



RAJALAKSHMI ENGINEERING COLLEGE

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Department of Computer Science and Engineering

CS23334 Fundamentals of Data Science Lab

III semester II Year (2023R)

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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()
    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

```
[ ]: 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"}
    ]
```

```

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

```
[ ]: 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('Sales Over 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')
```

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

exercise3

November 2, 2025

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

```
[139]: df
```

```
[139]:   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  61000.0     Yes  
5     France  35.0  58000.0     Yes  
6     Spain   44.0  52000.0      No  
7     France  48.0  79000.0     Yes  
8     France  50.0  83000.0      No  
9     France  37.0  67000.0     Yes
```

```
[140]: df['Country'].isnull()
```

```
[140]: 0    False  
1    False  
2    False  
3    False  
4    False  
5    False  
6    False  
7    False  
8    False  
9    False  
Name: Country, dtype: bool
```

```
[141]: df.loc[8]
```

```
[141]: Country        France  
Age            50.0  
Salary        83000.0  
Purchased      No  
Name: 8, dtype: object
```

```
[142]: n=df['Country'].mode()[0]
print(n)
```

France

```
[143]: df['Country']=df['Country'].fillna(n)
```

```
[144]: df
```

```
[144]:   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  61000.0     Yes
5    France  35.0  58000.0     Yes
6    Spain   44.0  52000.0      No
7    France  48.0  79000.0     Yes
8    France  50.0  83000.0      No
9    France  37.0  67000.0     Yes
```

```
[145]: df['Age'].count()
```

```
[145]: np.int64(10)
```

```
[146]: df['Age'].isna().sum()
```

```
[146]: np.int64(0)
```

```
[147]: df['Age']=df['Age'].fillna(df['Age'].mode())
```

```
[148]: df
```

```
[148]:   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  61000.0     Yes
5    France  35.0  58000.0     Yes
6    Spain   44.0  52000.0      No
7    France  48.0  79000.0     Yes
8    France  50.0  83000.0      No
9    France  37.0  67000.0     Yes
```

```
[149]: df['Salary']=df['Salary'].fillna(df['Salary'].mode())
```

```
[150]: df
```

```
[150]:   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   61000.0     Yes
      5   France    35.0   58000.0     Yes
      6   Spain     44.0   52000.0      No
      7   France    48.0   79000.0     Yes
      8   France    50.0   83000.0      No
      9   France    37.0   67000.0     Yes
```

```
[153]: df
```

```
[153]:   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   61000.0     Yes
      5   France    35.0   58000.0     Yes
      6   Spain     44.0   52000.0      No
      7   France    48.0   79000.0     Yes
      8   France    50.0   83000.0      No
      9   France    37.0   67000.0     Yes
```

```
[154]: df.to_csv('pre_process_datasample.csv',index=False)
```

```
[155]: df
```

```
[155]:   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   61000.0     Yes
      5   France    35.0   58000.0     Yes
      6   Spain     44.0   52000.0      No
      7   France    48.0   79000.0     Yes
      8   France    50.0   83000.0      No
      9   France    37.0   67000.0     Yes
```

```
[ ]: #next file pre-processing
```

```
[217]: df1=pd.read_csv('Hotel_Dataset.csv')
```

```
[218]: df1
```

```
[218]: CustomerID Age_Group Rating(1-5) Hotel FoodPreference Bill \
0 1 20-25 4 Ibis veg 1300
1 2 30-35 5 LemonTree Non-Veg 2000
2 3 25-30 6 RedFox Veg 1322
3 4 20-25 -1 LemonTree Veg 1234
4 5 35+ 3 Ibis Vegetarian 989
5 6 35+ 3 Ibys Non-Veg 1909
6 7 35+ 4 RedFox Vegetarian 1000
7 8 20-25 7 LemonTree Veg 2999
8 9 25-30 2 Ibis Non-Veg 3456
9 9 25-30 2 Ibis Non-Veg 3456
10 10 30-35 5 RedFox non-Veg -6755

NoOfPax EstimatedSalary Age_Group.1
0 2 40000 20-25
1 3 59000 30-35
2 2 30000 25-30
3 2 120000 20-25
4 2 45000 35+
5 2 122220 35+
6 -1 21122 35+
7 -10 345673 20-25
8 3 -99999 25-30
9 3 -99999 25-30
10 4 87777 30-35
```

```
[219]: df1.drop_duplicates(inplace=True)
```

```
[220]: df1
```

```
[220]: CustomerID Age_Group Rating(1-5) Hotel FoodPreference Bill \
0 1 20-25 4 Ibis veg 1300
1 2 30-35 5 LemonTree Non-Veg 2000
2 3 25-30 6 RedFox Veg 1322
3 4 20-25 -1 LemonTree Veg 1234
4 5 35+ 3 Ibis Vegetarian 989
5 6 35+ 3 Ibys Non-Veg 1909
6 7 35+ 4 RedFox Vegetarian 1000
7 8 20-25 7 LemonTree Veg 2999
8 9 25-30 2 Ibis Non-Veg 3456
10 10 30-35 5 RedFox non-Veg -6755

NoOfPax EstimatedSalary Age_Group.1
0 2 40000 20-25
1 3 59000 30-35
2 2 30000 25-30
3 2 120000 20-25
```

```

4          2        45000      35+
5          2       122220      35+
6         -1        21122      35+
7         -10       345673    20-25
8          3       -99999     25-30
10         4        87777     30-35

```

[221]: df1.reset_index(drop=True, inplace=False)

```

[221]:   CustomerID  Age_Group  Rating(1-5)      Hotel FoodPreference  Bill  NoOfPax \
0           1    20-25          4      Ibis      veg  1300        2
1           2    30-35          5  LemonTree  Non-Veg  2000        3
2           3    25-30          6     RedFox      Veg  1322        2
3           4    20-25         -1  LemonTree      Veg  1234        2
4           5      35+          3      Ibis  Vegetarian  989        2
5           6      35+          3      Ibys  Non-Veg  1909        2
6           7      35+          4     RedFox  Vegetarian  1000      -1
7           8    20-25          7  LemonTree      Veg  2999      -10
8           9    25-30          2      Ibis  Non-Veg  3456        3
9          10    30-35          5     RedFox  non-Veg -6755        4

```

```

EstimatedSalary  Age_Group.1
0        40000    20-25
1        59000    30-35
2        30000    25-30
3       120000    20-25
4        45000      35+
5       122220      35+
6        21122      35+
7       345673    20-25
8       -99999     25-30
9        87777    30-35

```

[222]: df1['FoodPreference']=df1['FoodPreference'].str.replace('Vegetarian', 'Veg')

[223]: df1['FoodPreference']=df1['FoodPreference'].str.replace('non-veg','Non-Veg')

[224]: df1

```

[224]:   CustomerID  Age_Group  Rating(1-5)      Hotel FoodPreference  Bill  \
0           1    20-25          4      Ibis      veg  1300
1           2    30-35          5  LemonTree  Non-Veg  2000
2           3    25-30          6     RedFox      Veg  1322
3           4    20-25         -1  LemonTree      Veg  1234
4           5      35+          3      Ibis      Veg  989
5           6      35+          3      Ibys  Non-Veg  1909
6           7      35+          4     RedFox      Veg  1000

```

7	8	20-25	7	LemonTree	Veg	2999
8	9	25-30	2	Ibis	Non-Veg	3456
10	10	30-35	5	RedFox	non-Veg	-6755

NoOfPax	EstimatedSalary	Age_Group.1
0	40000	20-25
1	59000	30-35
2	30000	25-30
3	120000	20-25
4	45000	35+
5	122220	35+
6	21122	35+
7	345673	20-25
8	-99999	25-30
10	87777	30-35

```
[225]: df1['FoodPreference']=df1['FoodPreference'].str.replace('veg', 'Veg')
```

```
[226]: df1
```

CustomerID	Age_Group	Rating(1-5)	Hotel	FoodPreference	Bill	\
0	1	20-25	4	Ibis	Veg	1300
1	2	30-35	5	LemonTree	Non-Veg	2000
2	3	25-30	6	RedFox	Veg	1322
3	4	20-25	-1	LemonTree	Veg	1234
4	5	35+	3	Ibis	Veg	989
5	6	35+	3	Ibys	Non-Veg	1909
6	7	35+	4	RedFox	Veg	1000
7	8	20-25	7	LemonTree	Veg	2999
8	9	25-30	2	Ibis	Non-Veg	3456
10	10	30-35	5	RedFox	non-Veg	-6755

NoOfPax	EstimatedSalary	Age_Group.1
0	40000	20-25
1	59000	30-35
2	30000	25-30
3	120000	20-25
4	45000	35+
5	122220	35+
6	21122	35+
7	345673	20-25
8	-99999	25-30
10	87777	30-35

```
[227]: df1['Hotel']=df1['Hotel'].str.replace('Ibys', 'Ibis')
```

```
[228]: df1
```

```
[228]:   CustomerID Age_Group Rating(1-5) Hotel FoodPreference Bill \
0           1    20-25          4     Ibis      Veg  1300
1           2    30-35          5 LemonTree Non-Veg 2000
2           3    25-30          6 RedFox      Veg 1322
3           4    20-25         -1 LemonTree      Veg 1234
4           5     35+           3     Ibis      Veg  989
5           6     35+           3     Ibis Non-Veg 1909
6           7     35+           4 RedFox      Veg 1000
7           8    20-25          7 LemonTree      Veg 2999
8           9    25-30          2     Ibis Non-Veg 3456
10          10   30-35          5 RedFox non-Veg -6755
```

```
NoOfPax EstimatedSalary Age_Group.1
0           2        40000    20-25
1           3        59000    30-35
2           2        30000    25-30
3           2       120000    20-25
4           2        45000    35+
5           2      122220    35+
6          -1        21122    35+
7          -10      345673    20-25
8           3       -99999    25-30
10          4        87777    30-35
```

```
[229]: condition = df1['Bill'] < 0
print(condition)
```

```
0    False
1    False
2    False
3    False
4    False
5    False
6    False
7    False
8    False
10   True
Name: Bill, dtype: bool
```

```
[230]: df1.loc[condition, 'Bill'] = 0
```

```
[231]: df1
```

```
[231]:   CustomerID Age_Group Rating(1-5) Hotel FoodPreference Bill \
0           1    20-25          4     Ibis      Veg  1300
1           2    30-35          5 LemonTree Non-Veg 2000
2           3    25-30          6 RedFox      Veg 1322
3           4    20-25         -1 LemonTree      Veg 1234
```

4	5	35+	3	Ibis	Veg	989
5	6	35+	3	Ibis	Non-Veg	1909
6	7	35+	4	RedFox	Veg	1000
7	8	20-25	7	LemonTree	Veg	2999
8	9	25-30	2	Ibis	Non-Veg	3456
10	10	30-35	5	RedFox	non-Veg	0

NoOfPax	EstimatedSalary	Age_Group.1
0	2	40000
1	3	59000
2	2	30000
3	2	120000
4	2	45000
5	2	122220
6	-1	21122
7	-10	345673
8	3	-999999
10	4	87777

```
[232]: condition = df1['EstimatedSalary'] < 0
```

```
[235]: df1.loc[condition, 'EstimatedSalary'] = 0
```

```
[236]: df1
```

CustomerID	Age_Group	Rating(1-5)	Hotel	FoodPreference	Bill	\
0	1	20-25	4	Ibis	Veg	1300
1	2	30-35	5	LemonTree	Non-Veg	2000
2	3	25-30	6	RedFox	Veg	1322
3	4	20-25	-1	LemonTree	Veg	1234
4	5	35+	3	Ibis	Veg	989
5	6	35+	3	Ibis	Non-Veg	1909
6	7	35+	4	RedFox	Veg	1000
7	8	20-25	7	LemonTree	Veg	2999
8	9	25-30	2	Ibis	Non-Veg	3456
10	10	30-35	5	RedFox	non-Veg	0

NoOfPax	EstimatedSalary	Age_Group.1
0	2	40000
1	3	59000
2	2	30000
3	2	120000
4	2	45000
5	2	122220
6	-1	21122
7	-10	345673
8	3	0

```
10        4        87777      30-35
```

```
[237]: condition1=[]
condition1.append(df1['NoOfPax'] < 0)
```

```
[241]: for i in condition1:
    df1.loc[i, 'NoOfPax'] = 0
```

```
[242]: df1
```

```
[242]:   CustomerID  Age_Group  Rating(1-5)  Hotel  FoodPreference  Bill \
0            1    20-25          4     Ibis       Veg    1300
1            2    30-35          5  LemonTree    Non-Veg    2000
2            3    25-30          6    RedFox       Veg    1322
3            4    20-25         -1  LemonTree       Veg    1234
4            5      35+          3     Ibis       Veg     989
5            6      35+          3     Ibis    Non-Veg    1909
6            7      35+          4    RedFox       Veg    1000
7            8    20-25          7  LemonTree       Veg    2999
8            9    25-30          2     Ibis    Non-Veg    3456
10           10    30-35          5    RedFox    non-Veg      0
```

	NoOfPax	EstimatedSalary	Age_Group.1
0	2	40000	20-25
1	3	59000	30-35
2	2	30000	25-30
3	2	120000	20-25
4	2	45000	35+
5	2	122220	35+
6	0	21122	35+
7	0	345673	20-25
8	0	0	25-30
10	4	87777	30-35

```
[243]: condition = df1['Rating(1-5)'] < 0
```

```
[244]: df1.loc[condition, 'Rating(1-5)'] = 0
```

```
[245]: df1
```

```
[245]:   CustomerID  Age_Group  Rating(1-5)  Hotel  FoodPreference  Bill \
0            1    20-25          4     Ibis       Veg    1300
1            2    30-35          5  LemonTree    Non-Veg    2000
2            3    25-30          6    RedFox       Veg    1322
3            4    20-25          0  LemonTree       Veg    1234
4            5      35+          3     Ibis       Veg     989
5            6      35+          3     Ibis    Non-Veg    1909
```

6	7	35+	4	RedFox	Veg	1000
7	8	20-25	7	LemonTree	Veg	2999
8	9	25-30	2	Ibis	Non-Veg	3456
10	10	30-35	5	RedFox	non-Veg	0

NoOfPax	EstimatedSalary	Age_Group.1
0	2	40000 20-25
1	3	59000 30-35
2	2	30000 25-30
3	2	120000 20-25
4	2	45000 35+
5	2	122220 35+
6	0	21122 35+
7	0	345673 20-25
8	0	0 25-30
10	4	87777 30-35

```
[246]: df1['FoodPreference']=df1['FoodPreference'].str.replace('non-Veg','Non-Veg')
```

```
[247]: df1
```

	CustomerID	Age_Group	Rating(1-5)	Hotel	FoodPreference	Bill	\
0	1	20-25	4	Ibis	Veg	1300	
1	2	30-35	5	LemonTree	Non-Veg	2000	
2	3	25-30	6	RedFox	Veg	1322	
3	4	20-25	0	LemonTree	Veg	1234	
4	5	35+	3	Ibis	Veg	989	
5	6	35+	3	Ibis	Non-Veg	1909	
6	7	35+	4	RedFox	Veg	1000	
7	8	20-25	7	LemonTree	Veg	2999	
8	9	25-30	2	Ibis	Non-Veg	3456	
10	10	30-35	5	RedFox	Non-Veg	0	

NoOfPax	EstimatedSalary	Age_Group.1
0	2	40000 20-25
1	3	59000 30-35
2	2	30000 25-30
3	2	120000 20-25
4	2	45000 35+
5	2	122220 35+
6	0	21122 35+
7	0	345673 20-25
8	0	0 25-30
10	4	87777 30-35

```
[248]: condition = df1['Rating(1-5)'] == 0
```

```
[261]: df1.loc[condition, 'Rating(1-5)'] = round(df1['Rating(1-5)'].mean(), 2)
```

```
[262]: df1
```

```
[262]:   CustomerID  Age_Group  Rating(1-5)  Hotel  FoodPreference  Bill  \
0           1    20-25       4.00     Ibis        Veg  1300
1           2    30-35       5.00  LemonTree      Non-Veg  2000
2           3    25-30       6.00     RedFox        Veg  1322
3           4    20-25      4.33  LemonTree        Veg  1234
4           5     35+       3.00     Ibis        Veg  989
5           6     35+       3.00     Ibis      Non-Veg  1909
6           7     35+       4.00     RedFox        Veg  1000
7           8    20-25       7.00  LemonTree        Veg  2999
8           9    25-30       2.00     Ibis      Non-Veg  3456
10          10    30-35       5.00     RedFox      Non-Veg    0

   NoOfPax  EstimatedSalary  Age_Group.1
0         2            40000    20-25
1         3            59000    30-35
2         2            30000    25-30
3         2            120000   20-25
4         2            45000     35+
5         2           122220    35+
6         0            21122     35+
7         0            345673   20-25
8         0              0    25-30
10        4            87777    30-35
```

```
[265]: condition = df1['Bill'] == 0
```

```
[266]: df1.loc[condition, 'Bill'] = round(df1['Bill'].mean(), 2)
```

```
[267]: df1
```

```
[267]:   CustomerID  Age_Group  Rating(1-5)  Hotel  FoodPreference  Bill  \
0           1    20-25       4.00     Ibis        Veg  1300.0
1           2    30-35       5.00  LemonTree      Non-Veg  2000.0
2           3    25-30       6.00     RedFox        Veg  1322.0
3           4    20-25      4.33  LemonTree        Veg  1234.0
4           5     35+       3.00     Ibis        Veg  989.0
5           6     35+       3.00     Ibis      Non-Veg  1909.0
6           7     35+       4.00     RedFox        Veg  1000.0
7           8    20-25       7.00  LemonTree        Veg  2999.0
8           9    25-30       2.00     Ibis      Non-Veg  3456.0
10          10    30-35       5.00     RedFox      Non-Veg  1620.9
```

```
NoOfPax  EstimatedSalary  Age_Group.1
```

```

0      2      40000    20-25
1      3      59000    30-35
2      2      30000    25-30
3      2     120000   20-25
4      2      45000    35+
5      2    122220    35+
6      0     21122    35+
7      0    345673   20-25
8      0        0    25-30
10     4     87777    30-35

```

```
[270]: condition1=[]
condition1.append(df1['NoOfPax'] == 0)
```

```
[276]: for i in condition1:
    df1.loc[i, 'NoOfPax'] = df1['NoOfPax'].mean()
```

```
[277]: df1
```

```
[277]: CustomerID  Age_Group  Rating(1-5)  Hotel  FoodPreference  Bill \
0          1    20-25       4.00    Ibis      Veg  1300.0
1          2    30-35       5.00  LemonTree  Non-Veg  2000.0
2          3    25-30       6.00   RedFox      Veg  1322.0
3          4    20-25       4.33  LemonTree      Veg  1234.0
4          5     35+       3.00    Ibis      Veg   989.0
5          6     35+       3.00    Ibis  Non-Veg  1909.0
6          7     35+       4.00   RedFox      Veg  1000.0
7          8    20-25       7.00  LemonTree      Veg  2999.0
8          9    25-30       2.00    Ibis  Non-Veg  3456.0
10         10   30-35       5.00   RedFox  Non-Veg  1620.9
```

	NoOfPax	EstimatedSalary	Age_Group.1
0	2.0	40000	20-25
1	3.0	59000	30-35
2	2.0	30000	25-30
3	2.0	120000	20-25
4	2.0	45000	35+
5	2.0	122220	35+
6	2.3	21122	35+
7	2.3	345673	20-25
8	2.3	0	25-30
10	4.0	87777	30-35

```
[280]: df1=df1.drop('Age_Group.1',axis=1)
```

```
[282]: condition = df1['EstimatedSalary'] == 0
```

```
[288]: df1.loc[condition, 'EstimatedSalary'] = int(round(df1['EstimatedSalary'].  
       ↪median(),0))
```

```
[289]: df1
```

```
[289]:    CustomerID  Age_Group  Rating(1-5)  Hotel  FoodPreference  Bill  \\\n      0            1   20-25        4.00    Ibis        Veg  1300.0\n      1            2   30-35        5.00  LemonTree  Non-Veg  2000.0\n      2            3   25-30        6.00  RedFox        Veg  1322.0\n      3            4   20-25        4.33  LemonTree        Veg  1234.0\n      4            5     35+        3.00    Ibis        Veg   989.0\n      5            6     35+        3.00    Ibis  Non-Veg  1909.0\n      6            7     35+        4.00  RedFox        Veg  1000.0\n      7            8   20-25        7.00  LemonTree        Veg  2999.0\n      8            9   25-30        2.00    Ibis  Non-Veg  3456.0\n     10           10   30-35        5.00  RedFox  Non-Veg  1620.9\n\n      NoOfPax  EstimatedSalary\n      0         2.0        40000.0\n      1         3.0        59000.0\n      2         2.0        30000.0\n      3         2.0       120000.0\n      4         2.0        45000.0\n      5         2.0       122220.0\n      6         2.3        21122.0\n      7         2.3       345673.0\n      8         2.3        62510.0\n     10         4.0        87777.0
```

```
[293]: df1.to_csv('Hotel_Dataset.csv',index=False)
```

```
[ ]: #create an own csv file in pandas
```

```
[314]: import pandas as pd  
import numpy as np
```

```
[315]: df2=pd.read_csv('bookstore_inventory.csv')
```

```
[316]: df2
```

```
[316]:    Book_ID          Title          Author  \\\n      0      101  The Great Gatsby  F. Scott Fitzgerald\n      1      102  To Kill a Mockingbird  Harper Lee\n      2      103                1984  George Orwell\n      3      104  Pride and Prejudice  Jane Austen\n      4      105  The Catcher in the Rye  J. D. Salinger\n      5      106        The Hobbit  J. R. R. Tolkien
```

6	107	Harry Potter and the Philosopher's Stone	J.K. Rowling
7	108	The Lord of the Rings	J. R. R. Tolkien
8	109	Animal Farm	George Orwell
9	110	The Alchemist	Paulo Coelho
10	111	The Alchemist	Paulo Coelho
11	112	The Davinci Code	Dan Brown
12	113	Inferno	Dan Brown
13	114	Angels & Demons	Dan Brown
14	115	The Kite Runner	Khaled Hosseini
15	116	One Hundred Years of Solitude	Gabriel García Márquez
16	117	Crime and Punishment	Fyodor Dostoevsky
17	118	Moby Dick	Herman Melville
18	119	War and Peace	Leo Tolstoy
19	120	The Odyssey	Homer

	Genre	Price	Stock	Publisher	\
0	Fiction	10.99	25.0	Scribner	
1	Fiction	8.5	NaN	J. B. Lippincott & Co	
2	Dystopian	9.99	40.0	Secker & Warburg	
3	Romance	abc	30.0	T. Egerton	
4	Fiction	7.5	20.0	Little, Brown and Company	
5	Fantasy	12.75	50.0	George Allen & Unwin	
6	Fantasy	11.2	100.0	Bloomsbury	
7	Fantasy	15	NaN	George Allen & Unwin	
8	Satire	5.99	70.0	Secker & Warburg	
9	Adventure	6.75	60.0	HarperOne	
10	Adventure	6.75	60.0	HarperOne	
11	Thriller	9.5	80.0	Doubleday	
12	NaN	10.25	90.0	Doubleday	
13	Thriller	8.9	85.0	Doubleday	
14	Drama	7.2	100.0	Riverhead Books	
15	Magical Realism	13.3	45.0	Harper & Row	
16	Philosophical	11.5	55.0	The Russian Messenger	
17	Adventure	not available	30.0	Harper & Brothers	
18	Historical	14	20.0	The Russian Messenger	
19	Epic Poetry	10	NaN	Ancient Greece Publishing	

	Year_Published	Language
0	1925	English
1	1960	ENGLISH
2	1949	English
3	1813	english
4	1951	EN
5	1937	Eng
6	1997	English
7	1954	English
8	1945	ENGLISH

```

9          1988    English
10         1988    English
11         2003    english
12         2013    English
13         2000    ENglish
14         2003    English
15         1970    Spansih
16         1866    Russian
17         1851    English
18         1869    English
19        -800     Greek

```

[317]: df2.drop_duplicates(inplace=True)

[318]: df2

	Book_ID	Title	Author	\
0	101	The Great Gatsby	F. Scott Fitzgerald	
1	102	To Kill a Mockingbird	Harper Lee	
2	103	1984	George Orwell	
3	104	Pride and Prejudice	Jane Austen	
4	105	The Catcher in the Rye	J. D. Salinger	
5	106	The Hobbit	J. R. R. Tolkien	
6	107	Harry Potter and the Philosopher's Stone	J.K. Rowling	
7	108	The Lord of the Rings	J. R. R. Tolkien	
8	109	Animal Farm	George Orwell	
9	110	The Alchemist	Paulo Coelho	
10	111	The Alchemist	Paulo Coelho	
11	112	The Davinci Code	Dan Brown	
12	113	Inferno	Dan Brown	
13	114	Angels & Demons	Dan Brown	
14	115	The Kite Runner	Khaled Hosseini	
15	116	One Hundred Years of Solitude	Gabriel García Márquez	
16	117	Crime and Punishment	Fyodor Dostoevsky	
17	118	Moby Dick	Herman Melville	
18	119	War and Peace	Leo Tolstoy	
19	120	The Odyssey	Homer	

	Genre	Price	Stock	Publisher	\
0	Fiction	10.99	25.0	Scribner	
1	Fiction	8.5	NaN	J. B. Lippincott & Co	
2	Dystopian	9.99	40.0	Secker & Warburg	
3	Romance	abc	30.0	T. Egerton	
4	Fiction	7.5	20.0	Little, Brown and Company	
5	Fantasy	12.75	50.0	George Allen & Unwin	
6	Fantasy	11.2	100.0	Bloomsburry	
7	Fantasy	15	NaN	George Allen & Unwin	

8	Satire	5.99	70.0	Secker & Warburg
9	Adventure	6.75	60.0	HarperOne
10	Adventure	6.75	60.0	HarperOne
11	Thriller	9.5	80.0	Doubleday
12	NaN	10.25	90.0	Doubleday
13	Thriler	8.9	85.0	Doubleday
14	Drama	7.2	100.0	Riverhead Books
15	Magical Realism	13.3	45.0	Harper & Row
16	Philosophical	11.5	55.0	The Russian Messenger
17	Adventure	not available	30.0	Harper & Brothers
18	Historical	14	20.0	The Russian Messenger
19	Epic Poetry	10	NaN	Ancient Greece Publishing

	Year_Published	Language
0	1925	English
1	1960	ENGLISH
2	1949	English
3	1813	english
4	1951	EN
5	1937	Eng
6	1997	English
7	1954	English
8	1945	ENGLISH
9	1988	English
10	1988	English
11	2003	english
12	2013	English
13	2000	ENglish
14	2003	English
15	1970	Spansih
16	1866	Russian
17	1851	English
18	1869	Englsh
19	-800	Greek

```
[319]: df2.drop_duplicates(subset=[col for col in df.columns if col != 'Book_ID'],  
↪inplace=True)
```

```
[320]: df2
```

	Book_ID	Title	Author	\
0	101	The Great Gatsby	F. Scott Fitzgerald	
1	102	To Kill a Mockingbird	Harper Lee	
2	103	1984	George Orwell	
3	104	Pride and Prejudice	Jane Austen	
4	105	The Catcher in the Rye	J. D. Salinger	
5	106	The Hobbit	J. R. R. Tolkien	

6	107	Harry Potter and the Philosopher's Stone	J.K. Rowling
7	108	The Lord of the Rings	J. R. R. Tolkien
8	109	Animal Farm	George Orwell
9	110	The Alchemist	Paulo Coelho
10	111	The Alchemist	Paulo Coelho
11	112	The Davinci Code	Dan Brown
12	113	Inferno	Dan Brown
13	114	Angels & Demons	Dan Brown
14	115	The Kite Runner	Khaled Hosseini
15	116	One Hundred Years of Solitude	Gabriel García Márquez
16	117	Crime and Punishment	Fyodor Dostoevsky
17	118	Moby Dick	Herman Melville
18	119	War and Peace	Leo Tolstoy
19	120	The Odyssey	Homer

	Genre	Price	Stock	Publisher	\
0	Fiction	10.99	25.0	Scribner	
1	Fiction	8.5	NaN	J. B. Lippincott & Co	
2	Dystopian	9.99	40.0	Secker & Warburg	
3	Romance	abc	30.0	T. Egerton	
4	Fiction	7.5	20.0	Little, Brown and Company	
5	Fantasy	12.75	50.0	George Allen & Unwin	
6	Fantasy	11.2	100.0	Bloomsbury	
7	Fantasy	15	NaN	George Allen & Unwin	
8	Satire	5.99	70.0	Secker & Warburg	
9	Adventure	6.75	60.0	HarperOne	
10	Adventure	6.75	60.0	HarperOne	
11	Thriller	9.5	80.0	Doubleday	
12	NaN	10.25	90.0	Doubleday	
13	Thriller	8.9	85.0	Doubleday	
14	Drama	7.2	100.0	Riverhead Books	
15	Magical Realism	13.3	45.0	Harper & Row	
16	Philosophical	11.5	55.0	The Russian Messenger	
17	Adventure	not available	30.0	Harper & Brothers	
18	Historical	14	20.0	The Russian Messenger	
19	Epic Poetry	10	NaN	Ancient Greece Publishing	

	Year_Published	Language
0	1925	English
1	1960	ENGLISH
2	1949	English
3	1813	english
4	1951	EN
5	1937	Eng
6	1997	English
7	1954	English
8	1945	ENGLISH

```

9          1988    English
10         1988  English
11          2003   english
12          2013    English
13          2000   ENglish
14          2003    English
15          1970   Spansih
16          1866   Russian
17          1851    English
18          1869    English
19          -800     Greek

```

```
[321]: for col in df2.columns:
    if df2[col].dtype == 'object':
        df2[col] = df2[col].str.strip()
    elif col != 'Book_ID':
        df2[col] = df2[col].astype(str)
```

```
[322]: df2 = df2.drop_duplicates(subset=[i for i in df2.columns if i != 'Book_ID'])
```

```
[323]: df2
```

	Book_ID	Title	Author	\	
0	101	The Great Gatsby	F. Scott Fitzgerald		
1	102	To Kill a Mockingbird	Harper Lee		
2	103	1984	George Orwell		
3	104	Pride and Prejudice	Jane Austen		
4	105	The Catcher in the Rye	J. D. Salinger		
5	106	The Hobbit	J. R. R. Tolkien		
6	107	Harry Potter and the Philosopher's Stone	J.K. Rowling		
7	108	The Lord of the Rings	J. R. R. Tolkien		
8	109	Animal Farm	George Orwell		
9	110	The Alchemist	Paulo Coelho		
11	112	The Davinci Code	Dan Brown		
12	113	Inferno	Dan Brown		
13	114	Angels & Demons	Dan Brown		
14	115	The Kite Runner	Khaled Hosseini		
15	116	One Hundred Years of Solitude	Gabriel García Márquez		
16	117	Crime and Punishment	Fyodor Dostoevsky		
17	118	Moby Dick	Herman Melville		
18	119	War and Peace	Leo Tolstoy		
19	120	The Odyssey	Homer		
	Genre	Price	Stock	Publisher	\
0	Fiction	10.99	25.0	Scribner	
1	Fiction	8.5	nan	J. B. Lippincott & Co	
2	Dystopian	9.99	40.0	Secker & Warburg	

3	Romance	abc	30.0	T. Egerton
4	Fiction	7.5	20.0	Little, Brown and Company
5	Fantasy	12.75	50.0	George Allen & Unwin
6	Fantasy	11.2	100.0	Bloomsburry
7	Fantasy	15	nan	George Allen & Unwin
8	Satire	5.99	70.0	Secker & Warburg
9	Adventure	6.75	60.0	HarperOne
11	Thriller	9.5	80.0	Doubleday
12	NaN	10.25	90.0	Doubleday
13	Thriler	8.9	85.0	Doubleday
14	Drama	7.2	100.0	Riverhead Books
15	Magical Realism	13.3	45.0	Harper & Row
16	Philosophical	11.5	55.0	The Russian Messenger
17	Adventure	not available	30.0	Harper & Brothers
18	Historical	14	20.0	The Russian Messenger
19	Epic Poetry	10	nan	Ancient Greece Publishing

	Year_Published	Language
0	1925	English
1	1960	ENGLISH
2	1949	English
3	1813	english
4	1951	EN
5	1937	Eng
6	1997	English
7	1954	English
8	1945	ENGLISH
9	1988	English
11	2003	english
12	2013	English
13	2000	ENglish
14	2003	English
15	1970	Spansih
16	1866	Russian
17	1851	English
18	1869	English
19	-800	Greek

```
[324]: column=[]
```

```
[325]: for i in range(len(df2['Stock'])):
    if(df2['Stock'].iloc[i]=='nan'):
        column.append(i)
```

```
[326]: column
```

```
[326]: [1, 7, 18]
```

```
[327]: df2['Stock'].info()

<class 'pandas.core.series.Series'>
Index: 19 entries, 0 to 19
Series name: Stock
Non-Null Count Dtype
-----
19 non-null    object
dtypes: object(1)
memory usage: 304.0+ bytes
```

```
[328]: df2['Stock'].info()

<class 'pandas.core.series.Series'>
Index: 19 entries, 0 to 19
Series name: Stock
Non-Null Count Dtype
-----
19 non-null    object
dtypes: object(1)
memory usage: 304.0+ bytes
```

```
[329]: for i in column:
         df2.loc[i, 'Stock'] = 0
```

```
[330]: df2
```

	Book_ID	Title	Author
0	101	The Great Gatsby	F. Scott Fitzgerald
1	102	To Kill a Mockingbird	Harper Lee
2	103	1984	George Orwell
3	104	Pride and Prejudice	Jane Austen
4	105	The Catcher in the Rye	J. D. Salinger
5	106	The Hobbit	J. R. R. Tolkien
6	107	Harry Potter and the Philosopher's Stone	J.K. Rowling
7	108	The Lord of the Rings	J. R. R. Tolkien
8	109	Animal Farm	George Orwell
9	110	The Alchemist	Paulo Coelho
11	112	The Davinci Code	Dan Brown
12	113	Inferno	Dan Brown
13	114	Angels & Demons	Dan Brown
14	115	The Kite Runner	Khaled Hosseini
15	116	One Hundred Years of Solitude	Gabriel García Márquez
16	117	Crime and Punishment	Fyodor Dostoevsky
17	118	Moby Dick	Herman Melville
18	119	War and Peace	Leo Tolstoy
19	120	The Odyssey	Homer

	Genre	Price	Stock	Publisher	\
0	Fiction	10.99	25.0	Scribner	
1	Fiction	8.5	0	J. B. Lippincott & Co	
2	Dystopian	9.99	40.0	Secker & Warburg	
3	Romance	abc	30.0	T. Egerton	
4	Fiction	7.5	20.0	Little, Brown and Company	
5	Fantasy	12.75	50.0	George Allen & Unwin	
6	Fantasy	11.2	100.0	Bloomsburry	
7	Fantasy	15	0	George Allen & Unwin	
8	Satire	5.99	70.0	Secker & Warburg	
9	Adventure	6.75	60.0	HarperOne	
11	Thriller	9.5	80.0	Doubleday	
12	NaN	10.25	90.0	Doubleday	
13	Thriler	8.9	85.0	Doubleday	
14	Drama	7.2	100.0	Riverhead Books	
15	Magical Realism	13.3	45.0	Harper & Row	
16	Philosophical	11.5	55.0	The Russian Messenger	
17	Adventure	not available	30.0	Harper & Brothers	
18	Historical	14	0	The Russian Messenger	
19	Epic Poetry	10	nan	Ancient Greece Publishing	

	Year_Published	Language
0	1925	English
1	1960	ENGLISH
2	1949	English
3	1813	english
4	1951	EN
5	1937	Eng
6	1997	English
7	1954	English
8	1945	ENGLISH
9	1988	English
11	2003	english
12	2013	English
13	2000	ENglish
14	2003	English
15	1970	Spansih
16	1866	Russian
17	1851	English
18	1869	Englsh
19	-800	Greek

```
[331]: df2.loc[:, 'Stock'] = df2['Stock'].fillna(0)
```

```
[332]: df2
```

[332] :	Book_ID	Title	Author \
0	101	The Great Gatsby	F. Scott Fitzgerald
1	102	To Kill a Mockingbird	Harper Lee
2	103	1984	George Orwell
3	104	Pride and Prejudice	Jane Austen
4	105	The Catcher in the Rye	J. D. Salinger
5	106	The Hobbit	J. R. R. Tolkien
6	107	Harry Potter and the Philosopher's Stone	J.K. Rowling
7	108	The Lord of the Rings	J. R. R. Tolkien
8	109	Animal Farm	George Orwell
9	110	The Alchemist	Paulo Coelho
11	112	The Davinci Code	Dan Brown
12	113	Inferno	Dan Brown
13	114	Angels & Demons	Dan Brown
14	115	The Kite Runner	Khaled Hosseini
15	116	One Hundred Years of Solitude	Gabriel García Márquez
16	117	Crime and Punishment	Fyodor Dostoevsky
17	118	Moby Dick	Herman Melville
18	119	War and Peace	Leo Tolstoy
19	120	The Odyssey	Homer

	Genre	Price	Stock	Publisher \
0	Fiction	10.99	25.0	Scribner
1	Fiction	8.5	0	J. B. Lippincott & Co
2	Dystopian	9.99	40.0	Secker & Warburg
3	Romance	abc	30.0	T. Egerton
4	Fiction	7.5	20.0	Little, Brown and Company
5	Fantasy	12.75	50.0	George Allen & Unwin
6	Fantasy	11.2	100.0	Bloomsburry
7	Fantasy	15	0	George Allen & Unwin
8	Satire	5.99	70.0	Secker & Warburg
9	Adventure	6.75	60.0	HarperOne
11	Thriller	9.5	80.0	Doubleday
12	NaN	10.25	90.0	Doubleday
13	Thriler	8.9	85.0	Doubleday
14	Drama	7.2	100.0	Riverhead Books
15	Magical Realism	13.3	45.0	Harper & Row
16	Philosophical	11.5	55.0	The Russian Messenger
17	Adventure	not available	30.0	Harper & Brothers
18	Historical	14	0	The Russian Messenger
19	Epic Poetry	10	nan	Ancient Greece Publishing

	Year_Published	Language
0	1925	English
1	1960	ENGLISH
2	1949	English
3	1813	english

```

4          1951      EN
5          1937      Eng
6          1997  English
7          1954  English
8          1945 ENGLISH
9          1988  English
11         2003  english
12         2013  English
13         2000 ENglish
14         2003  English
15         1970  Spansih
16         1866  Russian
17         1851  English
18         1869  English
19        -800   Greek

```

```
[333]: value = df2['Stock'].median()
```

```
[334]: df2.loc[df2['Stock'] == 0.0, 'Stock'] = value
```

```
[335]: df2
```

	Book_ID	Title	Author	\	
0	101	The Great Gatsby	F. Scott Fitzgerald		
1	102	To Kill a Mockingbird	Harper Lee		
2	103	1984	George Orwell		
3	104	Pride and Prejudice	Jane Austen		
4	105	The Catcher in the Rye	J. D. Salinger		
5	106	The Hobbit	J. R. R. Tolkien		
6	107	Harry Potter and the Philosopher's Stone	J.K. Rowling		
7	108	The Lord of the Rings	J. R. R. Tolkien		
8	109	Animal Farm	George Orwell		
9	110	The Alchemist	Paulo Coelho		
11	112	The Davinci Code	Dan Brown		
12	113	Inferno	Dan Brown		
13	114	Angels & Demons	Dan Brown		
14	115	The Kite Runner	Khaled Hosseini		
15	116	One Hundred Years of Solitude	Gabriel García Márquez		
16	117	Crime and Punishment	Fyodor Dostoevsky		
17	118	Moby Dick	Herman Melville		
18	119	War and Peace	Leo Tolstoy		
19	120	The Odyssey	Homer		
	Genre	Price	Stock	Publisher	\
0	Fiction	10.99	25.0	Scribner	
1	Fiction	8.5	47.5	J. B. Lippincott & Co	
2	Dystopian	9.99	40.0	Secker & Warburg	

3	Romance	abc	30.0	T. Egerton
4	Fiction	7.5	20.0	Little, Brown and Company
5	Fantasy	12.75	50.0	George Allen & Unwin
6	Fantasy	11.2	100.0	Bloomsburry
7	Fantasy	15	47.5	George Allen & Unwin
8	Satire	5.99	70.0	Secker & Warburg
9	Adventure	6.75	60.0	HarperOne
11	Thriller	9.5	80.0	Doubleday
12	NaN	10.25	90.0	Doubleday
13	Thriler	8.9	85.0	Doubleday
14	Drama	7.2	100.0	Riverhead Books
15	Magical Realism	13.3	45.0	Harper & Row
16	Philosophical	11.5	55.0	The Russian Messenger
17	Adventure	not available	30.0	Harper & Brothers
18	Historical	14	47.5	The Russian Messenger
19	Epic Poetry	10	nan	Ancient Greece Publishing

	Year_Published	Language
0	1925	English
1	1960	ENGLISH
2	1949	English
3	1813	english
4	1951	EN
5	1937	Eng
6	1997	English
7	1954	English
8	1945	ENGLISH
9	1988	English
11	2003	english
12	2013	English
13	2000	ENglish
14	2003	English
15	1970	Spansih
16	1866	Russian
17	1851	English
18	1869	Englsh
19	-800	Greek

```
[336]: df2['Stock'].astype(float)
```

```
[336]: 0    25.0
1    47.5
2    40.0
3    30.0
4    20.0
5    50.0
6   100.0
```

```
7      47.5
8      70.0
9      60.0
11     80.0
12     90.0
13     85.0
14    100.0
15     45.0
16     55.0
17     30.0
18     47.5
19      NaN
Name: Stock, dtype: float64
```

```
[337]: df2 = df.copy()
df2['Stock'].fillna(value)
```

```
0      46.315789
1      46.315789
2      40.000000
3      30.000000
4      20.000000
5      50.000000
6     100.000000
7      46.315789
8      70.000000
9      60.000000
11     80.000000
12     90.000000
13     85.000000
14    100.000000
15     45.000000
16     55.000000
17     30.000000
18      0.000000
19      0.000000
Name: Stock, dtype: float64
```

```
[338]: df2
```

```
[338]:   Book_ID          Title           Author \
0      101      The Great Gatsby  F. Scott Fitzgerald
1      102  To Kill a Mockingbird  Harper Lee
2      103            1984        George Orwell
3      104  Pride and Prejudice  Jane Austen
4      105  The Catcher in the Rye  J. D. Salinger
5      106        The Hobbit  J. R. R. Tolkien
```

6	107	Harry Potter and the Philosopher's Stone	J.K. Rowling
7	108	The Lord of the Rings	J. R. R. Tolkien
8	109	Animal Farm	George Orwell
9	110	The Alchemist	Paulo Coelho
11	112	The Davinci Code	Dan Brown
12	113	Inferno	Dan Brown
13	114	Angels & Demons	Dan Brown
14	115	The Kite Runner	Khaled Hosseini
15	116	One Hundred Years of Solitude	Gabriel García Márquez
16	117	Crime and Punishment	Fyodor Dostoevsky
17	118	Moby Dick	Herman Melville
18	119	War and Peace	Leo Tolstoy
19	120	The Odyssey	Homer

	Genre	Price	Stock	Publisher \
0	Fiction	10	46.315789	Scribner
1	Fiction	8	46.315789	J. B. Lippincott & Co
2	Dystopian	9	40.000000	Secker & Warburg
3	Romance	8	30.000000	T. Egerton
4	Fiction	7	20.000000	Little, Brown and Company
5	Fantasy	12	50.000000	George Allen & Unwin
6	Fantasy	11	100.000000	Bloomsbury
7	Fantasy	15	46.315789	George Allen & Unwin
8	Satire	5	70.000000	Secker & Warburg
9	Adventure	6	60.000000	HarperOne
11	Thriller	9	80.000000	Doubleday
12	NaN	10	90.000000	Doubleday
13	Thriller	8	85.000000	Doubleday
14	Drama	7	100.000000	Riverhead Books
15	Magical Realism	13	45.000000	Harper & Row
16	Philosophical	11	55.000000	The Russian Messenger
17	Adventure	8	30.000000	Harper & Brothers
18	Historical	14	0.000000	The Russian Messenger
19	Epic Poetry	10	0.000000	Ancient Greece Publishing

	Year_Published	Language
0	1925	English
1	1960	ENGLISH
2	1949	English
3	1813	english
4	1951	EN
5	1937	Eng
6	1997	English
7	1954	English
8	1945	ENGLISH
9	1988	English
11	2003	english

```
12          2013 English
13          2000 ENglish
14          2003 English
15          1970 Spansih
16          1866 Russian
17          1851 English
18          1869 English
19          -800 Greek
```

```
[339]: df2['Price'].info()
```

```
<class 'pandas.core.series.Series'>
Index: 19 entries, 0 to 19
Series name: Price
Non-Null Count Dtype
-----
19 non-null    int64
dtypes: int64(1)
memory usage: 860.0+ bytes
```

```
[340]: df2['Price'].info()
```

```
<class 'pandas.core.series.Series'>
Index: 19 entries, 0 to 19
Series name: Price
Non-Null Count Dtype
-----
19 non-null    int64
dtypes: int64(1)
memory usage: 860.0+ bytes
```

```
[341]: df2['Price'].fillna(0)
```

```
[341]: 0      10
1      8
2      9
3      8
4      7
5      12
6      11
7      15
8      5
9      6
11     9
12     10
13     8
14     7
15     13
```

```

16    11
17     8
18    14
19    10
Name: Price, dtype: int64

```

```
[342]: val=df2['Price'].mean()
```

```
[343]: for i in range(len(df2['Price'])):
    if df2.iloc[i]['Price'] == 0:
        df2.iloc[i]['Price'] =val
```

```
[344]: df2
```

	Book_ID	Title	Author
0	101	The Great Gatsby	F. Scott Fitzgerald
1	102	To Kill a Mockingbird	Harper Lee
2	103	1984	George Orwell
3	104	Pride and Prejudice	Jane Austen
4	105	The Catcher in the Rye	J. D. Salinger
5	106	The Hobbit	J. R. R. Tolkien
6	107	Harry Potter and the Philosopher's Stone	J.K. Rowling
7	108	The Lord of the Rings	J. R. R. Tolkien
8	109	Animal Farm	George Orwell
9	110	The Alchemist	Paulo Coelho
11	112	The Davinci Code	Dan Brown
12	113	Inferno	Dan Brown
13	114	Angels & Demons	Dan Brown
14	115	The Kite Runner	Khaled Hosseini
15	116	One Hundred Years of Solitude	Gabriel García Márquez
16	117	Crime and Punishment	Fyodor Dostoevsky
17	118	Moby Dick	Herman Melville
18	119	War and Peace	Leo Tolstoy
19	120	The Odyssey	Homer

	Genre	Price	Stock	Publisher
0	Fiction	10	46.315789	Scribner
1	Fiction	8	46.315789	J. B. Lippincott & Co
2	Dystopian	9	40.000000	Secker & Warburg
3	Romance	8	30.000000	T. Egerton
4	Fiction	7	20.000000	Little, Brown and Company
5	Fantasy	12	50.000000	George Allen & Unwin
6	Fantasy	11	100.000000	Bloomsbury
7	Fantasy	15	46.315789	George Allen & Unwin
8	Satire	5	70.000000	Secker & Warburg
9	Adventure	6	60.000000	HarperOne
11	Thriller	9	80.000000	Doubleday

12	NaN	10	90.000000	Doubleday
13	Thriler	8	85.000000	Doubleday
14	Drama	7	100.000000	Riverhead Books
15	Magical Realism	13	45.000000	Harper & Row
16	Philosophical	11	55.000000	The Russian Messenger
17	Adventure	8	30.000000	Harper & Brothers
18	Historical	14	0.000000	The Russian Messenger
19	Epic Poetry	10	0.000000	Ancient Greece Publishing

	Year_Published	Language
0	1925	English
1	1960	ENGLISH
2	1949	English
3	1813	english
4	1951	EN
5	1937	Eng
6	1997	English
7	1954	English
8	1945	ENGLISH
9	1988	English
11	2003	english
12	2013	English
13	2000	ENglish
14	2003	English
15	1970	Spansih
16	1866	Russian
17	1851	English
18	1869	English
19	-800	Greek

```
[345]: df2['Year_Published']=df2['Year_Published'].astype(int)
```

```
[346]: df2['Year_Published'].info()
```

```
<class 'pandas.core.series.Series'>
Index: 19 entries, 0 to 19
Series name: Year_Published
Non-Null Count Dtype
-----
19 non-null    int64
dtypes: int64(1)
memory usage: 860.0+ bytes
```

```
[347]: df2 = df2[df2['Year_Published'] >= 0]
```

```
[348]: df2
```

[348] :	Book_ID	Title	Author \
0	101	The Great Gatsby	F. Scott Fitzgerald
1	102	To Kill a Mockingbird	Harper Lee
2	103	1984	George Orwell
3	104	Pride and Prejudice	Jane Austen
4	105	The Catcher in the Rye	J. D. Salinger
5	106	The Hobbit	J. R. R. Tolkien
6	107	Harry Potter and the Philosopher's Stone	J.K. Rowling
7	108	The Lord of the Rings	J. R. R. Tolkien
8	109	Animal Farm	George Orwell
9	110	The Alchemist	Paulo Coelho
11	112	The Davinci Code	Dan Brown
12	113	Inferno	Dan Brown
13	114	Angels & Demons	Dan Brown
14	115	The Kite Runner	Khaled Hosseini
15	116	One Hundred Years of Solitude	Gabriel García Márquez
16	117	Crime and Punishment	Fyodor Dostoevsky
17	118	Moby Dick	Herman Melville
18	119	War and Peace	Leo Tolstoy

	Genre	Price	Stock	Publisher \
0	Fiction	10	46.315789	Scribner
1	Fiction	8	46.315789	J. B. Lippincott & Co
2	Dystopian	9	40.000000	Secker & Warburg
3	Romance	8	30.000000	T. Egerton
4	Fiction	7	20.000000	Little, Brown and Company
5	Fantasy	12	50.000000	George Allen & Unwin
6	Fantasy	11	100.000000	Bloomsbury
7	Fantasy	15	46.315789	George Allen & Unwin
8	Satire	5	70.000000	Secker & Warburg
9	Adventure	6	60.000000	HarperOne
11	Thriller	9	80.000000	Doubleday
12	NaN	10	90.000000	Doubleday
13	Thriller	8	85.000000	Doubleday
14	Drama	7	100.000000	Riverhead Books
15	Magical Realism	13	45.000000	Harper & Row
16	Philosophical	11	55.000000	The Russian Messenger
17	Adventure	8	30.000000	Harper & Brothers
18	Historical	14	0.000000	The Russian Messenger

	Year_Published	Language
0	1925	English
1	1960	ENGLISH
2	1949	English
3	1813	english
4	1951	EN
5	1937	Eng

```

6          1997 English
7          1954 English
8          1945 ENGLISH
9          1988 English
11         2003 english
12         2013 English
13         2000 ENglish
14         2003 English
15         1970 Spansih
16         1866 Russian
17         1851 English
18         1869 Englsh

```

[349]: df2.dropna()

	Book_ID	Title	Author
0	101	The Great Gatsby	F. Scott Fitzgerald
1	102	To Kill a Mockingbird	Harper Lee
2	103	1984	George Orwell
3	104	Pride and Prejudice	Jane Austen
4	105	The Catcher in the Rye	J. D. Salinger
5	106	The Hobbit	J. R. R. Tolkien
6	107	Harry Potter and the Philosopher's Stone	J.K. Rowling
7	108	The Lord of the Rings	J. R. R. Tolkien
8	109	Animal Farm	George Orwell
9	110	The Alchemist	Paulo Coelho
11	112	The Davinci Code	Dan Brown
13	114	Angels & Demons	Dan Brown
14	115	The Kite Runner	Khaled Hosseini
15	116	One Hundred Years of Solitude	Gabriel García Márquez
16	117	Crime and Punishment	Fyodor Dostoevsky
17	118	Moby Dick	Herman Melville
18	119	War and Peace	Leo Tolstoy

	Genre	Price	Stock	Publisher
0	Fiction	10	46.315789	Scribner
1	Fiction	8	46.315789	J. B. Lippincott & Co
2	Dystopian	9	40.000000	Secker & Warburg
3	Romance	8	30.000000	T. Egerton
4	Fiction	7	20.000000	Little, Brown and Company
5	Fantasy	12	50.000000	George Allen & Unwin
6	Fantasy	11	100.000000	Bloomsbury
7	Fantasy	15	46.315789	George Allen & Unwin
8	Satire	5	70.000000	Secker & Warburg
9	Adventure	6	60.000000	HarperOne
11	Thriller	9	80.000000	Doubleday
13	Thriller	8	85.000000	Doubleday

14	Drama	7	100.000000	Riverhead Books
15	Magical Realism	13	45.000000	Harper & Row
16	Philosophical	11	55.000000	The Russian Messenger
17	Adventure	8	30.000000	Harper & Brothers
18	Historical	14	0.000000	The Russian Messenger

	Year_Published	Language
0	1925	English
1	1960	ENGLISH
2	1949	English
3	1813	english
4	1951	EN
5	1937	Eng
6	1997	English
7	1954	English
8	1945	ENGLISH
9	1988	English
11	2003	english
13	2000	ENglish
14	2003	English
15	1970	Spansih
16	1866	Russian
17	1851	English
18	1869	Englsh

```
[353]: df2 = df2.copy()
df2['Language']=df2['Language'].str.
    .replace(r'\b(ENGLISH|EN|Eng|english|ENglish|Englsh)\b', 'English', regex=True)
```

```
[354]: df2
```

	Book_ID	Title	Author
0	101	The Great Gatsby	F. Scott Fitzgerald
1	102	To Kill a Mockingbird	Harper Lee
2	103	1984	George Orwell
3	104	Pride and Prejudice	Jane Austen
4	105	The Catcher in the Rye	J. D. Salinger
5	106	The Hobbit	J. R. R. Tolkien
6	107	Harry Potter and the Philosopher's Stone	J.K. Rowling
7	108	The Lord of the Rings	J. R. R. Tolkien
8	109	Animal Farm	George Orwell
9	110	The Alchemist	Paulo Coelho
11	112	The Davinci Code	Dan Brown
12	113	Inferno	Dan Brown
13	114	Angels & Demons	Dan Brown
14	115	The Kite Runner	Khaled Hosseini
15	116	One Hundred Years of Solitude	Gabriel García Márquez

16	117	Crime and Punishment	Fyodor Dostoevsky
17	118	Moby Dick	Herman Melville
18	119	War and Peace	Leo Tolstoy

	Genre	Price	Stock	Publisher \
0	Fiction	10	46.315789	Scribner
1	Fiction	8	46.315789	J. B. Lippincott & Co
2	Dystopian	9	40.000000	Secker & Warburg
3	Romance	8	30.000000	T. Egerton
4	Fiction	7	20.000000	Little, Brown and Company
5	Fantasy	12	50.000000	George Allen & Unwin
6	Fantasy	11	100.000000	Bloomsbury
7	Fantasy	15	46.315789	George Allen & Unwin
8	Satire	5	70.000000	Secker & Warburg
9	Adventure	6	60.000000	HarperOne
11	Thriller	9	80.000000	Doubleday
12	NaN	10	90.000000	Doubleday
13	Thriller	8	85.000000	Doubleday
14	Drama	7	100.000000	Riverhead Books
15	Magical Realism	13	45.000000	Harper & Row
16	Philosophical	11	55.000000	The Russian Messenger
17	Adventure	8	30.000000	Harper & Brothers
18	Historical	14	0.000000	The Russian Messenger

	Year_Published	Language
0	1925	English
1	1960	English
2	1949	English
3	1813	English
4	1951	English
5	1937	English
6	1997	English
7	1954	English
8	1945	English
9	1988	English
11	2003	English
12	2013	English
13	2000	English
14	2003	English
15	1970	Spansih
16	1866	Russian
17	1851	English
18	1869	English

[352] : df2

[352] :	Book_ID	Title	Author \
0	101	The Great Gatsby	F. Scott Fitzgerald
1	102	To Kill a Mockingbird	Harper Lee
2	103	1984	George Orwell
3	104	Pride and Prejudice	Jane Austen
4	105	The Catcher in the Rye	J. D. Salinger
5	106	The Hobbit	J. R. R. Tolkien
6	107	Harry Potter and the Philosopher's Stone	J.K. Rowling
7	108	The Lord of the Rings	J. R. R. Tolkien
8	109	Animal Farm	George Orwell
9	110	The Alchemist	Paulo Coelho
11	112	The Davinci Code	Dan Brown
12	113	Inferno	Dan Brown
13	114	Angels & Demons	Dan Brown
14	115	The Kite Runner	Khaled Hosseini
15	116	One Hundred Years of Solitude	Gabriel García Márquez
16	117	Crime and Punishment	Fyodor Dostoevsky
17	118	Moby Dick	Herman Melville
18	119	War and Peace	Leo Tolstoy

	Genre	Price	Stock	Publisher \
0	Fiction	10	46.315789	Scribner
1	Fiction	8	46.315789	J. B. Lippincott & Co
2	Dystopian	9	40.000000	Secker & Warburg
3	Romance	8	30.000000	T. Egerton
4	Fiction	7	20.000000	Little, Brown and Company
5	Fantasy	12	50.000000	George Allen & Unwin
6	Fantasy	11	100.000000	Bloomsbury
7	Fantasy	15	46.315789	George Allen & Unwin
8	Satire	5	70.000000	Secker & Warburg
9	Adventure	6	60.000000	HarperOne
11	Thriller	9	80.000000	Doubleday
12	NaN	10	90.000000	Doubleday
13	Thriller	8	85.000000	Doubleday
14	Drama	7	100.000000	Riverhead Books
15	Magical Realism	13	45.000000	Harper & Row
16	Philosophical	11	55.000000	The Russian Messenger
17	Adventure	8	30.000000	Harper & Brothers
18	Historical	14	0.000000	The Russian Messenger

	Year_Published	Language
0	1925	English
1	1960	English
2	1949	English
3	1813	English
4	1951	English
5	1937	English

```
6      1997 English
7      1954 English
8      1945 English
9      1988 English
11     2003 English
12     2013 English
13     2000 English
14     2003 English
15     1970 Spansih
16     1866 Russian
17     1851 English
18     1869 English
```

```
[355]: df2.to_csv('bookstore_inventory.csv')
```

exe-4

November 2, 2025

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

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

```
[3]: arr
```

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

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

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

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

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

47.125
86.125

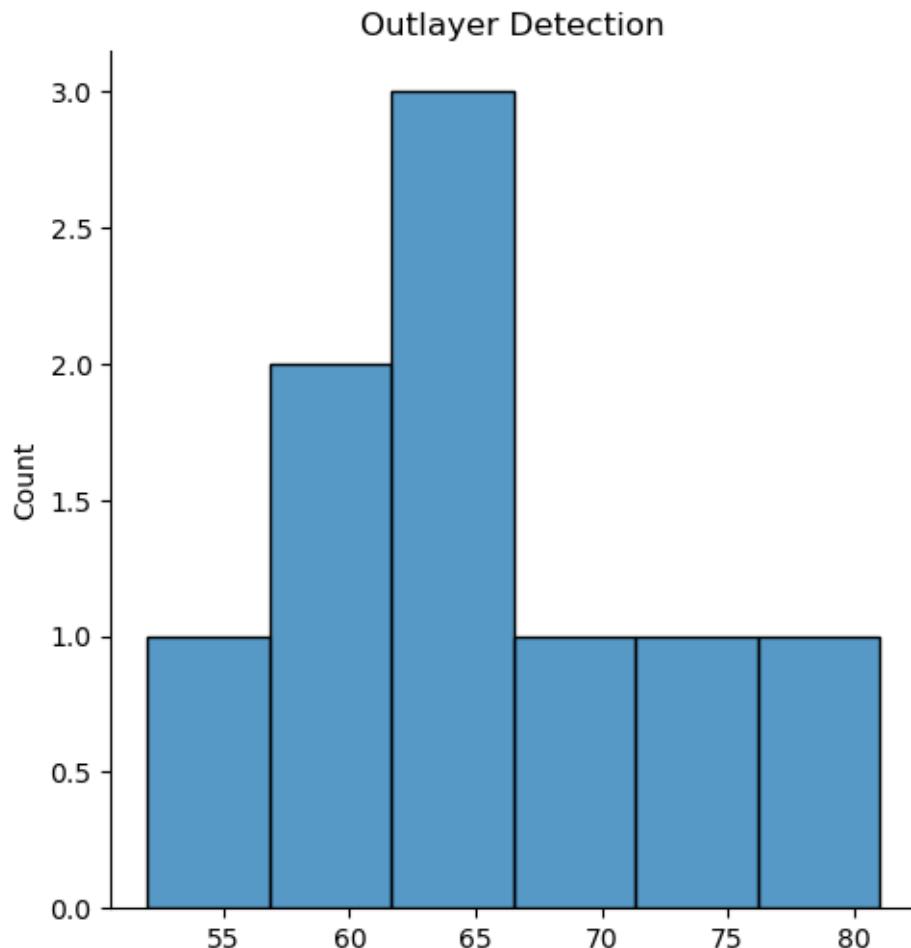
```
[9]: arr1=arr[(arr>n) & (arr<m)]
```

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

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

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

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

```
[20]: 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
```

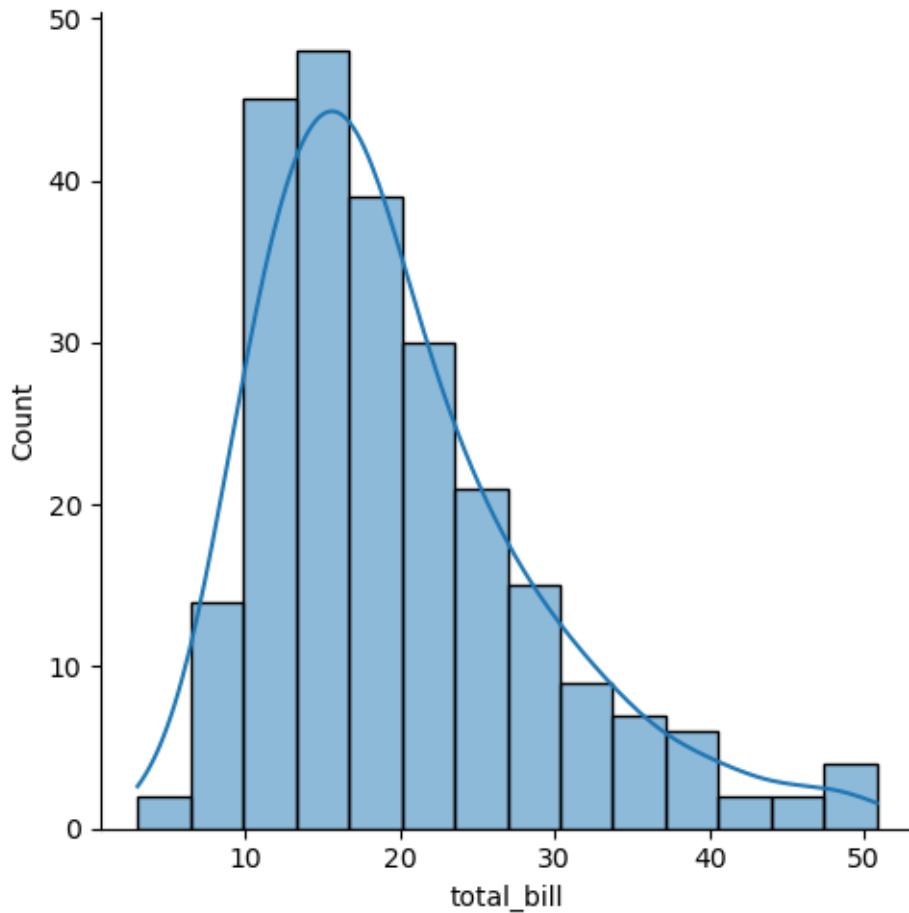
```
[14]: df=pd.read_csv('tips.csv')
```

```
[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
```

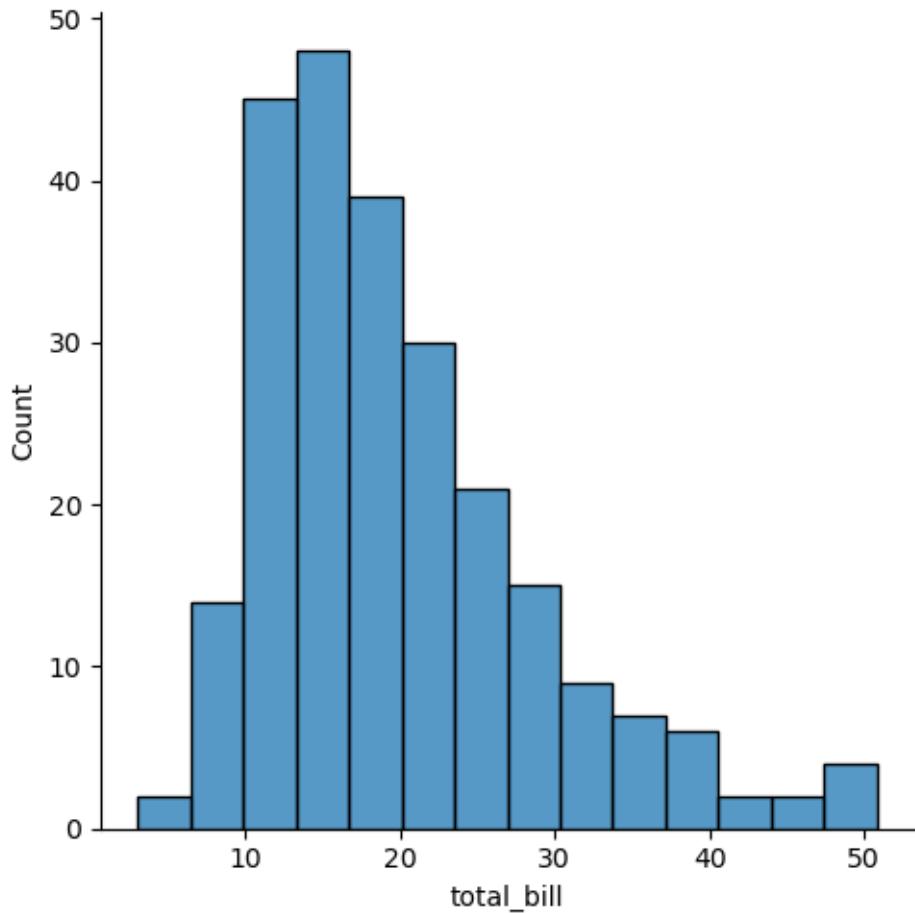
```
[16]: sn.displot(df.total_bill,kde=True)
```

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



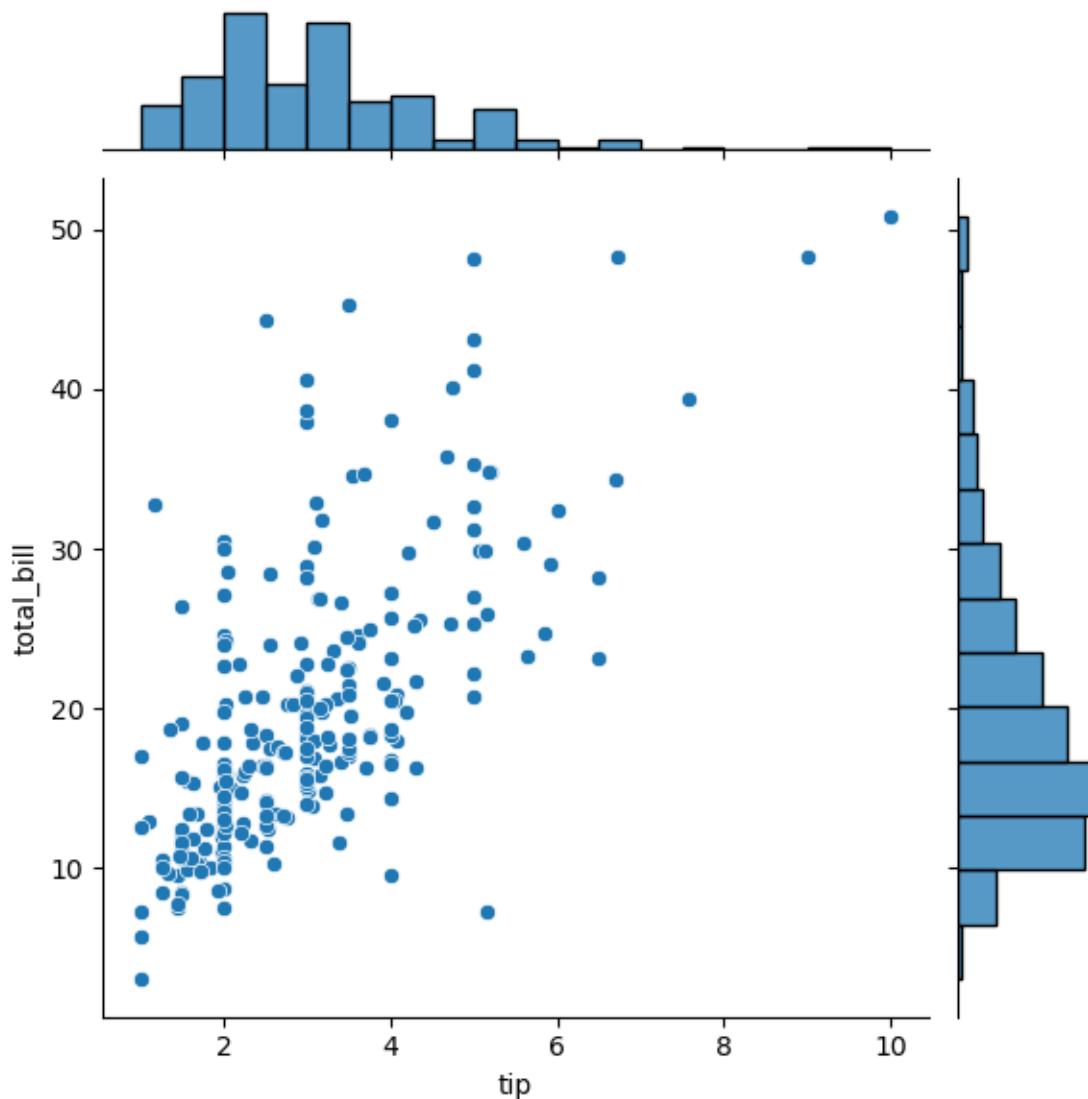
```
[17]: sn.displot(df.total_bill,kde=False)
```

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



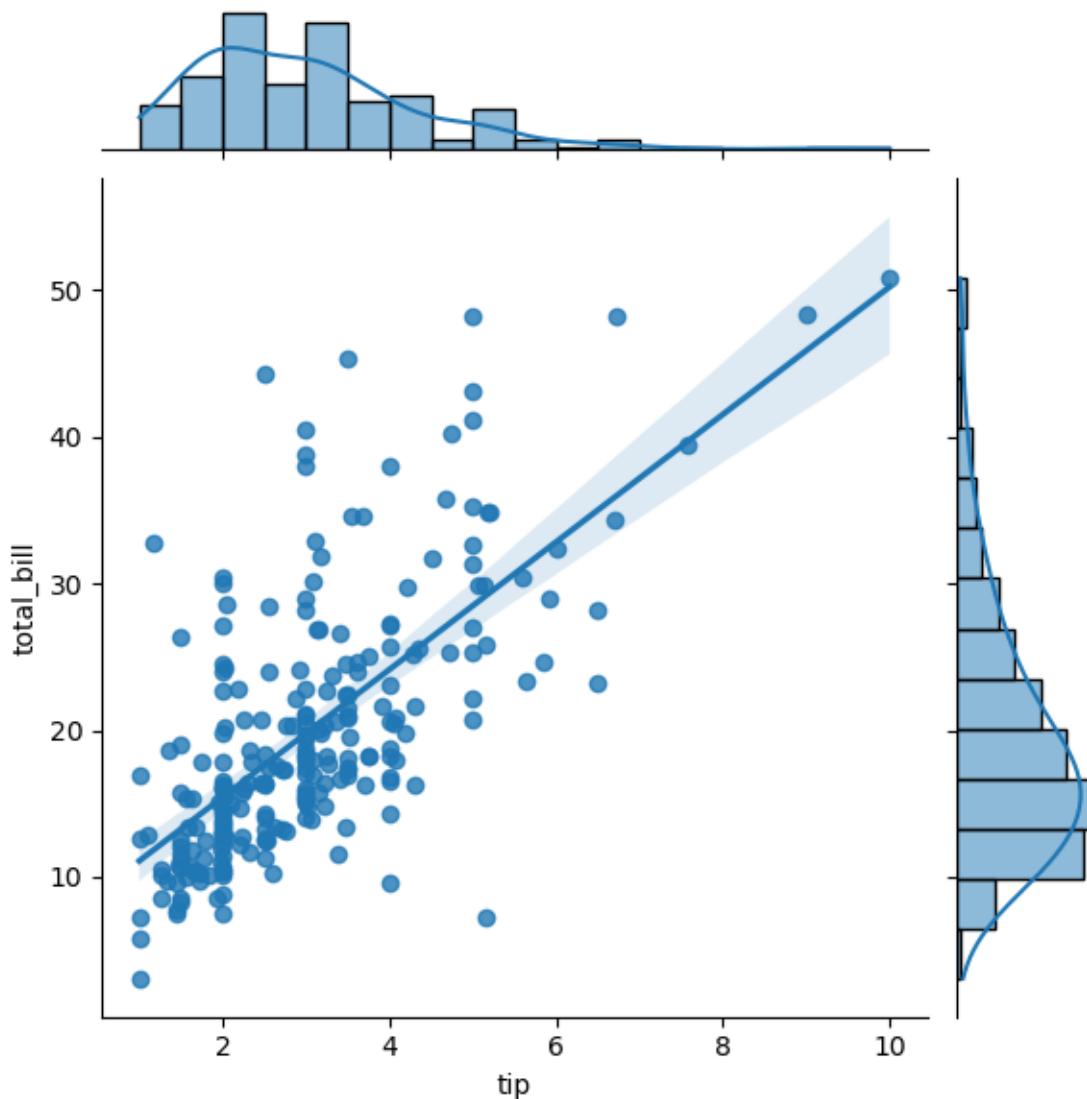
```
[21]: #plt.scatter(x=df.tip,y=df.total_bill)
sn.jointplot(x=df.tip,y=df.total_bill)
```

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



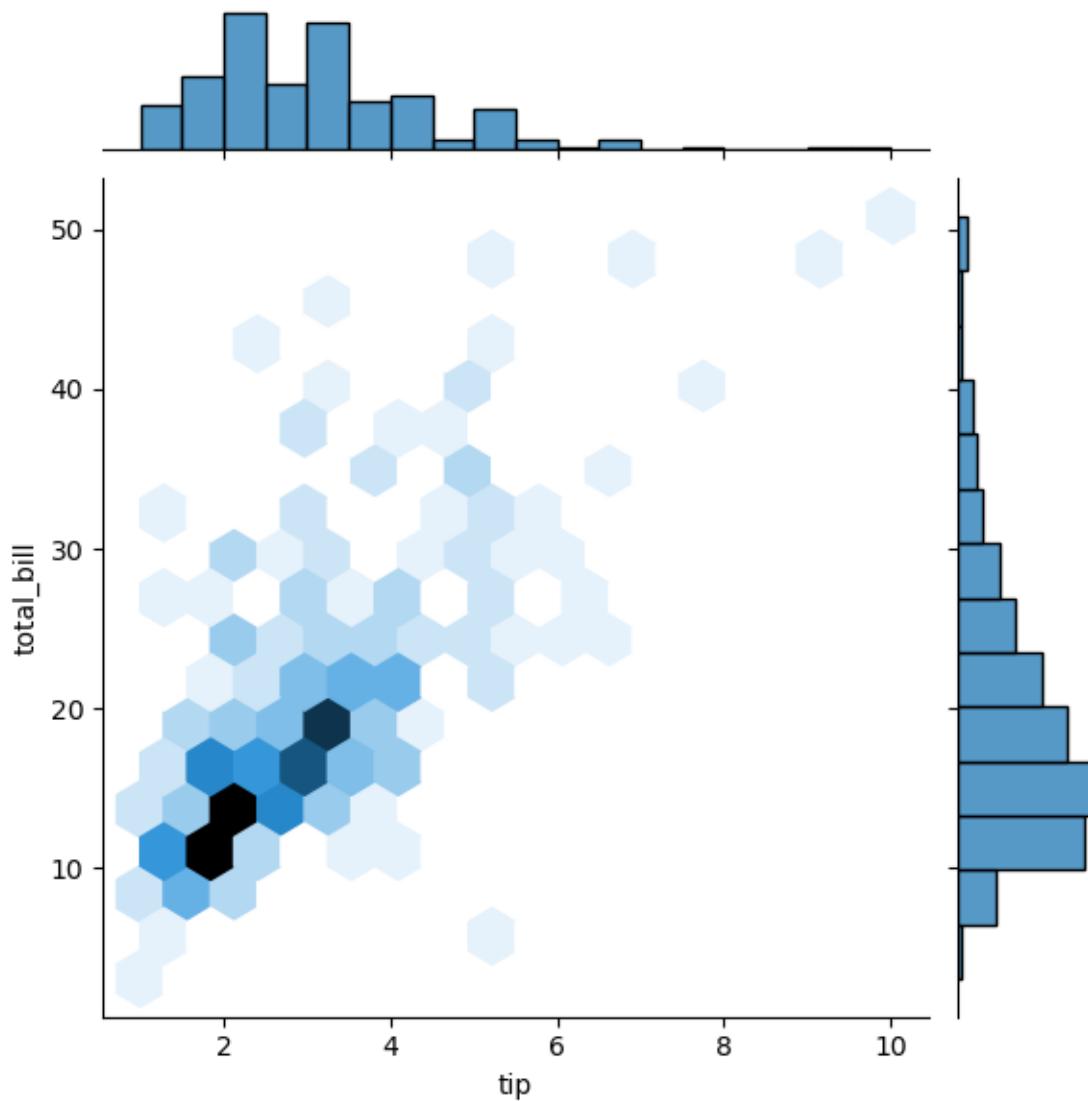
```
[22]: sn.jointplot(x=df.tip,y=df.total_bill,kind="reg")
```

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



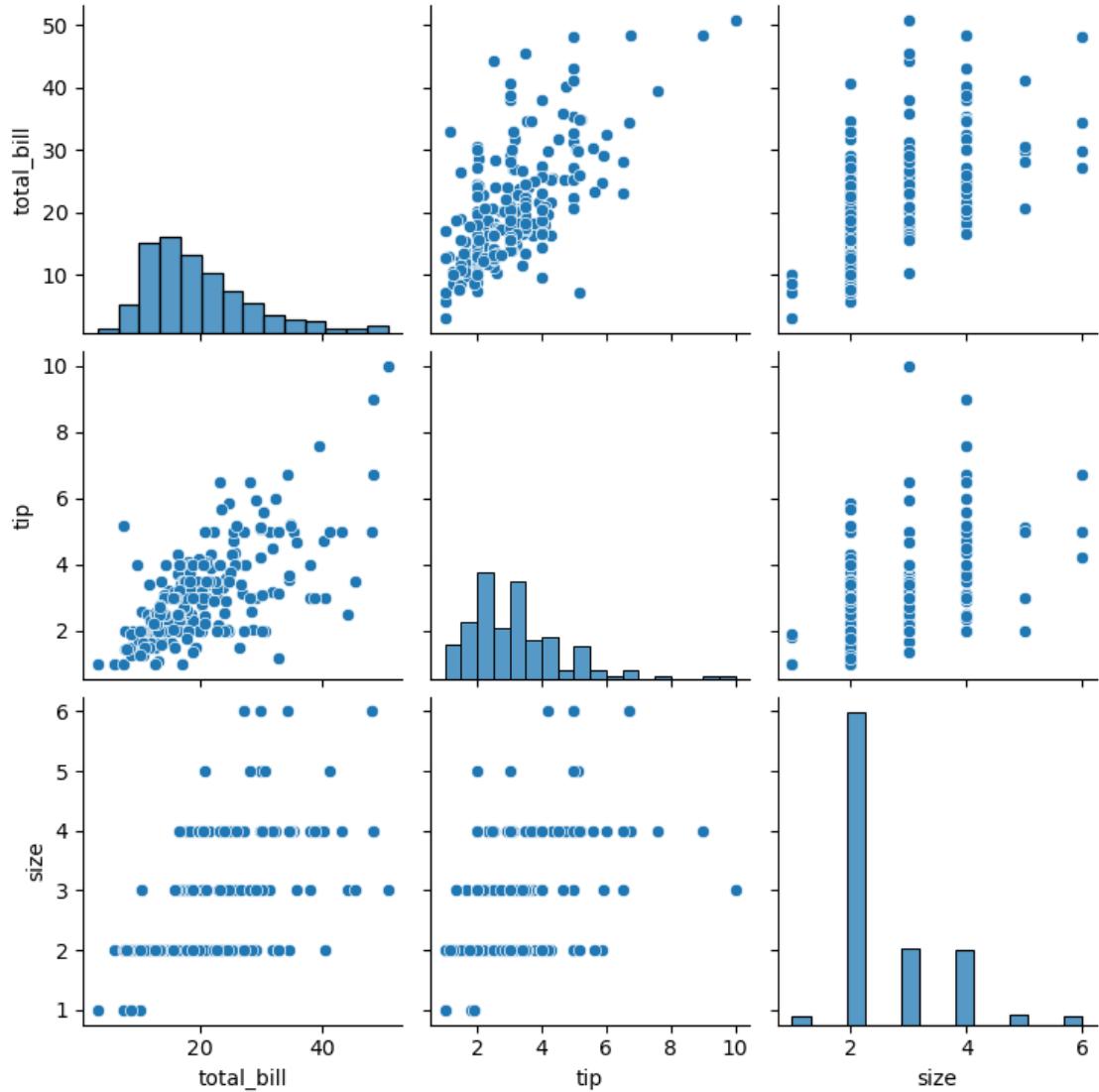
```
[25]: sn.jointplot(x=df.tip,y=df.total_bill,kind="hex")
```

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



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

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

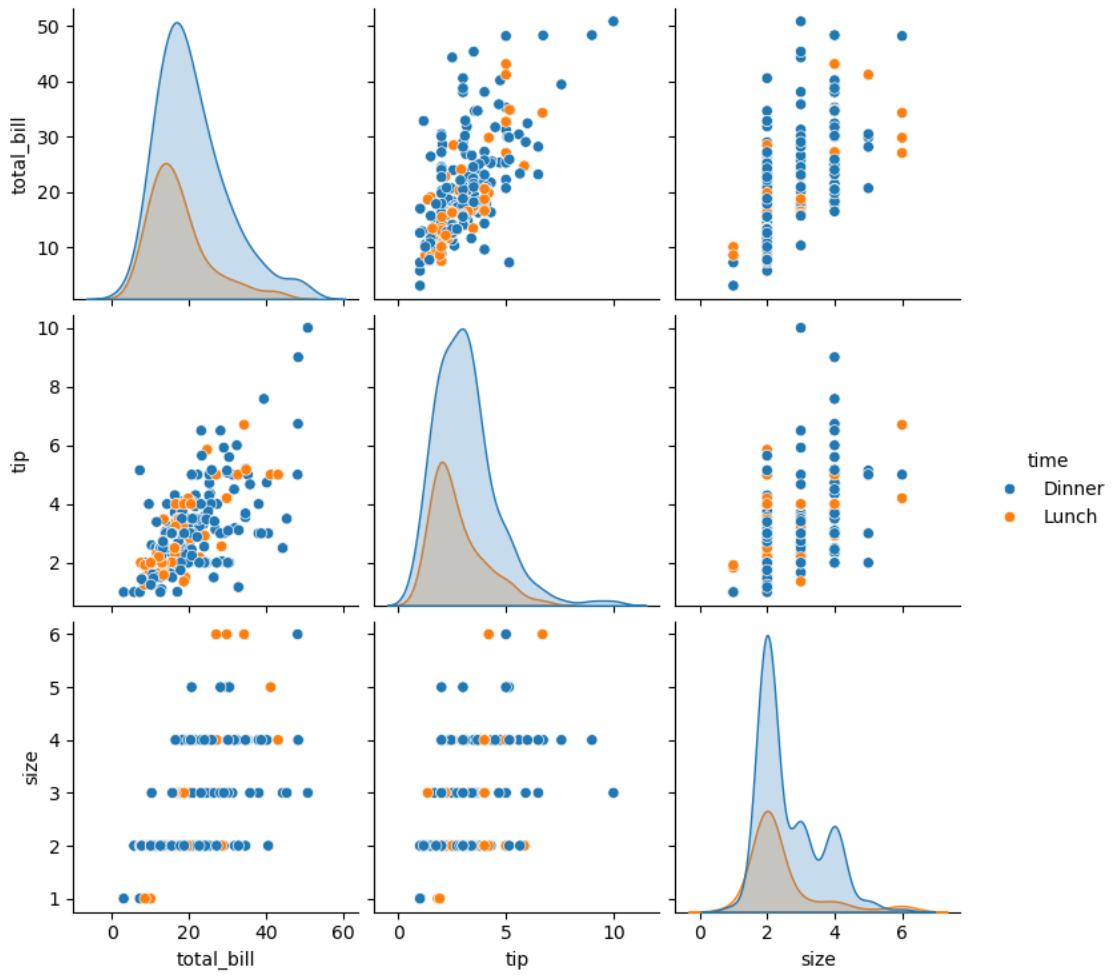


```
[29]: #df.info()
df.time.value_counts()
```

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

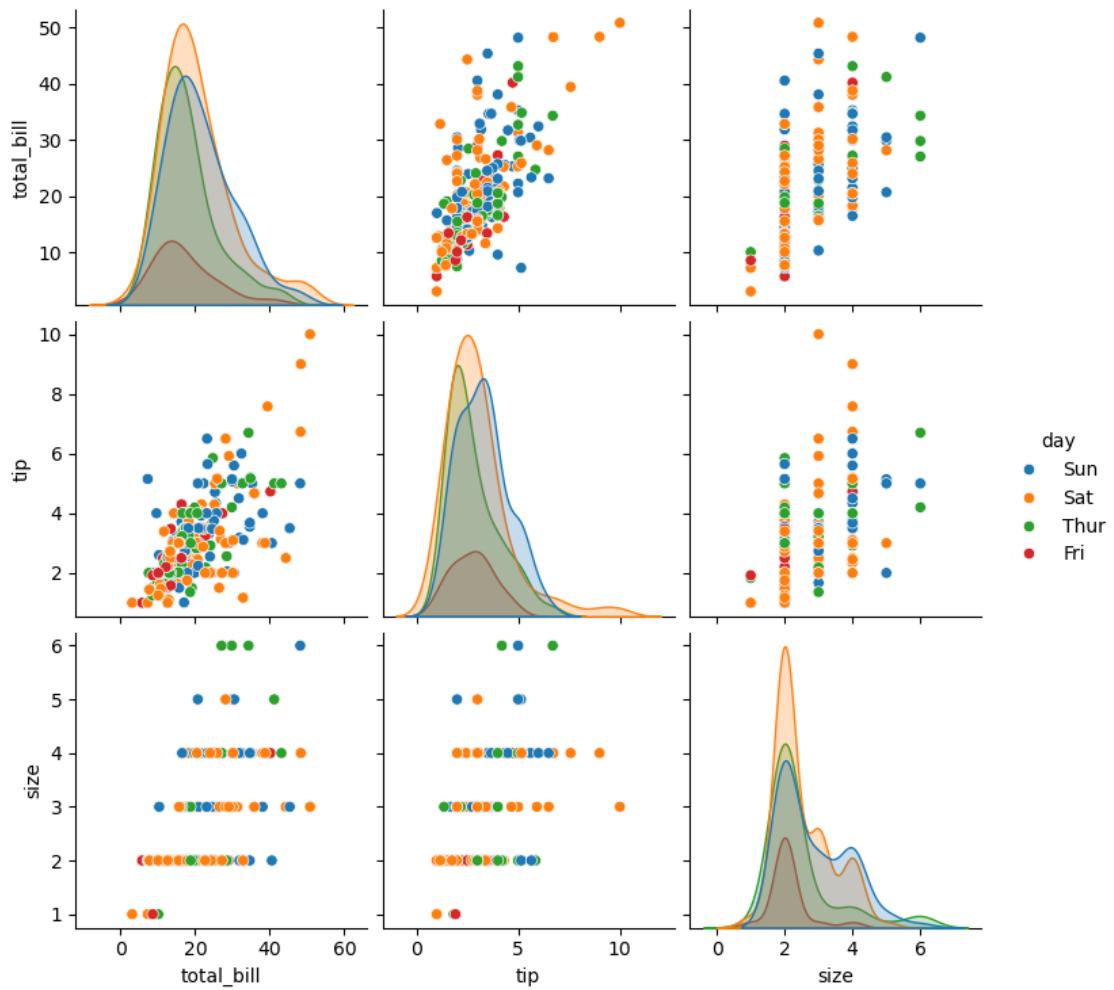
```
[30]: sn.pairplot(df,hue='time')
```

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



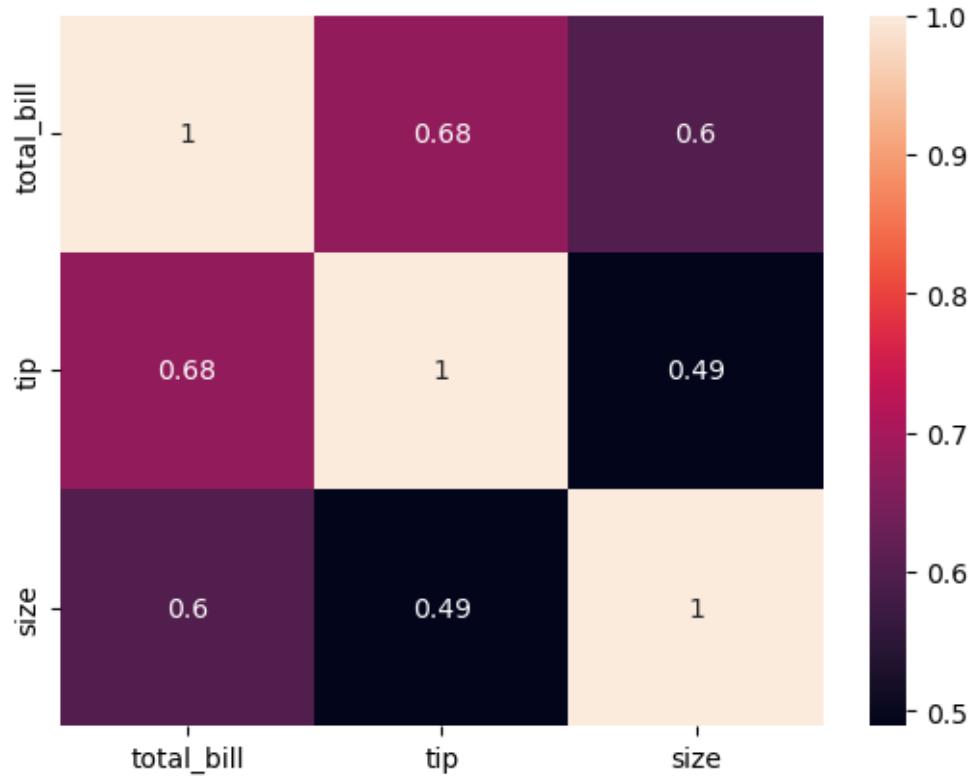
```
[31]: sn.pairplot(df,hue='day')
```

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



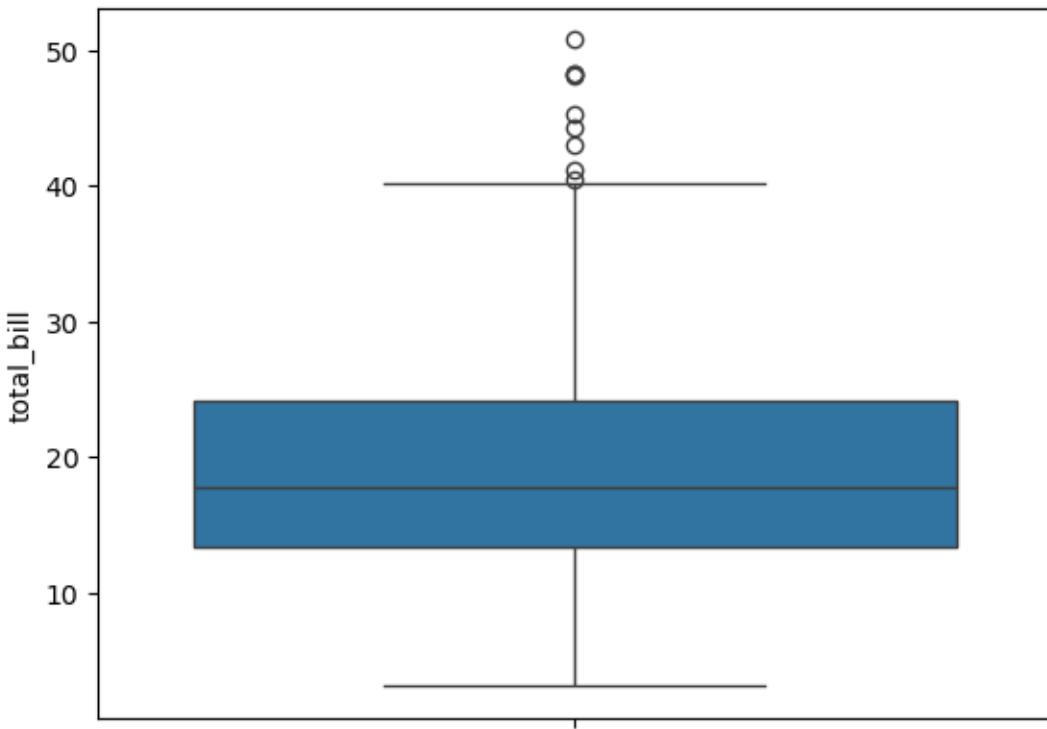
```
[32]: sn.heatmap(df.corr(numeric_only=True), annot=True)
```

```
[32]: <Axes: >
```



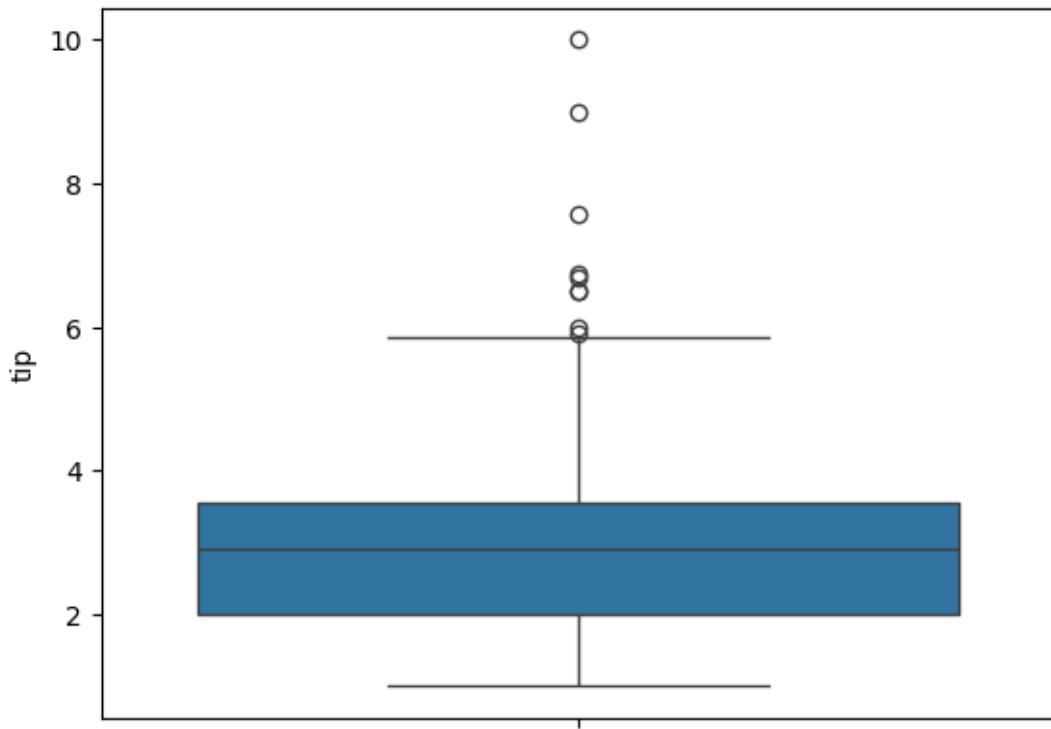
```
[34]: sn.boxplot(df.total_bill)
```

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



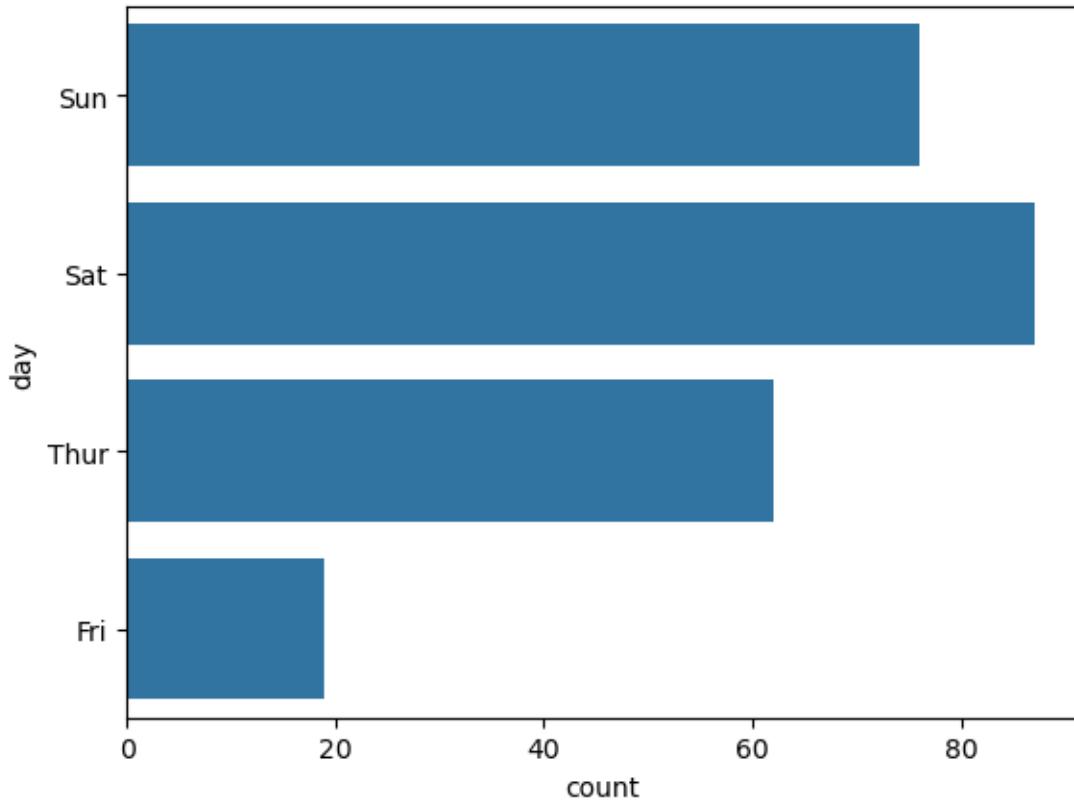
```
[36]: sn.boxplot(df.tip)
```

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



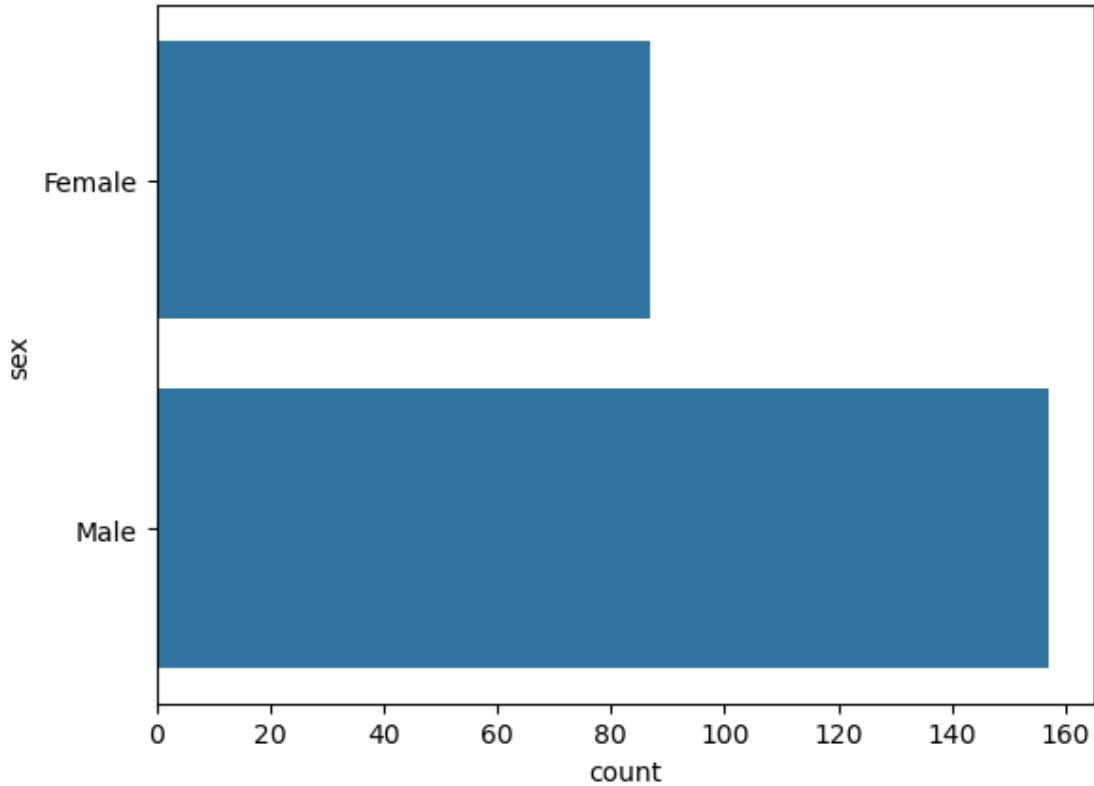
```
[37]: sns.countplot(df.day)
```

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



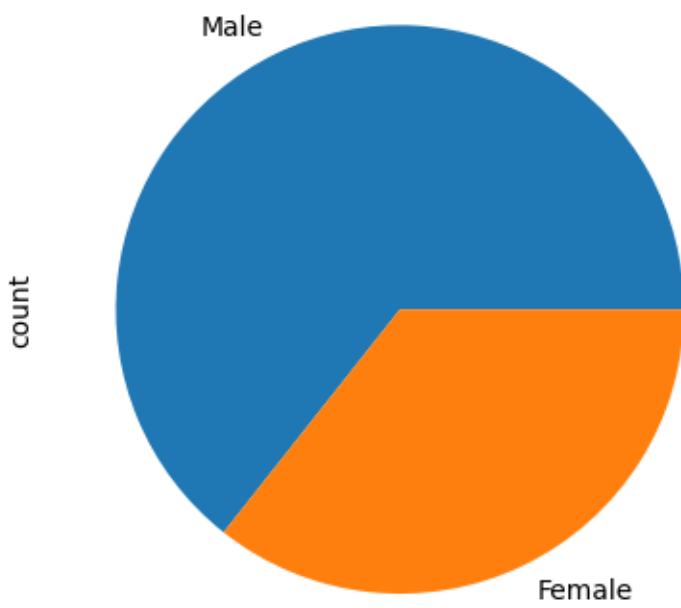
```
[38]: sn.countplot(df.sex)
```

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



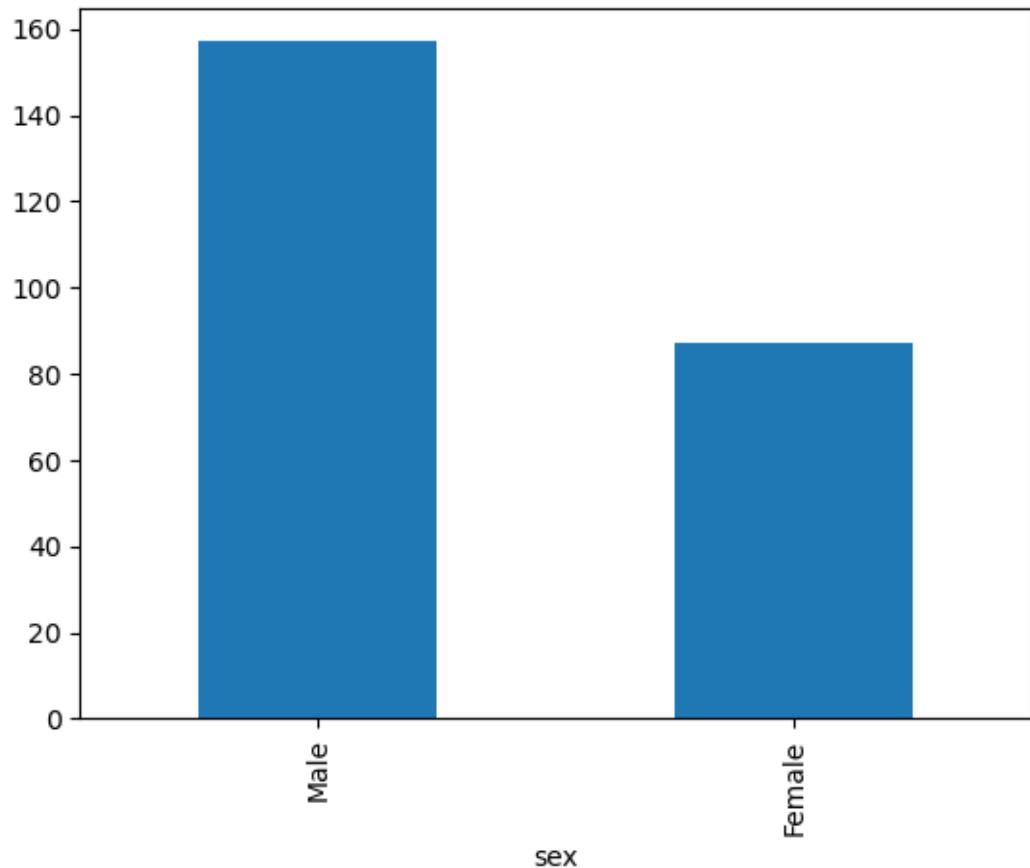
```
[39]: df.sex.value_counts().plot(kind='pie')
```

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



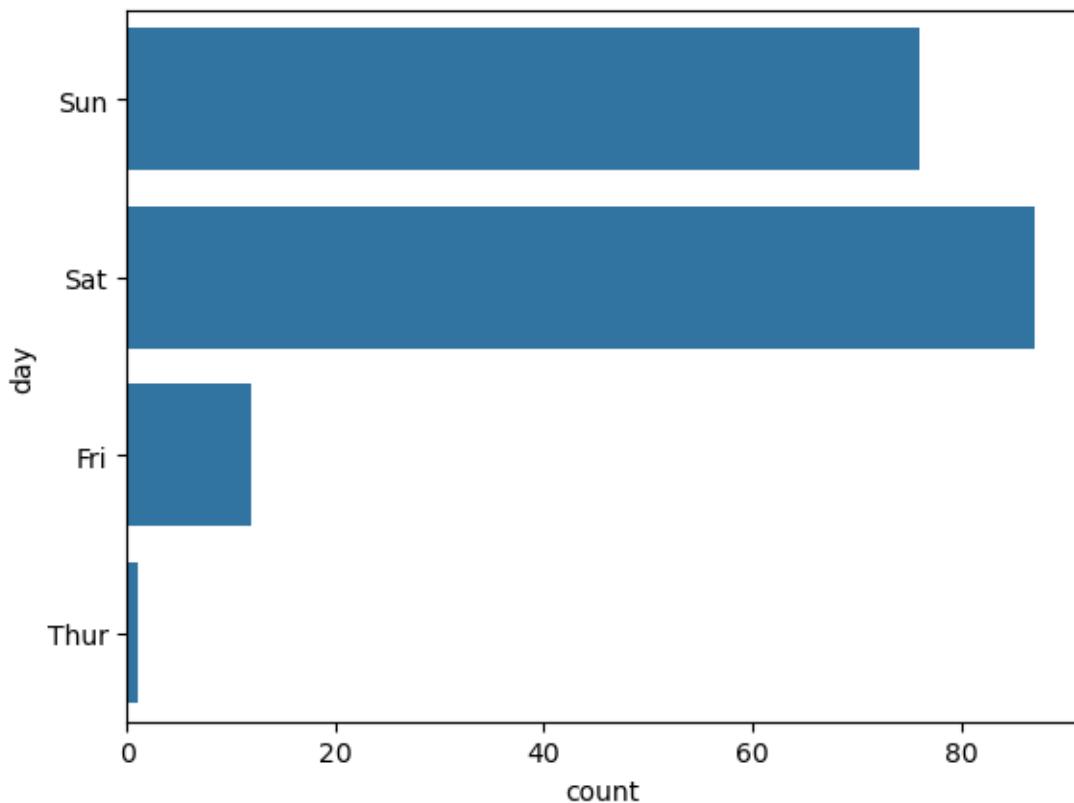
```
[40]: df.sex.value_counts().plot(kind='bar')
```

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



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

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



[]:

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 knowledge about the 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]])

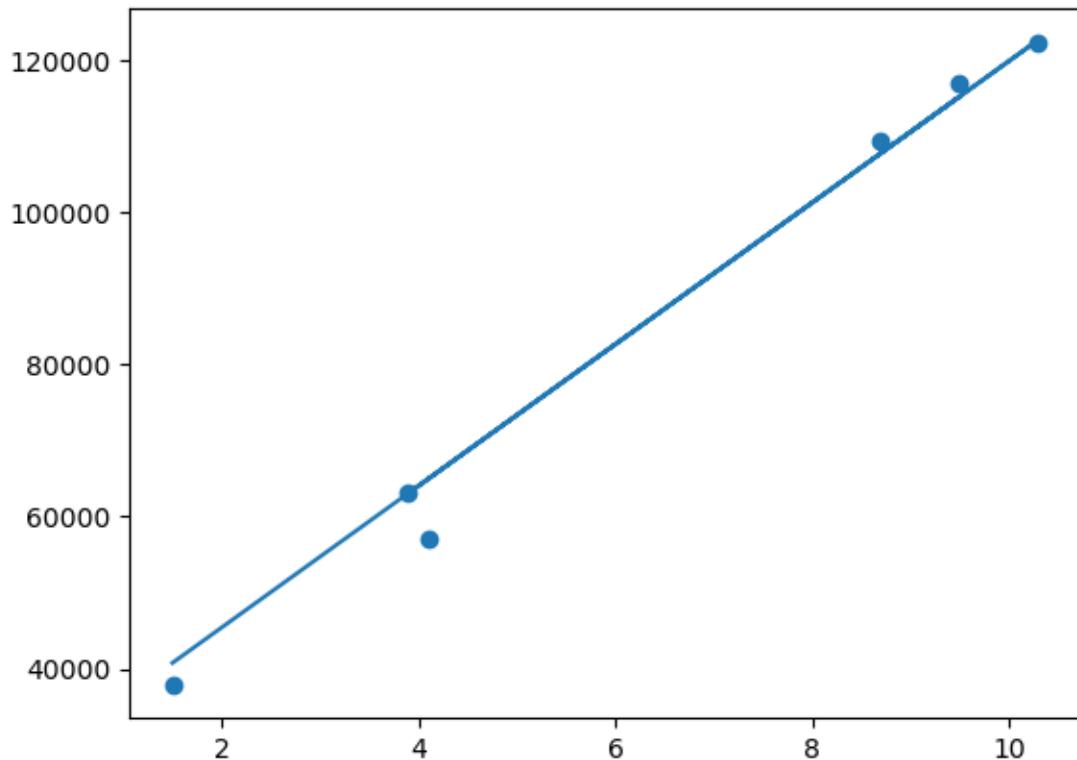
[14]: errors=y_pred-y_test
errors

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

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

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

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



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

```
[17]: accuracy
```

```
[17]: 0.988169515729126
```

```
[18]: 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]])
```

```
[ ]:
```

Exercice8

November 2, 2025

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

```
[8]: 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]: df.variety.value_counts()
```

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

```
[10]: 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]: df["output"] = 0
```

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

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

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

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

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

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

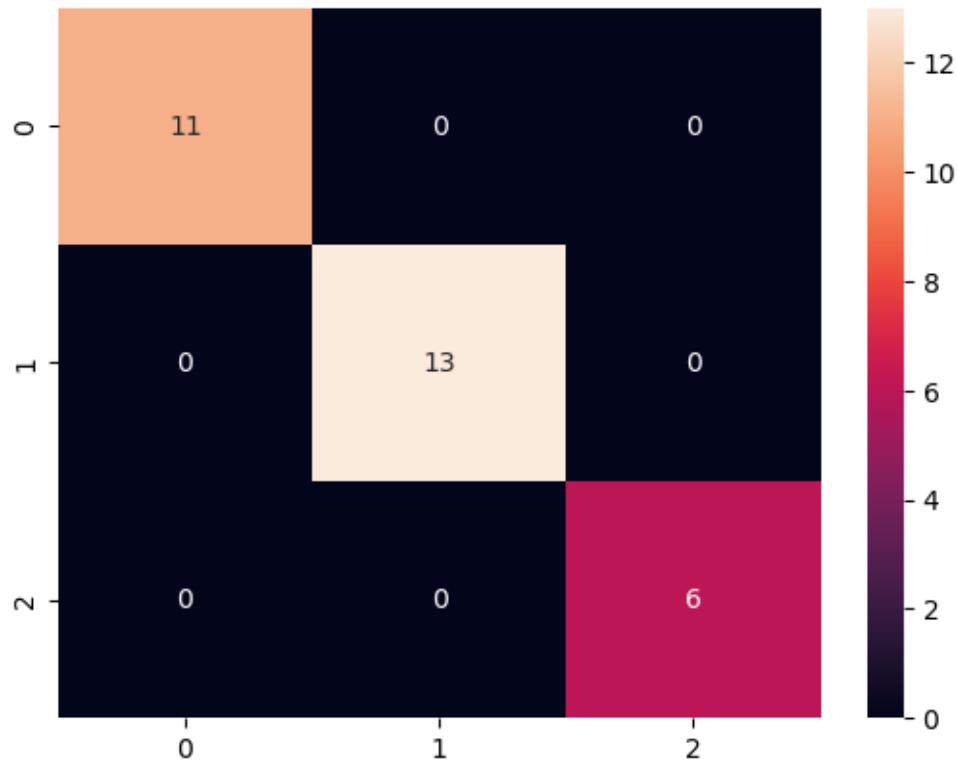
```
1.0
```

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

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

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

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



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

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

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

```
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```

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

```
[6]: 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
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Test 0.925 Train 0.838 Random State 277
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Test 0.912 Train 0.834 Random State 286
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Test 0.850 Train 0.841 Random State 291
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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
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[103,  23],  
[103,  69],  
[113,   8],  
[113,  91],  
[120,  16],  
[120,  79],  
[126,  28],  
[126,  74],  
[137,  18],  
[137,  83]])
```

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

```
[39]: 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
```

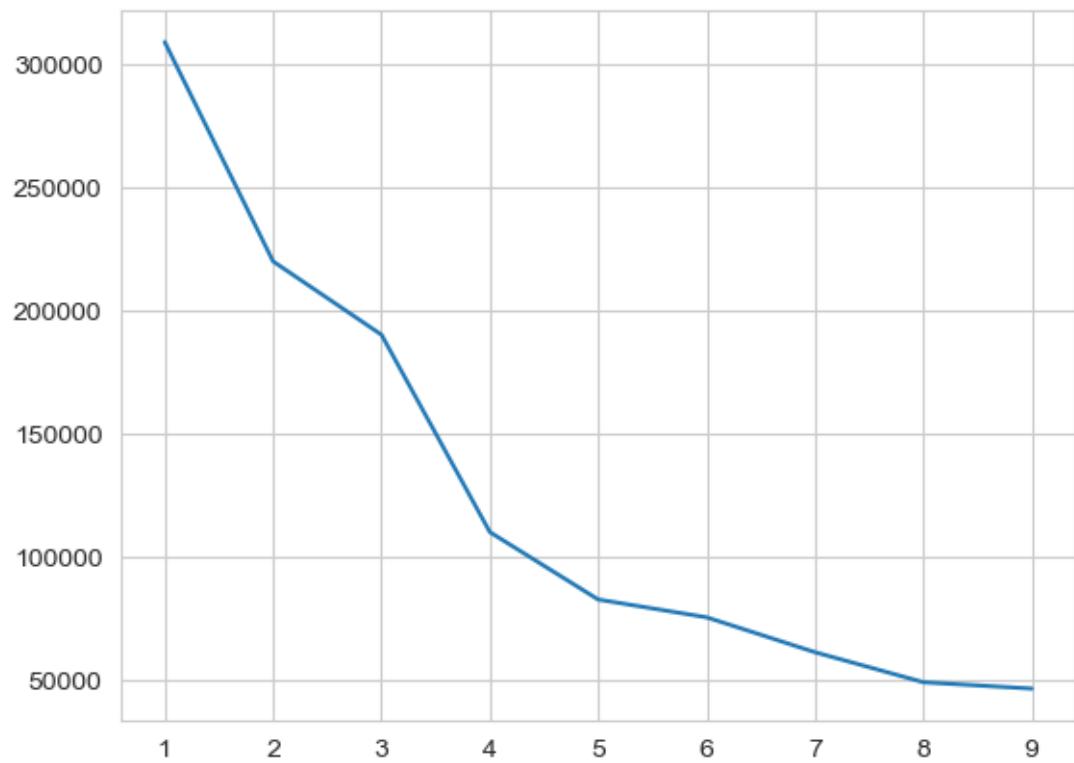
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

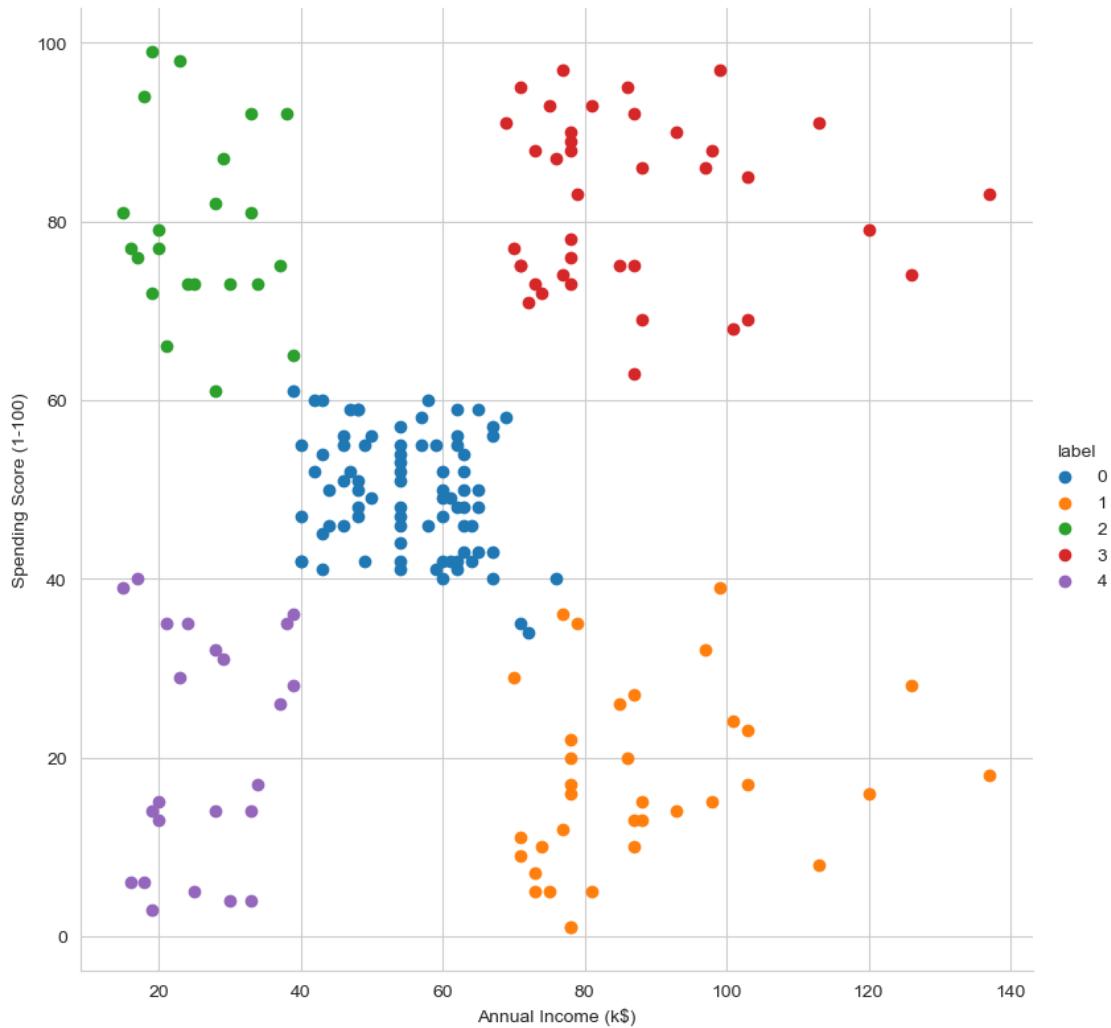
```
    Final['label']=model.predict(feature)
```

```
[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()
```





Exercie-11

November 2, 2025

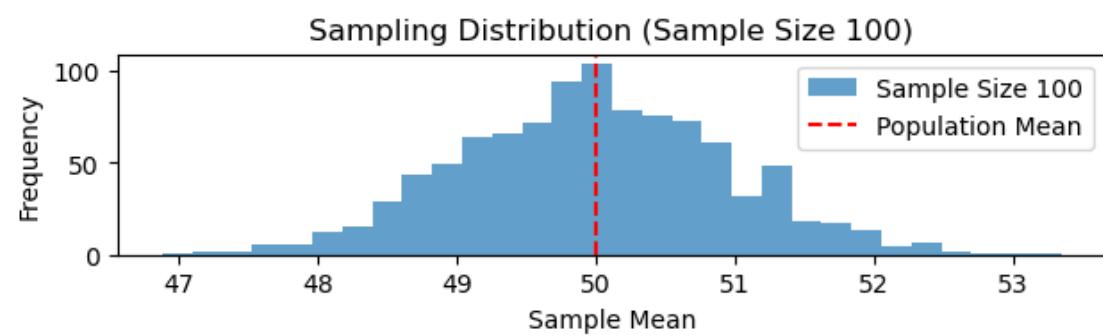
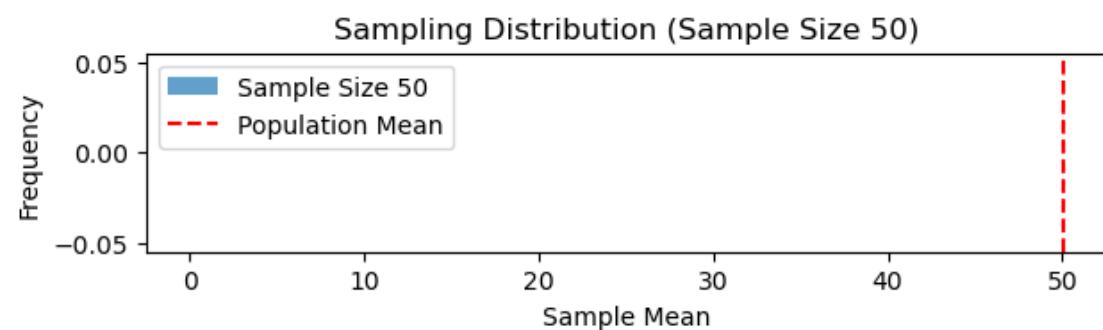
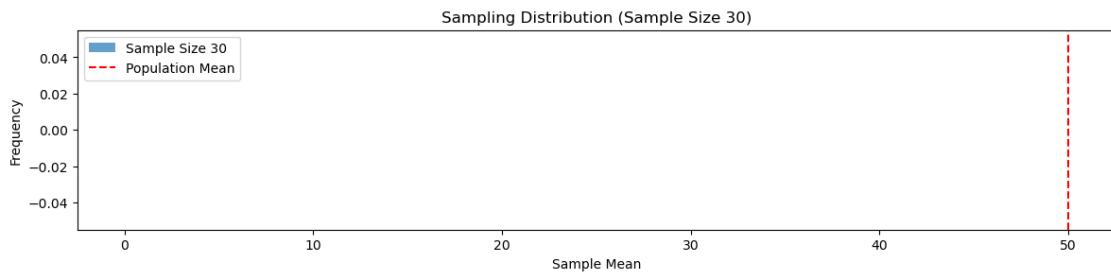
```
[8]: import numpy as np
import matplotlib.pyplot as plt

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

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

[11]: 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]: 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()
```



[]:

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

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

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

```
[5]: 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]: 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
-----
```

[]: