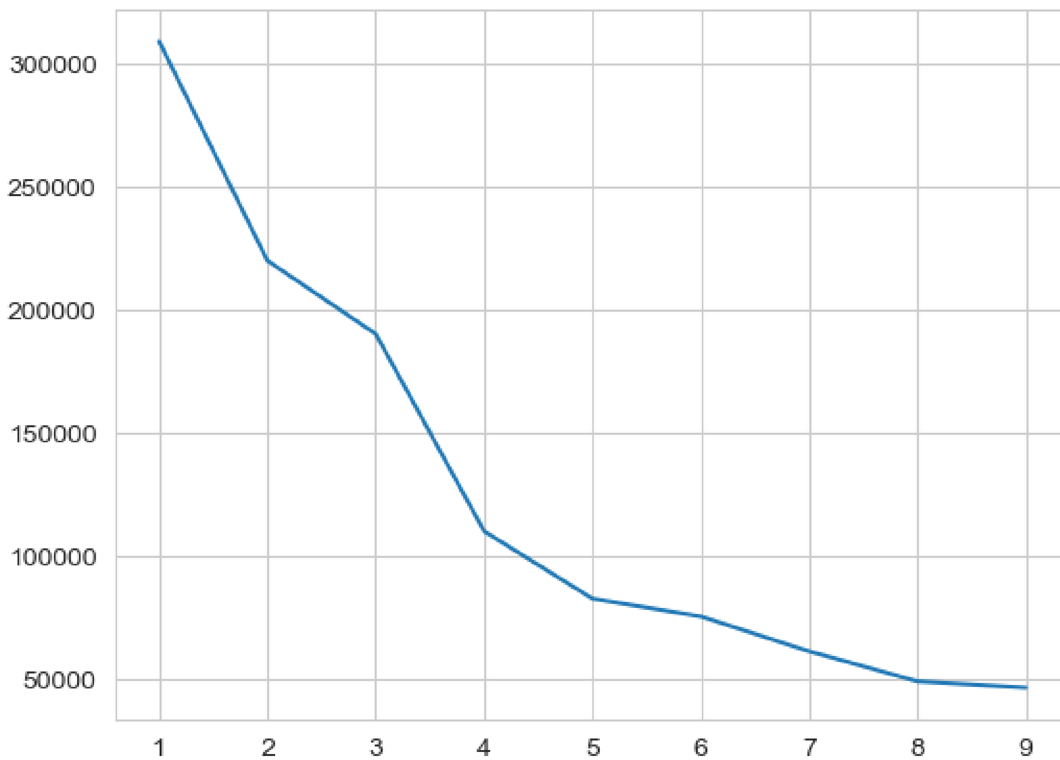
```
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_9408\551092936.py:2:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  Final['label']=model.predict(feature)
```

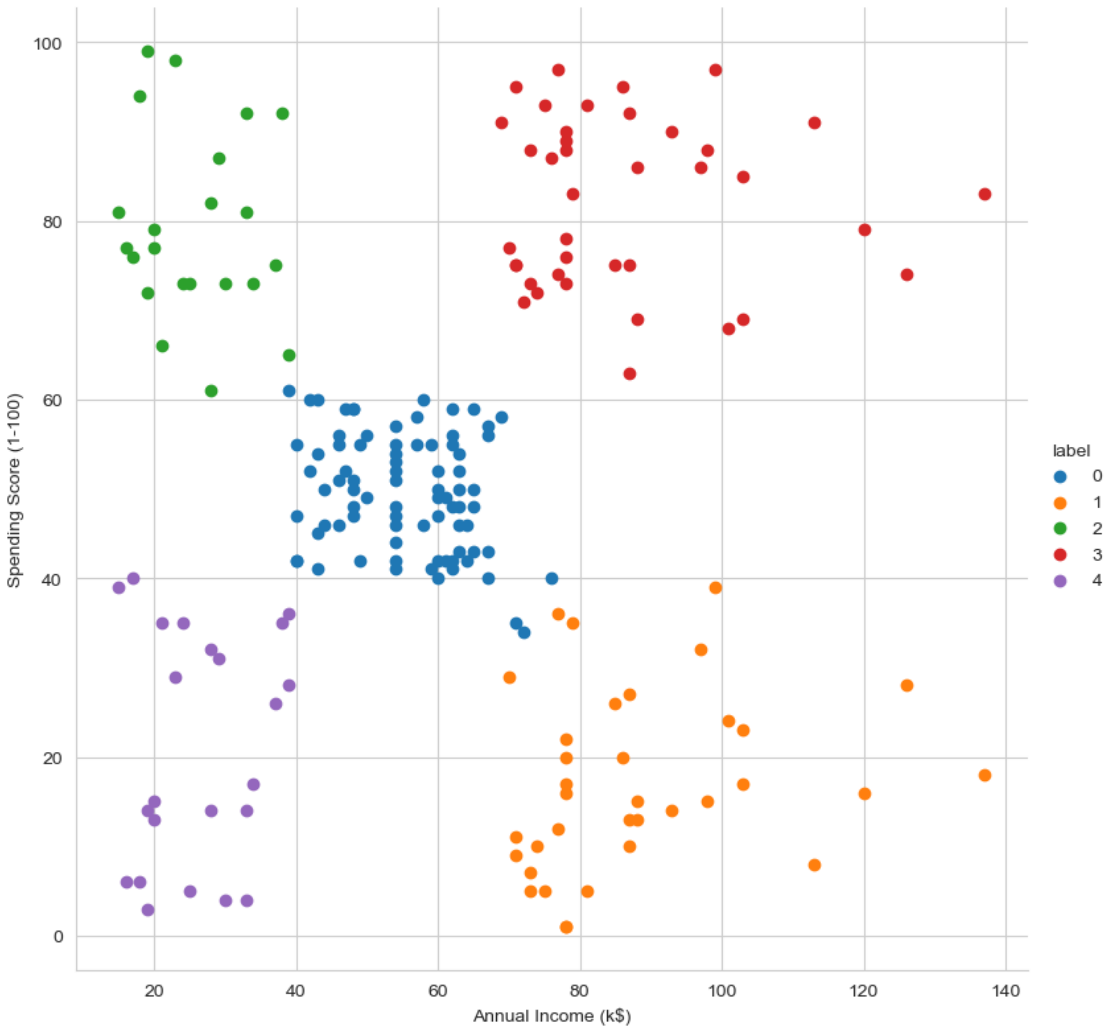
[40]:

	Annual Income (k$)	Spending Score (1-100)	label
0	15	39	4
1	15	81	2
2	16	6	4
3	16	77	2
4	17	40	4
..	…	…	…
195	120	79	3
196	126	28	1
197	126	74	3
198	137	18	1
199	137	83	3

[200 rows x 3 columns]

[41]:
```
sns.set_style("whitegrid")
sns.FacetGrid(Final,hue="label",height=8).map(plt.scatter,"Annual Income (k$)",␣
 ↪"Spending Score (1-100)").add_legend();
plt.show()
```


300000
250000
200000
150000
100000
50000
1
2
3
4
5
6
7
8
9


Spending Score (1-100)
Annual Income (k$)
label
0
1
2
3
4
0
20
40
60
80
100
20
40
60
80
100
120
140

Exercie-11

November 2, 2025

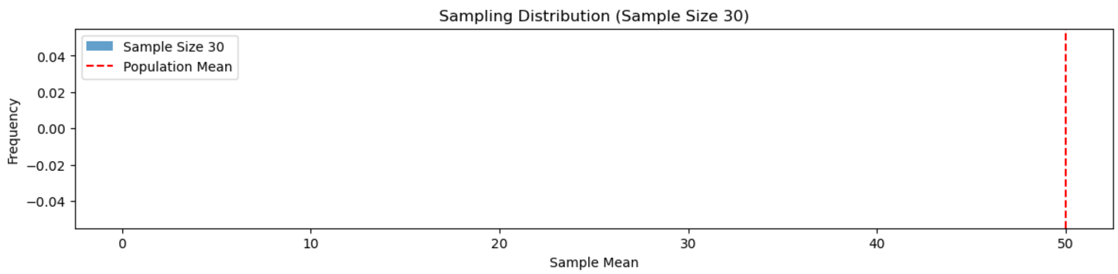
[8]:
```python
import numpy as np
import matplotlib.pyplot as plt
```

[9]:
```python
population_mean = 50
population_std = 10
population_size = 100000
population = np.random.normal(population_mean, population_std, population_size)
```

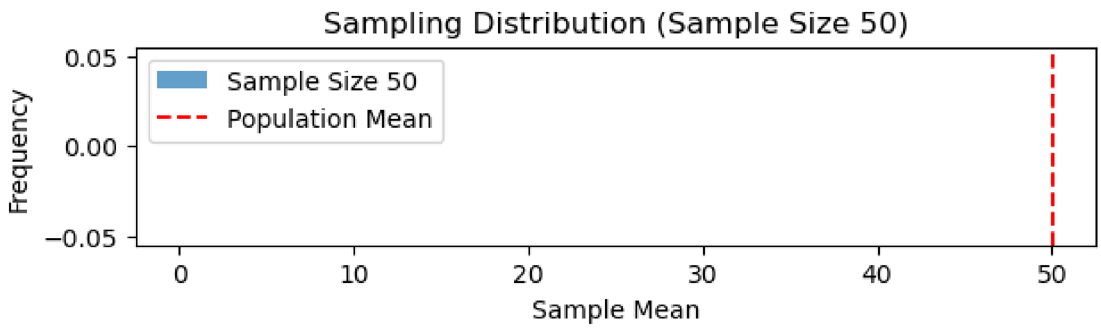
[10]:
```python
sample_sizes = [30, 50, 100]
num_samples = 1000
```

[11]:
```python
sample_means = {}
for size in sample_sizes:
    sample_means[size] = []
for _ in range(num_samples):
    sample = np.random.choice(population, size=size, replace=False)
    sample_means[size].append(np.mean(sample))
```

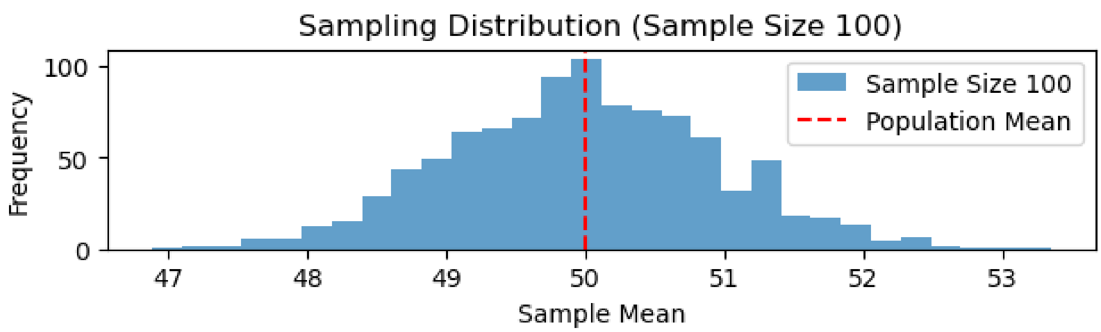
[12]:
```python
plt.figure(figsize=(12, 8))
for i, size in enumerate(sample_sizes):
    plt.subplot(len(sample_sizes), 1, i+1)
    plt.hist(sample_means[size], bins=30, alpha=0.7, label=f'Sample Size␣
 ↪{size}')
    plt.axvline(np.mean(population), color='red', linestyle='dashed',␣
 ↪linewidth=1.5,label='Population Mean')
    plt.title(f'Sampling Distribution (Sample Size {size})')
    plt.xlabel('Sample Mean')
    plt.ylabel('Frequency')
    plt.legend()
    plt.tight_layout()
    plt.show()
```



Sampling Distribution (Sample Size 30)
Sample Size 30
Population Mean
Frequency
Sample Mean
0.04
0.02
0.00
−0.02
−0.04
0
10
20
30
40
50



Sampling Distribution (Sample Size 50)
Sample Size 50
Population Mean
Frequency
Sample Mean
0.05
0.00
−0.05
0
10
20
30
40
50



Sampling Distribution (Sample Size 100)
Sample Size 100
Population Mean
Frequency
Sample Mean
100
50
0
47
48
49
50
51
52
53

[ ]:

```

```

Experiment-12

November 2, 2025

[1]:
```
import numpy as np
import scipy.stats as stats
```

[2]:
```
sample_data = np.array([152, 148, 151, 149, 147, 153, 150, 148, 152,
149,151, 150, 149, 152, 151, 148, 150, 152, 149, 150,148, 153, 151,
150, 149, 152, 148, 151, 150, 153])
```

[3]:
```
population_mean = 150
```

[4]:
```
sample_mean = np.mean(sample_data)
sample_std = np.std(sample_data, ddof=1)
```

[5]:
```
n = len(sample_data)
```

[6]:
```
z_statistic = (sample_mean - population_mean) / (sample_std /np.sqrt(n))
```

[7]:
```
p_value = 2 * (1 - stats.norm.cdf(np.abs(z_statistic)))
```

[8]:
```
print(f"Sample Mean: {sample_mean:.2f}")
print(f"Z-Statistic: {z_statistic:.4f}")
print(f"P-Value: {p_value:.4f}")
```

```
Sample Mean: 150.20
Z-Statistic: 0.6406
P-Value: 0.5218
```

[9]:
```
alpha = 0.05
if p_value<alpha:
    print("Reject the null hypothesis: The average weight is significantly␣
 ↪different from 150 grams")
else:
    print("Fail to reject the null hypothesis: There is nosignificant␣
 ↪difference in average weight from 150 grams")
```

```
Fail to reject the null hypothesis: There is nosignificant difference in average
weight from 150 grams
```

[ ]:
```
```

Exercise-13

November 2, 2025

[1]:
```
import numpy as np
import scipy.stats as stats
```

[2]:
```
np.random.seed(42)
```

[3]:
```
sample_size = 25
sample_data = np.random.normal(loc=102, scale=15, size=sample_size)
```

[4]:
```
population_mean = 100
sample_mean = np.mean(sample_data)
sample_std = np.std(sample_data, ddof=1)
```

[5]:
```
n = len(sample_data)
```

[6]:
```
t_statistic, p_value = stats.ttest_1samp(sample_data,population_mean)
print(f"Sample Mean: {sample_mean:.2f}")
print(f"T-Statistic: {t_statistic:.4f}")
print(f"P-Value: {p_value:.4f}")
```

```
Sample Mean: 99.55
T-Statistic: -0.1577
P-Value: 0.8760
```

[8]:
```
alpha = 0.05
if p_value<alpha:
    print("Reject the null hypothesis: The average IQ score is significantly␣
 ↪different from 100")
else:
    print("Fail to reject the null hypothesis: There is no significant␣
 ↪difference in average IQ score from 100")
```

```
Fail to reject the null hypothesis: There is no significant difference in
average IQ score from 100
```

[ ]:
```

```

Exercise-14

November 2, 2025

[1]:
```python
import numpy as np
import scipy.stats as stats
```

[2]:
```python
np.random.seed(42)
n_plants = 25
growth_A = np.random.normal(loc=10, scale=2, size=n_plants)
growth_B = np.random.normal(loc=12, scale=3, size=n_plants)
growth_C = np.random.normal(loc=15, scale=2.5, size=n_plants)
```

[3]:
```python
all_data = np.concatenate([growth_A, growth_B, growth_C])
treatment_labels = ['A'] * n_plants + ['B'] * n_plants + ['C'] *n_plants
```

[4]:
```python
f_statistic, p_value = stats.f_oneway(growth_A, growth_B, growth_C)
```

[5]:
```python
print("Treatment A Mean Growth:", np.mean(growth_A))
print("Treatment B Mean Growth:", np.mean(growth_B))
print("Treatment C Mean Growth:", np.mean(growth_C))
print()
print(f"F-Statistic: {f_statistic:.4f}")
print(f"P-Value: {p_value:.4f}")
```

```
Treatment A Mean Growth: 9.672983882683818
Treatment B Mean Growth: 11.137680744437432
Treatment C Mean Growth: 15.265234904828972

F-Statistic: 36.1214
P-Value: 0.0000
```

[8]:
```python
alpha = 0.05
if p_value<alpha:
    print("Reject the null hypothesis: There is a significant difference in␣
 ↪mean growth rates among the three treatments")
else:
    print("Fail to reject the null hypothesis: There is no significant␣
 ↪difference in mean growth rates among the three treatments")
if p_value<alpha:
    from statsmodels.stats.multicomp import pairwise_tukeyhsd
    tukey_results = pairwise_tukeyhsd(all_data, treatment_labels,alpha=0.05)
```

```
print("\nTukey's HSD Post-hoc Test:")
print(tukey_results)
```

```
Reject the null hypothesis: There is a significant difference in mean growth
rates among the three treatments

Tukey's HSD Post-hoc Test:
Multiple Comparison of Means - Tukey HSD, FWER=0.05
===================================================
group1 group2 meandiff p-adj   lower  upper  reject
---------------------------------------------------
     A      B   1.4647 0.0877 -0.1683 3.0977  False
     A      C   5.5923    0.0  3.9593 7.2252   True
     B      C   4.1276    0.0  2.4946 5.7605   True
---------------------------------------------------
```

[ ]: