```
# Importing libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy.stats import skew
from statsmodels.distributions.empirical_distribution import ECDF

import plotly.express as px
import plotly.figure_factory as ff

import itertools

import os
from google.colab import files
```

```
# Upload dataset to Colab workspace
uploaded = files.upload()
```

Choose files India_State…ata_RBI.csv

- **India_Statewise_Power_Infrastructure_Data_RBI.csv**(text/csv) - 24415 bytes, last modified: 06/09/2023 - 100% done

```
Saving India_Statewise_Power_Infrastructure_Data_RBI.csv to India_Statewise_Power_Infrastructure_Data_RBI.csv
```

```
os.getcwd()
```

```
'/content'
```

```
os.listdir()
```

```
['.config',
 'India_Statewise_Power_Infrastructure_Data_RBI.csv',
 '.ipynb_checkpoints',
 'sample_data']
```

Step 2.a

```
# Import the dataset into a DataFrame

power_infra = pd.read_csv('India_Statewise_Power_Infrastructure_Data_RBI.csv')
power_infra.head()
```

	State/Union Territory	Year	Power_Requirement_Net_Crore_Units	Availability_Of_Power_Net_Crore_Units	Availability_Of_Power_Per_Capita_kiloWatt-Hour	Inst
0	Andaman and Nicobar Islands	2004-05	-	-	-	
1	Andhra Pradesh	2004-05	5042	5006	656.9	
2	Arunachal Pradesh	2004-05	16	16	143.9	
3	Assam	2004-05	379	358	134.4	
4	Bihar	2004-05	720	648	78	

```
power_infra.shape
```

```
(612, 6)
```

```
# Print the column headers

print(power_infra.columns)
```

```
Index(['State/Union Territory', 'Year', 'Power_Requirement_Net_Crore_Units',
       'Availability_Of_Power_Net_Crore_Units',
       'Availability_Of_Power_Per_Capita_kiloWatt-Hour',
       'Installed_Power_Capacity_MegaWatt'],
      dtype='object')
```

```
power_infra.columns.values
```

```
array(['State/Union Territory', 'Year',
       'Power_Requirement_Net_Crore_Units',
       'Availability_Of_Power_Net_Crore_Units',
       'Availability_Of_Power_Per_Capita_kiloWatt-Hour',
       'Installed_Power_Capacity_MegaWatt'], dtype=object)
```

Step 2.b

```
power_infra.describe()
```

	State/Union Territory	Year	Power_Requirement_Net_Crore_Units	Availability_Of_Power_Net_Crore_Units	Availability_Of_Power_Per_Capita_kiloWatt-Hour
count	612	612	612	612	612
unique	36	17	505	509	576
top	Andaman and Nicobar Islands	2004-05	24	.	
freq	17	36	14	10	10

To check for missing values

```
power_infra.isna().sum()    # Observation - There are no NaN values in the dataset
```

```
State/Union Territory                             0
Year                                              0
Power_Requirement_Net_Crore_Units                 0
Availability_Of_Power_Net_Crore_Units             0
Availability_Of_Power_Per_Capita_kiloWatt-Hour    0
Installed_Power_Capacity_MegaWatt                 0
dtype: int64
```

To check for duplicate entries

```
power_infra[power_infra.duplicated(keep=False)]   # Observation - There are no duplicate values in the dataset
```

State/Union Territory	Year	Power_Requirement_Net_Crore_Units	Availability_Of_Power_Net_Crore_Units	Availability_Of_Power_Per_Capita_kiloWatt-Hour	Insta

To remove strings entered in numeric data fields

```
# Check the data types of each field

power_infra.dtypes

# Observation - The last 4 fields should be interger or float.
# However the observed data type 'object' indicates the presence of a likely string data in these numeric attribute fields
```

```
State/Union Territory                             object
Year                                              object
Power_Requirement_Net_Crore_Units                 object
Availability_Of_Power_Net_Crore_Units             object
Availability_Of_Power_Per_Capita_kiloWatt-Hour    object
Installed_Power_Capacity_MegaWatt                 object
dtype: object
```

```
power_infra.iloc[:, 2:].head()
```

	Power_Requirement_Net_Crore_Units	Availability_Of_Power_Net_Crore_Units	Availability_Of_Power_Per_Capita_kiloWatt-Hour	Installed_Power_Capaci
0	-	-	-	
1	5042	5006	656.9	

```
power_infra['Power_Requirement_Net_Crore_Units'].unique()

#power_infra.iloc[:, 2].unique()
```

```
       '2116', '215', '5968', '2180', '400', '814', '363', '3516', '1269',
       '3481', '9272', '54', '137', '24', '33', '1398', '154', '3339',
       '2921', '4787', '.', '70', '5202', '463', '2316', '5303', '21',
       '405', '796', '126', '1301', '254', '135', '2160', '234', '5714',
       '2379', '430', '927', '403', '3460', '1367', '2', '3685', '10277',
       '51', '138', '23', '41', '1521', '168', '3568', '3205', '5419',
       '75', '5568', '516', '2494', '6096', '29', '843', '134', '1406',
       '292', '160', '2240', '262', '6246', '2625', '514', '1173', '437',
       '4080', '1502', '3', '3871', '11001', '45', '34', '1710', '181',
       '3864', '3324', '22', '6150', '80', '5744', '596', '2654', '6414',
       '39', '482', '916', '145', '1408', '339', '177', '2244', '274',
       '6875', '2935', '599', '1178', '4032', '1566', '4156', '11489',
       '53', '162', '38', '1885', '184', '4237', '3674', '6578', '78',
       '6263', '705', '2902', '7151', '43', '511', '1053', '141', '1487',
       '357', '180', '280', '6748', '2909', '626', '1147', '536', '4317',
       '1765', '4205', '12190', '56', '171', '48', '2052', '202', '4164',
       '3780', '6967', '6921', '784', '3129', '7900', '40', '512', '1159',
       '158', '1101', '401', '193', '2428', '309', '7037', '3344', '1320',
       '587', '4555', '1762', '4318', '12494', '52', '155', '35', '2114',
       '212', '4573', '4411', '7629', '86', '7593', '892', '3375', '7897',
       '540', '1238', '152', '1034', '443', '218', '2563', '315', '7165',
       '3455', '763', '1357', '620', '5047', '1802', '4844', '12830',
       '57', '37', '58', '2251', '4448', '4526', '8031', '88', '985',
       '3648', '9173', '60', '603', '1431', '157', '1501', '438', '214',
       '2675', '302', '7470', '3687', '816', '1425', '628', '6083',
       '1989', '4', '4979', '14138', '2304', '217', '4519', '5147',
       '8569', '95', '8134', '1051', '3868', '9969', '59', '650', '1541',
       '164', '1730', '457', '199', '2609', '318', '9366', '4141', '899',
       '704', '6627', '2124', '5178', '12398', '2516', '233', '4872',
       '5554', '9230', '111', '9165', '1133', '4214', '9566', '55', '754',
       '1539', '1893', '539', '225', '2687', '389', '8850', '4346', '909',
       '1561', '714', '6415', '2158', '5', '4941', '12629', '179', '2496',
       '4782', '5820', '9351', '120', '9489', '1194', '4289', '5920',
       '68', '853', '1929', '2150', '531', '209', '2923', '397', '9624',
       '4662', '881', '1621', '760', '6264', '2246', '5337', '13490',
       '71', '46', '69', '2648', '240', '4863', '6572', '9576', '4334',
       '124', '10318', '1245', '4709', '5044', '63', '876', '2396', '161',
       '2565', '593', '2963', '10354', '4751', '882', '1657', '774',
       '6430', '2332', '6238', '14182', '84', '47', '76', '2676', '244',
       '4969', '6742', '9728', '5025', '10635', '1289', '4736', '5430',
       '73', '902', '2571', '165', '2375', '602', '3083', '432', '10370',
       '4889', '883', '1740', '6690', '2430', '6576', '13929', '255',
       '5310', '6784', '10451', '10757', '1307', '4795', '5838', '910',
       '2702', '2592', '617', '253', '3183', '412', '10999', '5078',
       '940', '1881', '791', '6787', '2500', '6993', '14976', '87', '156',
       '50', '2880', '267', '5481', '7119', '49', '10601', '6032', '260',
       '12005', '1346', '5076', '6374', '953', '3005', '2613', '632',
       '256', '3230', '428', '11659', '5367', '1959', '868', '7176',
       '2503', '7567', '15829', '92', '196', '67', '90', '3181', '276',
       '5529', '7983', '10938', '6670', '186', '11710', '1385', '5224',
       '6545', '980', '3163', '173', '3011', '653', '257', '3309', '435',
       '11394', '5451', '1042', '2003', '894', '7280', '2632', '7617',
       '15517', '211', '65', '81', '2969', '285', '5678', '8128', '10882',
       '6831', '12255', '1447', '5295', '6208', '72', '1019', '3417',
       '3047', '550', '222', '2956', '408', '11162', '5316', '1977',
       '995', '6885', '2512', '6', '8344', '15068', '97', '203', '83',
       '2985', '264', '5845', '8531', '10119', '6700', '148', '12437',
       '1383', '5164'], dtype=object)
```

```
power_uniq = power_infra.iloc[:, 2:].apply(lambda col: col.unique())
power_uniq
```

```
Power_Requirement_Net_Crore_Units                [-, 5042, 16, 379, 720, 116, 1175, 183, 112, 2...
Availability_Of_Power_Net_Crore_Units            [-, 5006, 16, 358, 648, 115, 1155, 183, 112, 2...
Availability_Of_Power_Per_Capita_kiloWatt-Hour   [-, 656.9, 143.9, 134.4, 78, 1274.7, 554.5, 82...
Installed_Power_Capacity_MegaWatt                [65, 10809, 187, 1133, 1644, 79, 1633, 38, 14,...
dtype: object
```

```
# A function to check if the given string represents a decimal number

def isfloat(numpy_arr):
  N = len(numpy_arr)
```

```
  result_bool = np.empty(N, dtype = bool)
  for idx in range(N):
    string = numpy_arr[idx]
    try:
      float(string)
    except ValueError:
      result_bool[idx] = False
    else:
      result_bool[idx] = True
  return result_bool
```

```
# Verifying the functioning of isfloat() method

a = np.array(['12345', '4.99', '123ABC', '', '.','-'])
isfloat(a)
```

```
array([ True,  True, False, False, False, False])
```

```
power_uniq_bool = power_uniq.apply(lambda col: isfloat(col))
power_uniq_bool
```

```
Power_Requirement_Net_Crore_Units                 [False, True, True, True, True, True, True, Tr...
Availability_Of_Power_Net_Crore_Units             [False, True, True, True, True, True, True, Tr...
Availability_Of_Power_Per_Capita_kiloWatt-Hour    [False, True, True, True, True, True, True, Tr...
Installed_Power_Capacity_MegaWatt                 [True, True, True, True, True, True, True, Tru...
dtype: object
```

```
non_num_positions = []

for ind in range(len(power_uniq_bool)):
  col = power_uniq_bool[ind]
  false_pos = np.where(col == False)[0]
  non_num_positions.append(false_pos)
  print(false_pos)
```

```
[ 0 29]
[ 0 29]
[ 0 29]
[31]
```

```
non_nums_set = set()

for ind in range(len(non_num_positions)):
  non_num_pos_arr = non_num_positions[ind]
  for non_num_pos in non_num_pos_arr:
    non_nums_set.add(power_uniq[ind][non_num_pos])

print(non_nums_set)
```

```
{'.', '-'}
```

```
power_infra.replace({k: 0 for k in non_nums_set}, inplace = True)
power_infra.head()
```

	State/Union Territory	Year	Power_Requirement_Net_Crore_Units	Availability_Of_Power_Net_Crore_Units	Availability_Of_Power_Per_Capita_kiloWatt-Hour	Ins
0	Andaman and Nicobar Islands	2004-05	0	0	0	
1	Andhra Pradesh	2004-05	5042	5006	656.9	
2	Arunachal Pradesh	2004-05	16	16	143.9	
3	Assam	2004-05	379	358	134.4	
4	Bihar	2004-05	720	648	78	

```
power_infra.dtypes
```

```
State/Union Territory                             object
Year                                              object
```

```
Power_Requirement_Net_Crore_Units                 object
Availability_Of_Power_Net_Crore_Units             object
Availability_Of_Power_Per_Capita_kiloWatt-Hour    object
Installed_Power_Capacity_MegaWatt                 object
dtype: object
```

```
power_uniq = power_infra.iloc[:, 2:].apply(lambda col: col.unique())
power_uniq_bool = power_uniq.apply(lambda col: isfloat(col))
if (False in power_uniq_bool) == False:
  print('There are no more symbols in fields which should ideally represent numbers.')
```

```
There are no more symbols in fields which should ideally represent numbers.
```

```
# Using a dictionary to convert the data type of columns

data_type_dict = {'State/Union Territory': 'category',
                'Year': 'category',
                'Power_Requirement_Net_Crore_Units': int,
                'Availability_Of_Power_Net_Crore_Units': int,
                'Availability_Of_Power_Per_Capita_kiloWatt-Hour': float,
                'Installed_Power_Capacity_MegaWatt': int
                }

power_infra = power_infra.astype(data_type_dict)
power_infra.dtypes
```

```
State/Union Territory                             category
Year                                              category
Power_Requirement_Net_Crore_Units                    int64
Availability_Of_Power_Net_Crore_Units                int64
Availability_Of_Power_Per_Capita_kiloWatt-Hour     float64
Installed_Power_Capacity_MegaWatt                    int64
dtype: object
```

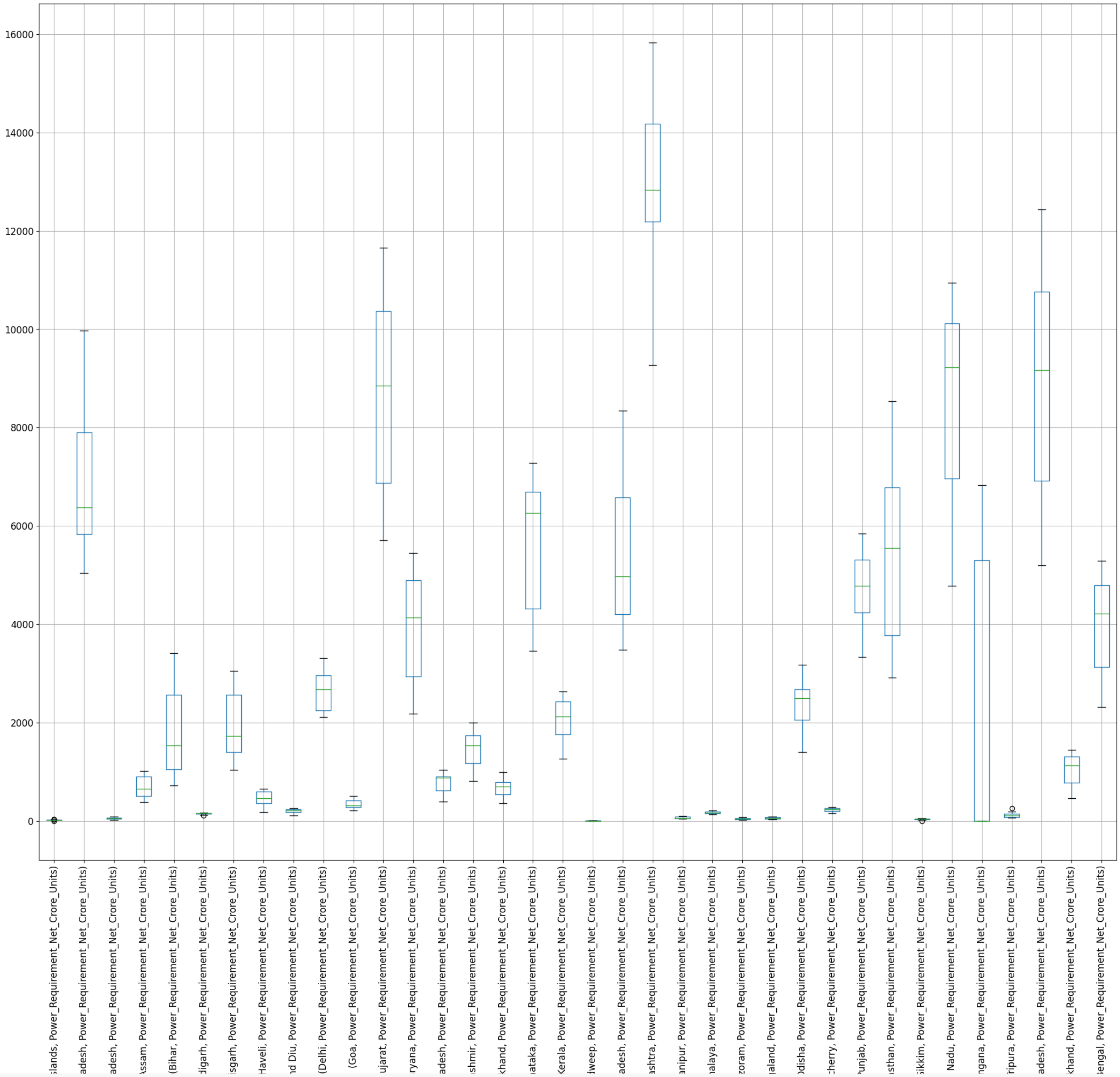
To check for potential outliers

```
power_infra.describe()
```

	Power_Requirement_Net_Crore_Units	Availability_Of_Power_Net_Crore_Units	Availability_Of_Power_Per_Capita_kiloWatt-Hour	Installed_Power_Ca
count	612.000000	612.000000	612.000000	
mean	2640.746732	2513.454248	1515.851634	
std	3390.529156	3234.833732	2882.449324	
min	0.000000	0.000000	0.000000	
25%	152.000000	138.000000	408.800000	
50%	982.500000	887.500000	746.250000	
75%	4337.000000	4082.750000	1384.225000	
max	15829.000000	15816.000000	20064.400000	

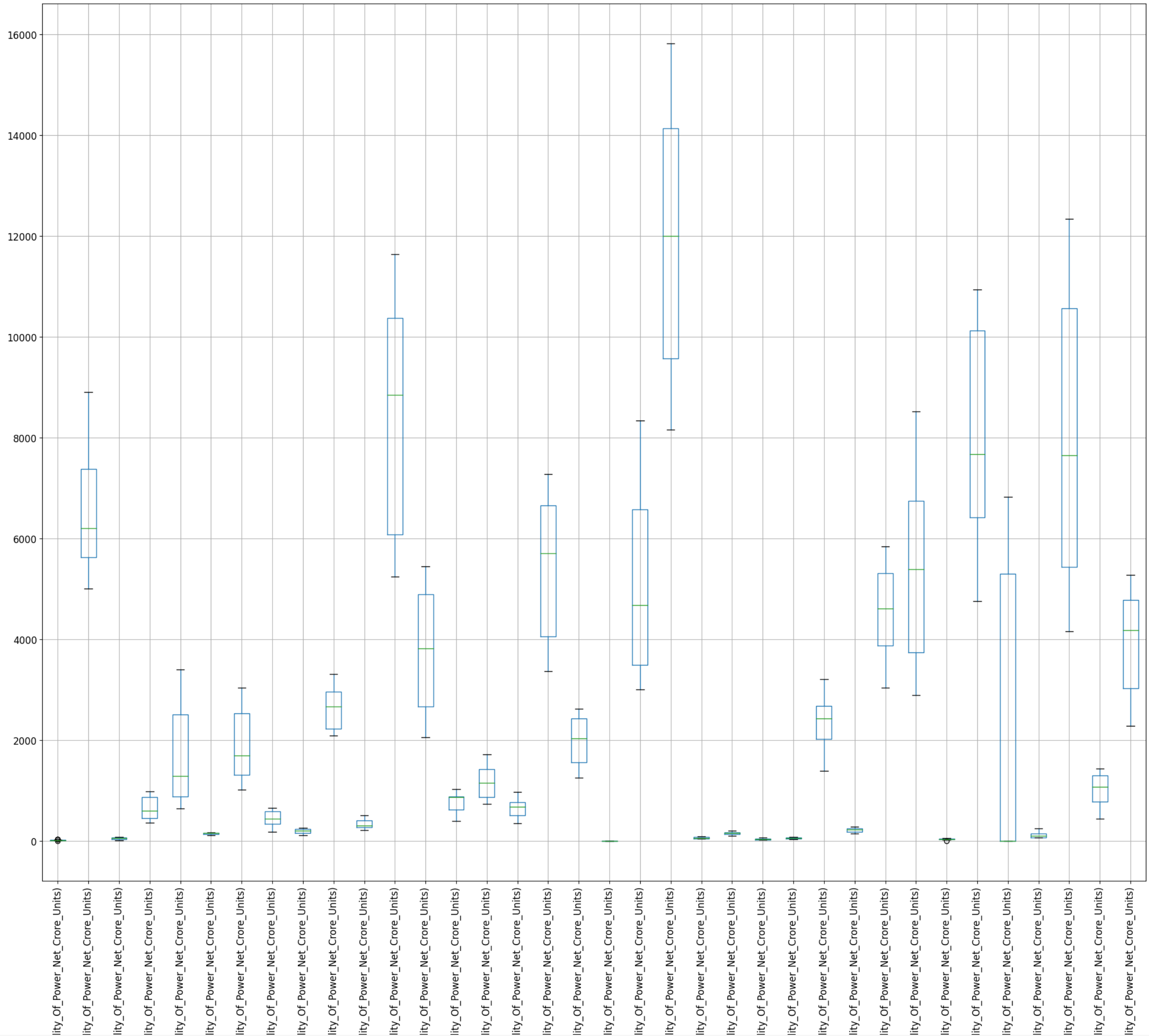
```
power_req_state_grp = power_infra.groupby('State/Union Territory')

power_req_state_grp.boxplot(column = 'Power_Requirement_Net_Crore_Units',
                            subplots = False,
                            rot = 90, fontsize=12, figsize=(25,20))
```

```
<Axes: >
```



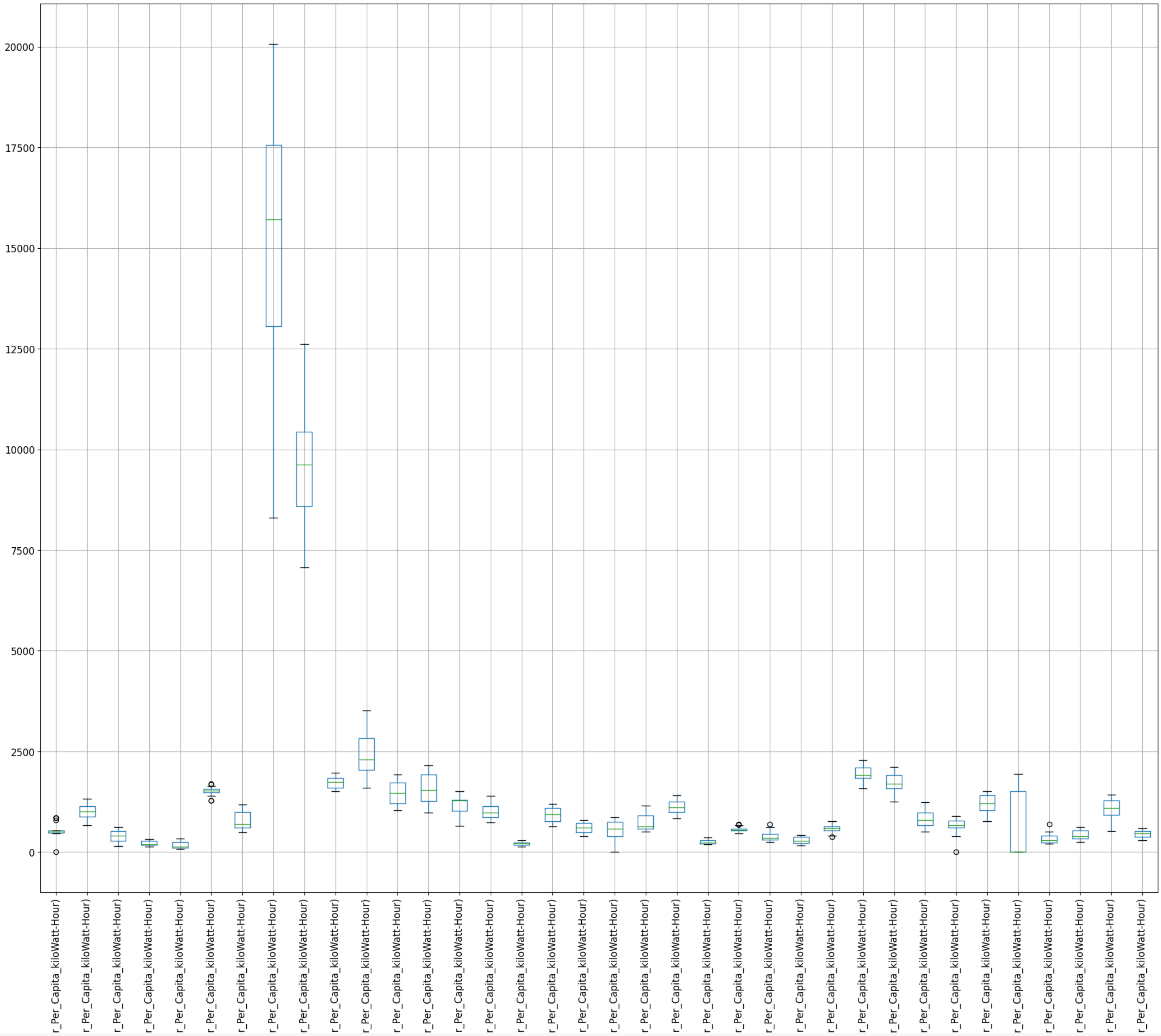

```
power_req_state_grp.boxplot(column = 'Availability_Of_Power_Net_Crore_Units',
                            subplots = False,
                            rot = 90, fontsize=12, figsize=(25,20))
```

<Axes: >



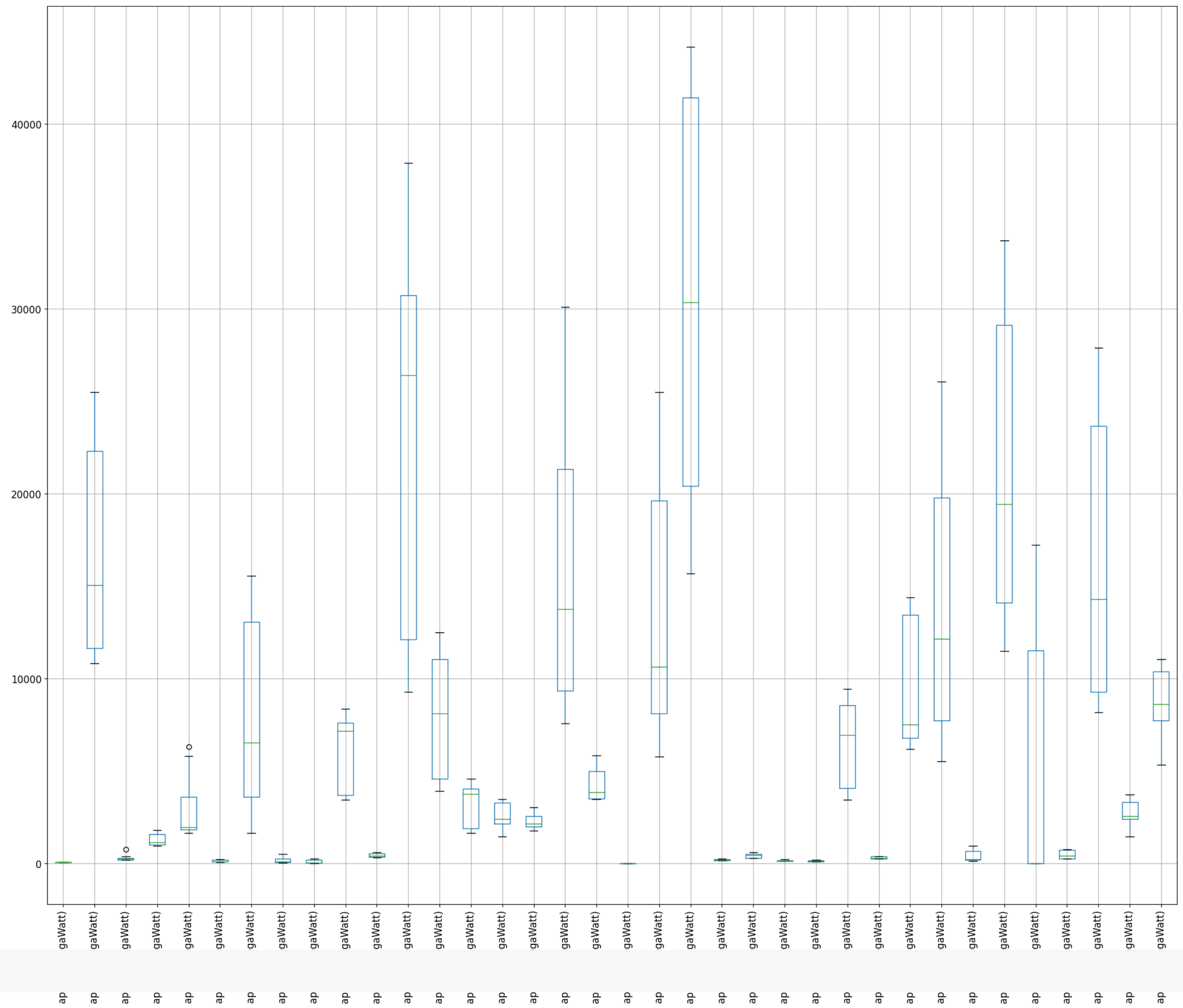

```
power_req_state_grp.boxplot(column = 'Availability_Of_Power_Per_Capita_kiloWatt-Hour',
                            subplots = False,
                            rot = 90, fontsize=12, figsize=(25,20))
```

<Axes: >




```
power_req_state_grp.boxplot(column = 'Installed_Power_Capacity_MegaWatt',
                            subplots = False,
                            rot = 90, fontsize=12, figsize=(25,20))
```

<Axes: >



Step 2.c

Step 2.c.i - Simple Random Sampling to select a subset of states

```
states = power_infra['State/Union Territory'].unique()
states
```

```
['Andaman and Nicobar Islands', 'Andhra Pradesh', 'Arunachal Pradesh', 'Assam', 'Bihar', ..., 'Telangana', 'Tripura', 'Uttar Pradesh',
'Uttarakhand', 'West Bengal']
Length: 36
Categories (36, object): ['Andaman and Nicobar Islands', 'Andhra Pradesh', 'Arunachal Pradesh', 'Assam', ...,
                          'Tripura', 'Uttar Pradesh', 'Uttarakhand', 'West Bengal']
```

```
# To select 5 states randomly

rand_states = np.random.choice(states, 5)
rand_states
```

```
array(['Arunachal Pradesh', 'Rajasthan', 'Manipur', 'Sikkim', 'Bihar'],
      dtype=object)
```

Step 2.c.ii - Stratified Sampling

The power_infra dataset can be stratified by States or Union Territories based on specific criteria such as power demand or installed capacity.

Advantages:

1. Stratified sampling ensures that each subgroup is represented in the sample making the sample more representative of the population as a whole.
2. It allows for more precise estimates for each stratum, especially when there is significant variation within the strata

Disadvantages:

- More complex than simple random sampling
- Selecting the appropriate stratification criteria may be subjective and could introduce bias if not chosen carefully.

Step 2.c.iii - Descriptive Statistics

```
req_avail_data = power_infra.loc[:,['State/Union Territory', 'Power_Requirement_Net_Crore_Units', 'Availability_Of_Power_Net_Crore_Units']]
req_avail_data.head()
```

	State/Union Territory	Power_Requirement_Net_Crore_Units	Availability_Of_Power_Net_Crore_Units
0	Andaman and Nicobar Islands	0	0
1	Andhra Pradesh	5042	5006
2	Arunachal Pradesh	16	16
3	Assam	379	358
4	Bihar	720	648

```
# To compute the mean

req_avail_data.iloc[:,1:].mean(axis = 0)
```

```
Power_Requirement_Net_Crore_Units        2640.746732
Availability_Of_Power_Net_Crore_Units    2513.454248
dtype: float64
```

```
# To compute the median

req_avail_data.iloc[:,1:].median(axis = 0)
```

```
Power_Requirement_Net_Crore_Units        982.5
Availability_Of_Power_Net_Crore_Units    887.5
dtype: float64
```

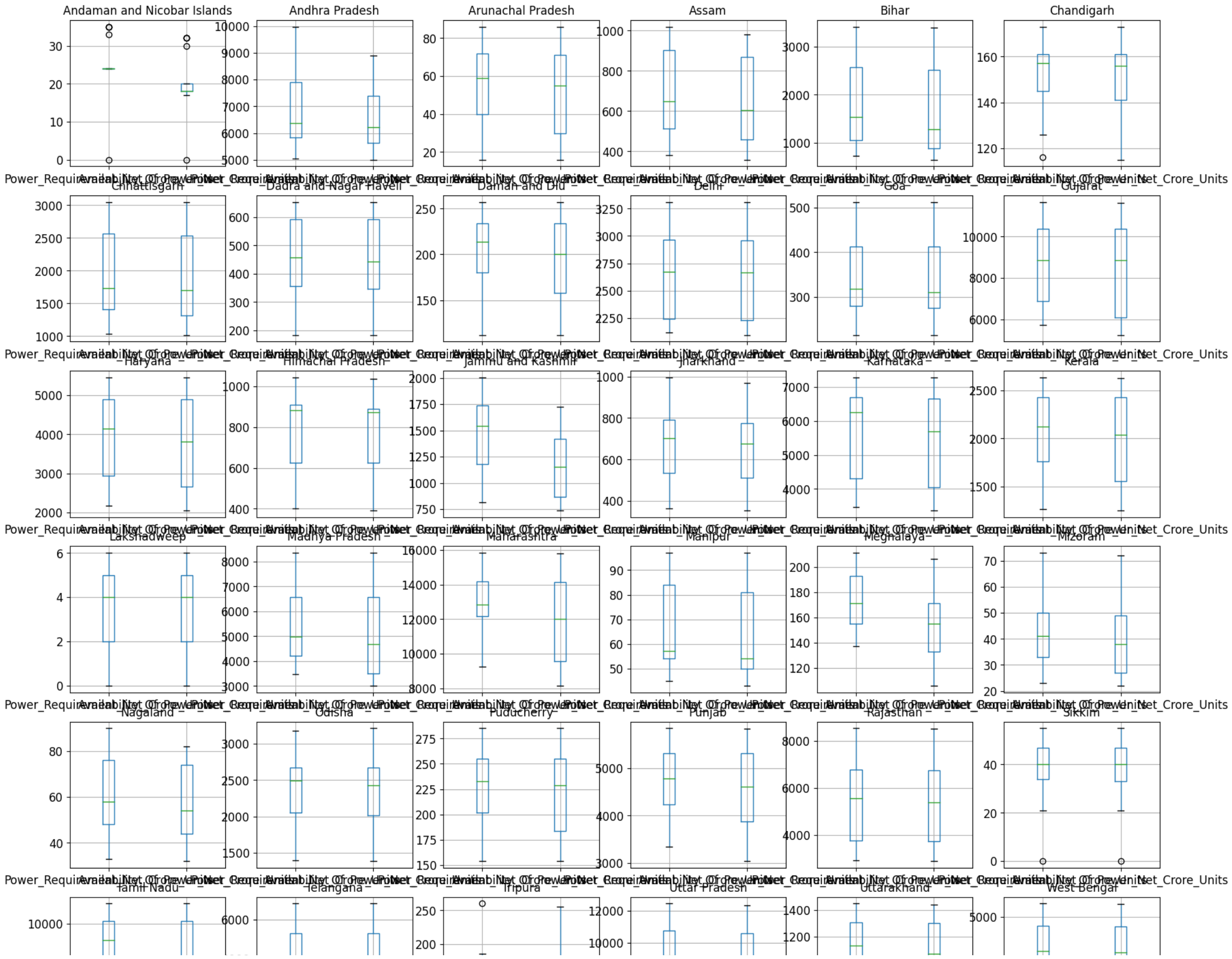
```
# To compute the standard deviation

req_avail_data.iloc[:,1:].std(axis = 0)
```

```
Power_Requirement_Net_Crore_Units        3390.529156
Availability_Of_Power_Net_Crore_Units    3234.833732
dtype: float64
```

Step 2.c.iv - Visualizing distribution of power requirements and availability across states

```
power_req_avail_state_grp = req_avail_data.groupby('State/Union Territory')

power_req_avail_state_grp.boxplot(column = ['Power_Requirement_Net_Crore_Units', 'Availability_Of_Power_Net_Crore_Units'],
                                  sharey = False,
                                  fontsize=12, figsize=(20,20))
```

```
Andaman and Nicobar Islands        Axes(0.1,0.792857;0.114286x0.107143)
Andhra Pradesh                Axes(0.237143,0.792857;0.114286x0.107143)
Arunachal Pradesh             Axes(0.374286,0.792857;0.114286x0.107143)
Assam                         Axes(0.511429,0.792857;0.114286x0.107143)
Bihar                         Axes(0.648571,0.792857;0.114286x0.107143)
Chandigarh                    Axes(0.785714,0.792857;0.114286x0.107143)
Chhattisgarh                       Axes(0.1,0.664286;0.114286x0.107143)
Dadra and Nagar Haveli        Axes(0.237143,0.664286;0.114286x0.107143)
Daman and Diu                 Axes(0.374286,0.664286;0.114286x0.107143)
Delhi                         Axes(0.511429,0.664286;0.114286x0.107143)
Goa                           Axes(0.648571,0.664286;0.114286x0.107143)
Gujarat                       Axes(0.785714,0.664286;0.114286x0.107143)
Haryana                            Axes(0.1,0.535714;0.114286x0.107143)
Himachal Pradesh              Axes(0.237143,0.535714;0.114286x0.107143)
Jammu and Kashmir             Axes(0.374286,0.535714;0.114286x0.107143)
Jharkhand                     Axes(0.511429,0.535714;0.114286x0.107143)
Karnataka                     Axes(0.648571,0.535714;0.114286x0.107143)
Kerala                        Axes(0.785714,0.535714;0.114286x0.107143)
Lakshadweep                        Axes(0.1,0.407143;0.114286x0.107143)
Madhya Pradesh                Axes(0.237143,0.407143;0.114286x0.107143)
Maharashtra                   Axes(0.374286,0.407143;0.114286x0.107143)
Manipur                       Axes(0.511429,0.407143;0.114286x0.107143)
Meghalaya                     Axes(0.648571,0.407143;0.114286x0.107143)
Mizoram                       Axes(0.785714,0.407143;0.114286x0.107143)
Nagaland                           Axes(0.1,0.278571;0.114286x0.107143)
Odisha                        Axes(0.237143,0.278571;0.114286x0.107143)
Puducherry                    Axes(0.374286,0.278571;0.114286x0.107143)
Punjab                        Axes(0.511429,0.278571;0.114286x0.107143)
Rajasthan                     Axes(0.648571,0.278571;0.114286x0.107143)
Sikkim                        Axes(0.785714,0.278571;0.114286x0.107143)
Tamil Nadu                           Axes(0.1,0.15;0.114286x0.107143)
Telangana                       Axes(0.237143,0.15;0.114286x0.107143)
Tripura                         Axes(0.374286,0.15;0.114286x0.107143)
Uttar Pradesh                   Axes(0.511429,0.15;0.114286x0.107143)
Uttarakhand                     Axes(0.648571,0.15;0.114286x0.107143)
West Bengal                     Axes(0.785714,0.15;0.114286x0.107143)
dtype: object
```



Step 2.c.v - Random Variables:

```
rand_states
```

```
array(['Arunachal Pradesh', 'Rajasthan', 'Manipur', 'Sikkim', 'Bihar'],
      dtype=object)
```

```
rand_state_power_req_avail = power_req_avail_state_grp.filter(lambda x: x.name in rand_states)
rand_state_power_req_avail.head()
```

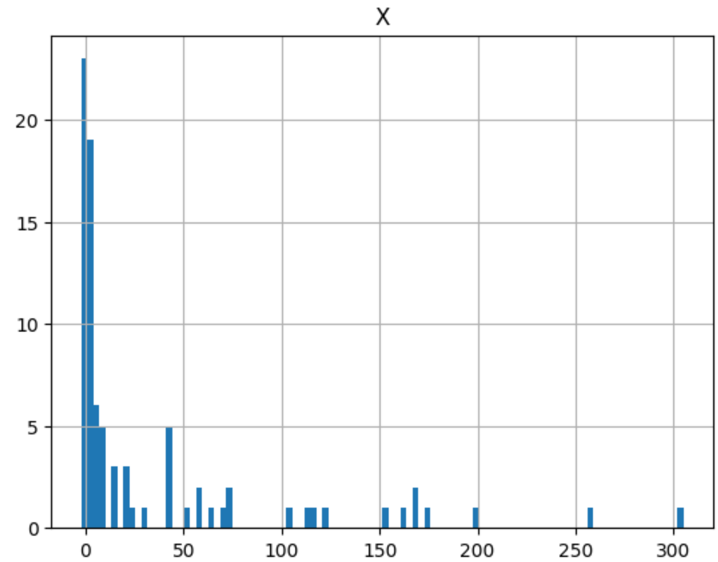
	State/Union Territory	Power_Requirement_Net_Crore_Units	Availability_Of_Power_Net_Crore_Units
2	Arunachal Pradesh	16	16
4	Bihar	720	648
21	Manipur	54	52
28	Rajasthan	2921	2897
29	Sikkim	0	0

```
# Define a new random variable X

rand_state_power_req_avail['X']  = rand_state_power_req_avail['Power_Requirement_Net_Crore_Units'] - rand_state_power_req_avail['Availability_Of_Powe
rand_state_power_req_avail.head()
```

	State/Union Territory	Power_Requirement_Net_Crore_Units	Availability_Of_Power_Net_Crore_Units	X
2	Arunachal Pradesh	16	16	0
4	Bihar	720	648	72
21	Manipur	54	52	2
28	Rajasthan	2921	2897	24
29	Sikkim	0	0	0

```
# Distribution of Column X

rand_state_power_req_avail.hist(column = 'X', bins = 100)   # Observation - Multimodal distribution
```

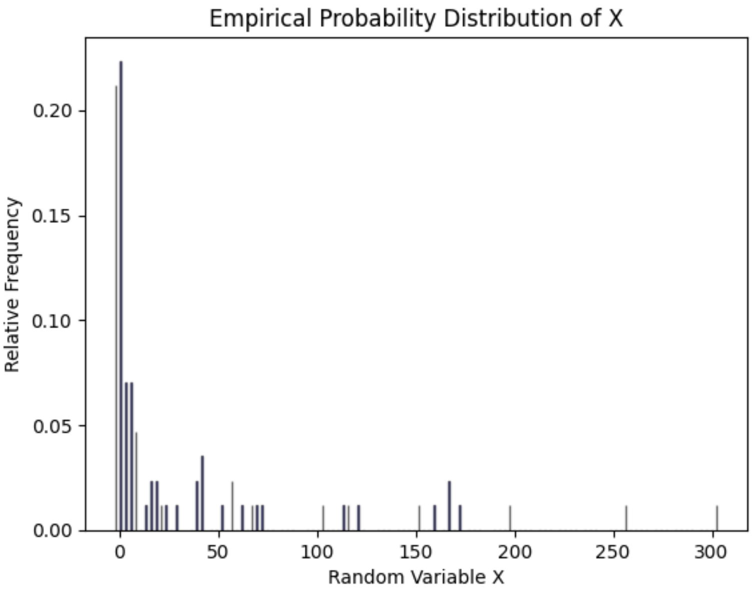
```
array([[<Axes: title={'center': 'X'}>]], dtype=object)
```



Empirical Probability Distribution of X

```
# Create a histogram
hist, bins = np.histogram(rand_state_power_req_avail['X'], bins=120)  # Adjust the bin edges based on your data

# Calculate relative frequencies
total_data_points = len(rand_state_power_req_avail)
relative_frequencies = hist / total_data_points
```

```
# Plot the histogram
plt.bar(bins[:-1], relative_frequencies, width=0.5, align='center', alpha=0.6, color='b', edgecolor='k')
plt.xlabel('Random Variable X')
plt.ylabel('Relative Frequency')
plt.title('Empirical Probability Distribution of X')
plt.show()

print('\n')
emperical_probability_dist = pd.DataFrame({'Value_of_X' : [bins[i] for i in range(len(bins) - 1)], 'Emperical_Probability': [relative_frequencies[i]
emperical_probability_dist.head(8)
```



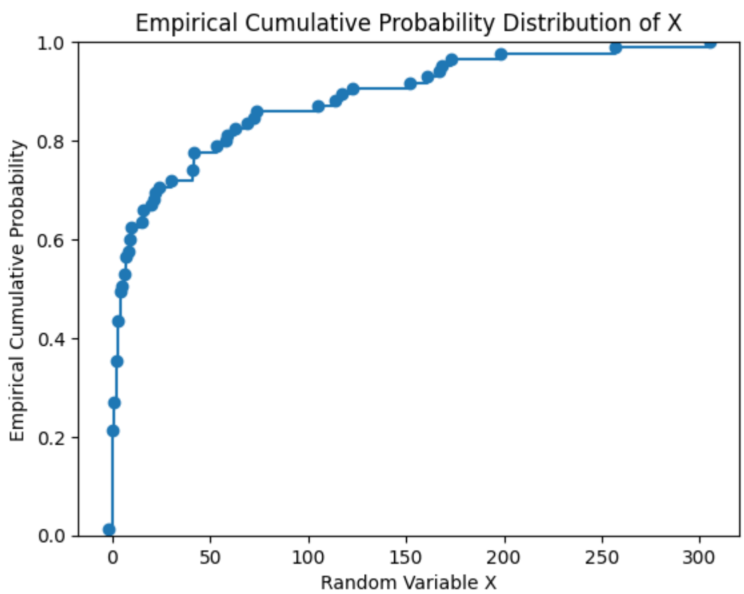
	Value_of_X	Emperical_Probability
0	-2.000000	0.211765
1	0.558333	0.223529
2	3.116667	0.070588
3	5.675000	0.070588
4	8.233333	0.047059
5	10.791667	0.000000
6	13.350000	0.011765
7	15.908333	0.023529

```
 # To plot a displot showing Probability density function (pdf) using Kernel Density Estimator (KDE)

fig = ff.create_distplot([rand_state_power_req_avail['X']], group_labels = 'X'  , bin_size = 12)
fig.show()
```

Empirical Cumulative Probability Distribution of X

Method 1

```
# To calculate the empirical cumulative probability distribution of X

X_col = rand_state_power_req_avail['X']
unique_X = np.sort((X_col).unique())

ecdf_list = []
for value in unique_X:
    cumulative_probability = np.sum(X_col <= value) / len(X_col)
    ecdf_list.append(cumulative_probability)

# Plot the empirical cumulative distribution
plt.step(unique_X, ecdf_list, where='post', marker='o')
plt.xlabel('Random Variable X')
plt.ylabel('Empirical Cumulative Probability')
plt.title('Empirical Cumulative Probability Distribution of X')
plt.ylim(0, 1)  # Ensure the y-axis ranges from 0 to 1
plt.show()

print('\n')
emperical_cumul_probability_dist = pd.DataFrame({'Value_of_X' : unique_X, 'Emperical_Probability': [ecdf_list[i] for i in range(len(unique_X))]})
emperical_cumul_probability_dist.head()
```



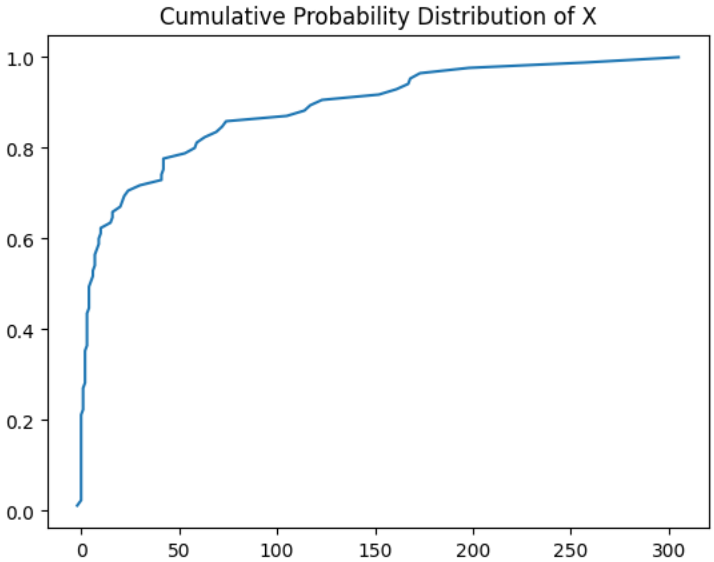
	Value_of_X	Emperical_Probability
0	-2	0.011765
1	0	0.211765
2	1	0.270588
3	2	0.352941
4	3	0.435294

Method 2

```
# To calculate the empirical cumulative probability distribution of X

ecdf = ECDF(rand_state_power_req_avail['X'])   # Fit a Cumulative Distribution Function
ecdf
```

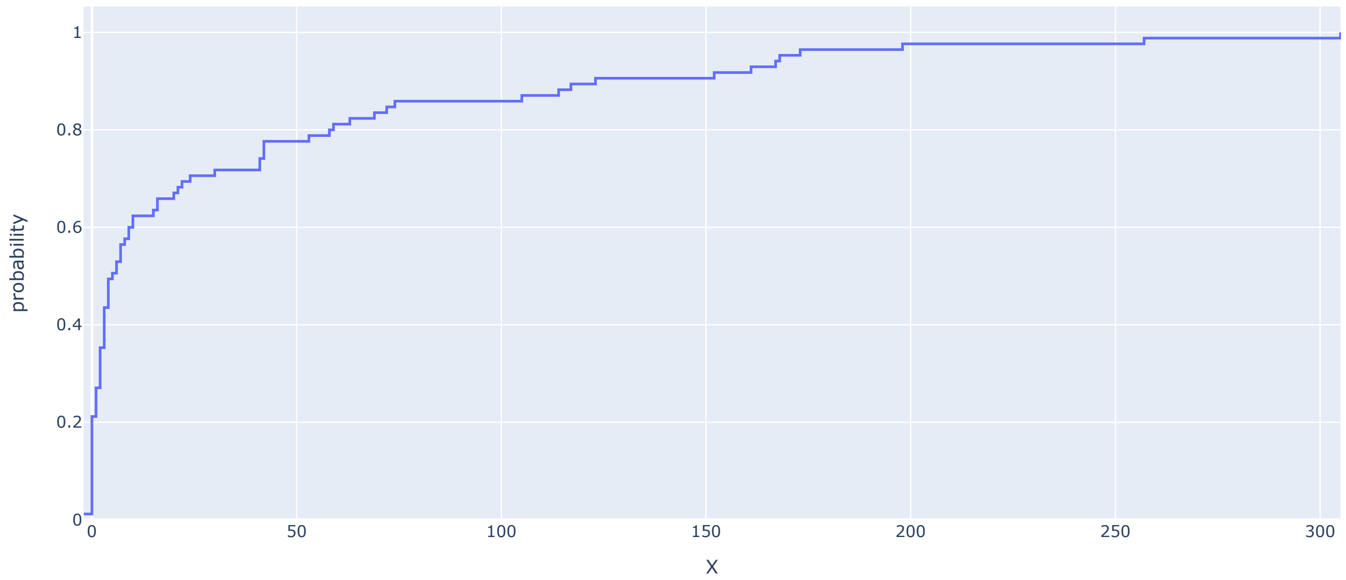
```
<statsmodels.distributions.empirical_distribution.ECDF at 0x7e09b673e350>
```

```
# To plot the cdf
plt.plot(ecdf.x, ecdf.y)

plt.title('Cumulative Probability Distribution of X')
plt.xlabel = 'X = Power Requirement - Power Availability '
plt.ylabel = 'Probability'
plt.show()
```



Method 3

```
# To plot the cdf usning interactive plotly

fig = px.ecdf(rand_state_power_req_avail['X'], x='X')
fig.show()
```



Step 2.c.vi - To find probability P(X> 0)

Method 1

```
# Assuming you have already calculated the empirical probability distribution
# You can use the 'relative_frequencies' and 'bins' variables from the previous code

# Find the index of the first positive value in 'bins' (assuming 'bins' is sorted)
first_positive_idx = next((i for i, val in enumerate(bins) if val > 0), None)

# Calculate the probability P(X > 0)
probability_x_greater_than_zero = 1 - np.sum(relative_frequencies[:first_positive_idx])
print('P(X > 0): %.3f' % (probability_x_greater_than_zero))
```

```
P(X > 0): 0.788
```

Method 2

```
probability_x_greater_than_zero = 1 - ecdf_list[first_positive_idx]
print('P(X > 0): %.3f' % (probability_x_greater_than_zero))
```

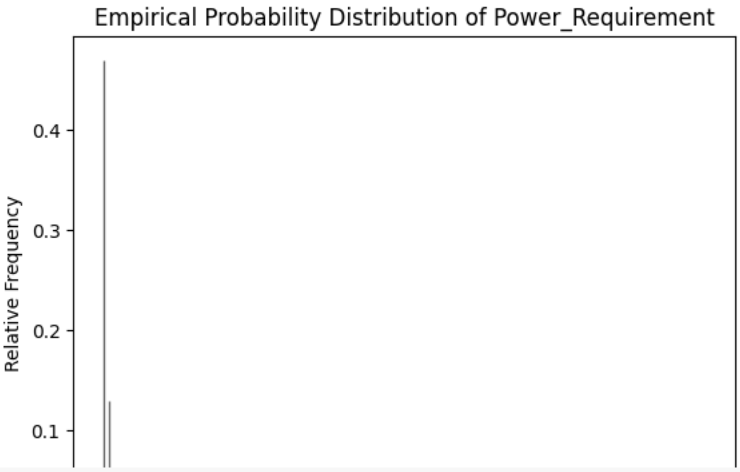
```
P(X > 0): 0.788
```

Step 2.c.vii - Expectated power requirement

Method 1 - Using histogram

```
from importlib import reload
plt=reload(plt)
```

```
# To calculate the empirical  probability distribution of  power requirement

power_req = rand_state_power_req_avail['Power_Requirement_Net_Crore_Units']

# Create a histogram
hist, bins = np.histogram(power_req, bins=120)  # Adjust the bin edges based on your data

# Calculate relative frequencies
total_data_points = len(rand_state_power_req_avail)
relative_frequencies = hist / total_data_points

# Plot the histogram
plt.bar(bins[:-1], relative_frequencies, width=0.5, align='center', alpha=0.6, color='b', edgecolor='k')
plt.xlabel('Random Variable Power_Requirement')
plt.ylabel('Relative Frequency')
plt.title('Empirical Probability Distribution of Power_Requirement')
plt.show()

print('\n')
emperical_probability_dist = pd.DataFrame({'Power_Requirement' : [bins[i] for i in range(len(bins) - 1)], 'Emperical_Probability': [relative_frequenc
emperical_probability_dist.head(8)
```




```
# Calculate the expected power requirement

# E(X)=∑ x.·P(X=x)

expected_power_requirement = 0
for i in range(len(emperical_probability_dist)):
  expected_power_requirement += emperical_probability_dist.iloc[i, 0] * emperical_probability_dist.iloc[i, 1]

expected_power_requirement
```

```
1463.651960784314
```

Method 2 - Using Frequency table

Function to find the frequency table for a given column

5 355.458333 0.000000

```
def find_freq_table(df, col):
  # Create a frequency table for col in df
  frequency_table = df.value_counts().reset_index()
  frequency_table.columns = [col, 'Frequency']

  # Calculate the total number of entries
  total_data_points  = len(df)

  # Calculate empirical probabilities
  frequency_table['Probability'] = frequency_table['Frequency'] / total_data_points

  # Sort the table by col
  frequency_table = frequency_table.sort_values(by=col)


  plt.bar(frequency_table[col], frequency_table['Probability'], width=0.5, align='center', alpha=0.6, color='b', edgecolor='k')

  return frequency_table
```

Function to find the expectation of a given column

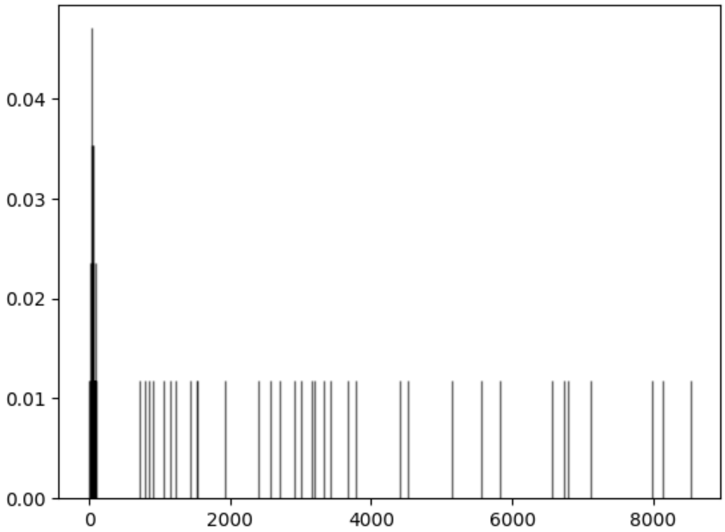
```
def find_expectation(freq_table):
  # E(X)=∑ x.·P(X=x)

  col_names = freq_table.columns
  expected_value = np.sum(freq_table[col_names[0]] * freq_table[col_names[2]])
  return expected_value
```

To find the expected power requirement

```
power_req = rand_state_power_req_avail['Power_Requirement_Net_Crore_Units']

# Create a frequency table for Power_Requirement_Net_Crore_Units
frequency_table = find_freq_table(power_req, 'Power_Requirement_Net_Crore_Units')

# Display the empirical probability distribution
```

```
print('\n')
pd.DataFrame(frequency_table).head()
```

	Power_Requirement_Net_Crore_Units	Frequency	Probability
43	0	1	0.011765
10	16	1	0.011765
6	21	2	0.023529
49	22	1	0.011765
7	29	2	0.023529




```
# Calculate the expected power requirement

expected_power_requirement = find_expectation(frequency_table)
expected_power_requirement
```

```
1498.2235294117647
```

Step 2.c.viii - Expectated per capita power availability for all states

```
power_avail_per_cap = power_infra['Availability_Of_Power_Per_Capita_kiloWatt-Hour']

# Create a frequency table for Availability_Of_Power_Per_Capita_kiloWatt-Hour
frequency_table = find_freq_table(power_avail_per_cap, 'Availability_Of_Power_Per_Capita_kiloWatt-Hour')

# Display the empirical probability distribution
print('\n')
pd.DataFrame(frequency_table).head()
```

	Availability_Of_Power_Per_Capita_kiloWatt-Hour	Frequency	Probability
0	0.0	13	0.021242
386	78.0	1	0.001634
399	87.0	1	0.001634
382	93.3	1	0.001634
305	95.6	1	0.001634

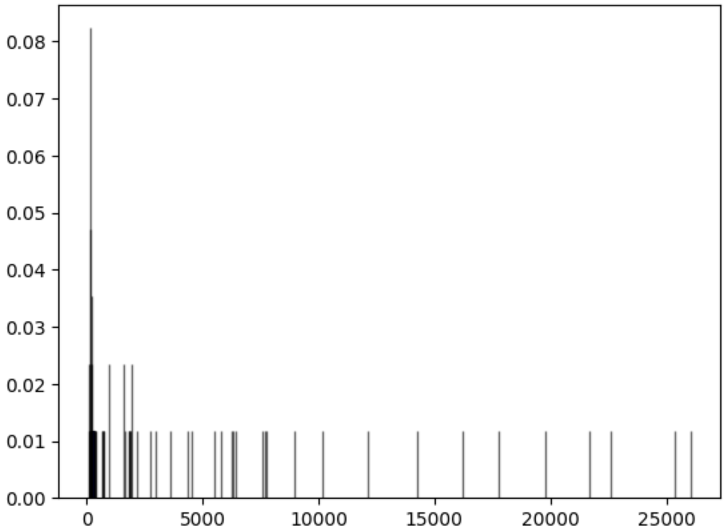
```
# Calculate the expected power availability per capita for all states

expected_power_avail = find_expectation(frequency_table)
expected_power_avail
```

```
1515.8516339869282
```

Step 2.c.ix - Expectated installed power capacity

```
indexes = rand_state_power_req_avail.index
power_installed = power_infra.loc[indexes, 'Installed_Power_Capacity_MegaWatt']

# Create a frequency table for Power_Requirement_Net_Crore_Units
frequency_table = find_freq_table(power_installed, 'Installed_Power_Capacity_MegaWatt')

# Display the empirical probability distribution
print('\n')
pd.DataFrame(frequency_table).head()
```

	Installed_Power_Capacity_MegaWatt	Frequency	Probability
6	114	2	0.023529
43	141	1	0.011765
0	158	7	0.082353
41	159	1	0.011765
1	179	4	0.047059




```
# Calculate the expected installed power capacity

expected_power_installed = find_expectation(frequency_table)
expected_power_installed
```

```
3526.5647058823533
```

Step 2.c.x - Calculate the sample mean and variance of the "Power Requirement Net Crore Units" for states with a population size greater than 1 million.

```
power_infra['Population'] = power_infra['Availability_Of_Power_Net_Crore_Units'] * 1000000 / power_infra['Availability_Of_Power_Per_Capita_kiloWatt-H
print(power_infra.shape, '\n')
power_infra[['State/Union Territory', 'Population']].head()
```

```
(612, 7)
```

	State/Union Territory	Population
0	Andaman and Nicobar Islands	NaN
1	Andhra Pradesh	7.620642e+06
2	Arunachal Pradesh	1.111883e+05
3	Assam	2.663690e+06
4	Bihar	8.307692e+06

```
POPULATION_THRESHOLD = 1000000

filtered_dataset = power_infra[power_infra['Population'] > POPULATION_THRESHOLD]
print(filtered_dataset.shape, '\n')
```

```
(340, 7)
```

```
power_req = filtered_dataset['Power_Requirement_Net_Crore_Units']

sample_mean = power_req.mean()

print('Sample Mean:', sample_mean)
```

```
Sample Mean: 4600.844117647059
```

```
sample_variance = power_req.var()

print('Sample Variance:', sample_variance)
```

```
Sample Variance: 12007710.002177684
```

Step 2.c.xi - Calculate the sample mean and variance of the "Power Requirement Net Crore Units" for states with a population size less than 1 million.

```
filtered_dataset = power_infra[~ power_infra.index.isin(filtered_dataset.index)]

print(filtered_dataset.shape, '\n')
filtered_dataset.head()
```

```
(272, 7)
```

	State/Union Territory	Year	Power_Requirement_Net_Crore_Units	Availability_Of_Power_Net_Crore_Units	Availability_Of_Power_Per_Capita_kiloWatt-Hour	Ins
0	Andaman and Nicobar Islands	2004-05	0	0	0.0	
2	Arunachal Pradesh	2004-05	16	16	143.9	
5	Chandigarh	2004-05	116	115	1274.7	
7	Dadra and Nagar Haveli	2004-05	183	183	8299.7	
8	Daman and Diu	2004-05	112	112	7073.1	

```
power_req = filtered_dataset['Power_Requirement_Net_Crore_Units']

sample_mean = power_req.mean()

print('Sample Mean:', sample_mean)
```

```
Sample Mean: 190.625
```

```
sample_variance = power_req.var()

print('Sample Variance:', sample_variance)
```

```
Sample Variance: 52160.906826568265
```

Step 2.c.xii - Compute the skewness of the "Availability Of Power Net Crore Units" for all states

```
power_avail = power_infra['Availability_Of_Power_Net_Crore_Units']

skew_avail = skew(power_avail)

print('Skewness for Availability_Of_Power_Net_Crore_Units:', skew_avail)
```

```
Skewness for Availability_Of_Power_Net_Crore_Units: 1.5796751778877218
```

Step 2.c.xiii - Calculate the skewness of the "Power Requirement Net Crore Units" for states with a population size greater than 500,000.

```
POPULATION_THRESHOLD = 500000

filtered_dataset = power_infra[power_infra['Population'] > POPULATION_THRESHOLD]
print(filtered_dataset.shape, '\n')
```

```
(364, 7)
```

```
power_req = filtered_dataset['Power_Requirement_Net_Crore_Units']

skew_req = skew(power_req)
print('Skewness for Power_Requirement_Net_Crore_Units:', skew_req)
```

```
Skewness for Power_Requirement_Net_Crore_Units: 1.0626627738190983
```

Step 2.c.xiv - Stratify the states into three clusters based on their population size: small, medium, and large. Define the thresholds for each cluster.

```
np.min(power_infra['Population'])
```

```
5054.334091483447
```

```
np.max(power_infra['Population'])
```

```
19961251.037918627
```

```
# Define population thresholds for each cluster
SMALL_THRESHOLD = 2500000  # 2.5 million
MEDIUM_THRESHOLD = 10000000  # 10 million

# Create a new column 'Population_Category' to store the cluster labels
power_infra['Population_Category'] = 'Small'  # Initialize all as 'Small'

# Update the cluster labels based on population size
power_infra.loc[power_infra['Population'] > SMALL_THRESHOLD, 'Population_Category'] = 'Medium'
power_infra.loc[power_infra['Population'] > MEDIUM_THRESHOLD, 'Population_Category'] = 'Large'

# Print the updated dataset with population categories
power_infra[['State/Union Territory', 'Population', 'Population_Category']].head()
```

	State/Union Territory	Population	Population_Category
0	Andaman and Nicobar Islands	NaN	Small
1	Andhra Pradesh	7.620642e+06	Medium
2	Arunachal Pradesh	1.111883e+05	Small
3	Assam	2.663690e+06	Medium

Step 2.c.xv - Calculate the mean, median, and standard deviation of "Power Requirement Net Crore Units" for each cluster

Function for finding mean, median, standard deviation a given column for a cluster

```
def find_cluster_stats(pop_category, column):
  filtered_dataset = power_infra[power_infra['Population_Category'] == pop_category]
  power_req_category = filtered_dataset[column]

  print('Mean:', np.mean(power_req_category))
  print('Median:', np.median(power_req_category))
  print('Sample deviation:', np.std(power_req_category))
```

```
# For small cluster

find_cluster_stats('Small', 'Power_Requirement_Net_Crore_Units')
```

```
Mean: 571.0741839762611
Median: 164.0
Sample deviation: 910.0033148689104
```

```
# For medium cluster

find_cluster_stats('Medium', 'Power_Requirement_Net_Crore_Units')
```

```
Mean: 4647.100840336135
Median: 4608.5
Sample deviation: 3049.7203533322045
```

```
# For large cluster

find_cluster_stats('Large', 'Power_Requirement_Net_Crore_Units')
```

```
Mean: 8585.81081081081
Median: 9165.0
Sample deviation: 4713.039031257156
```

Step 2.c.xvi - Calculate the mean, median, and standard deviation of "Availability Of Power Net Crore Units" for each cluster.

```
# For small cluster

find_cluster_stats('Small', 'Availability_Of_Power_Net_Crore_Units')
```

```
Mean: 536.2017804154302
Median: 158.0
Sample deviation: 852.3643922686545
```

```
# For medium cluster

find_cluster_stats('Medium', 'Availability_Of_Power_Net_Crore_Units')
```

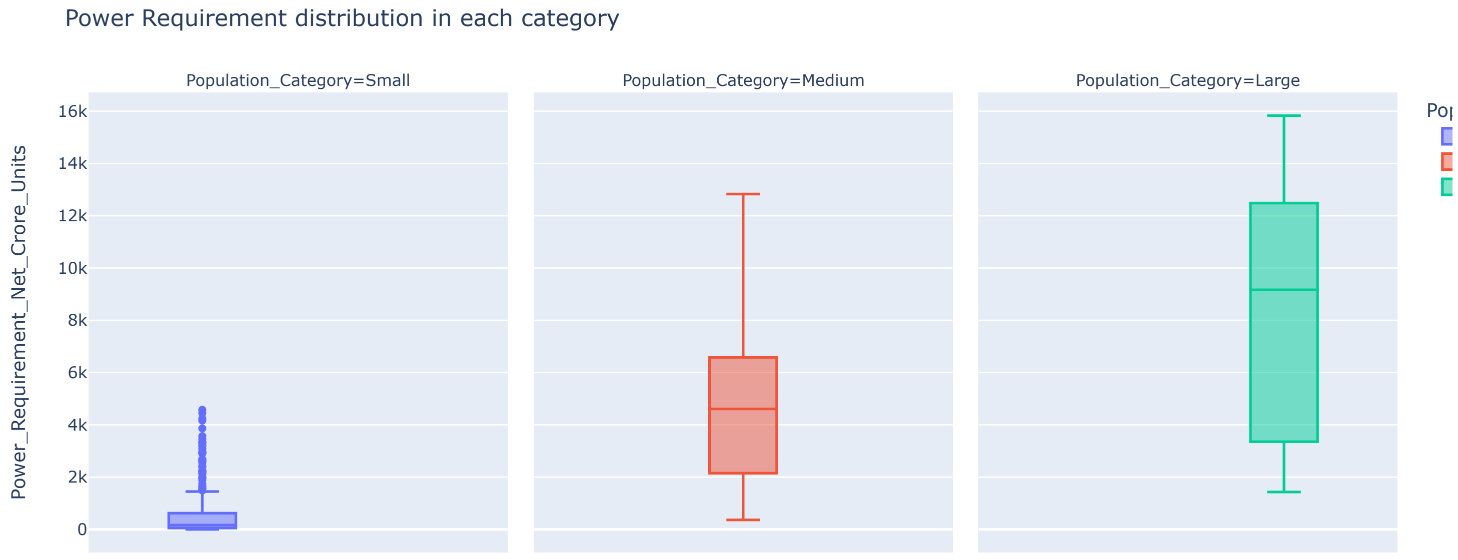
```
Mean: 4453.621848739495
Median: 4350.0
Sample deviation: 2879.7488335611115
```

```
# For large cluster

find_cluster_stats('Large', 'Availability_Of_Power_Net_Crore_Units')
```

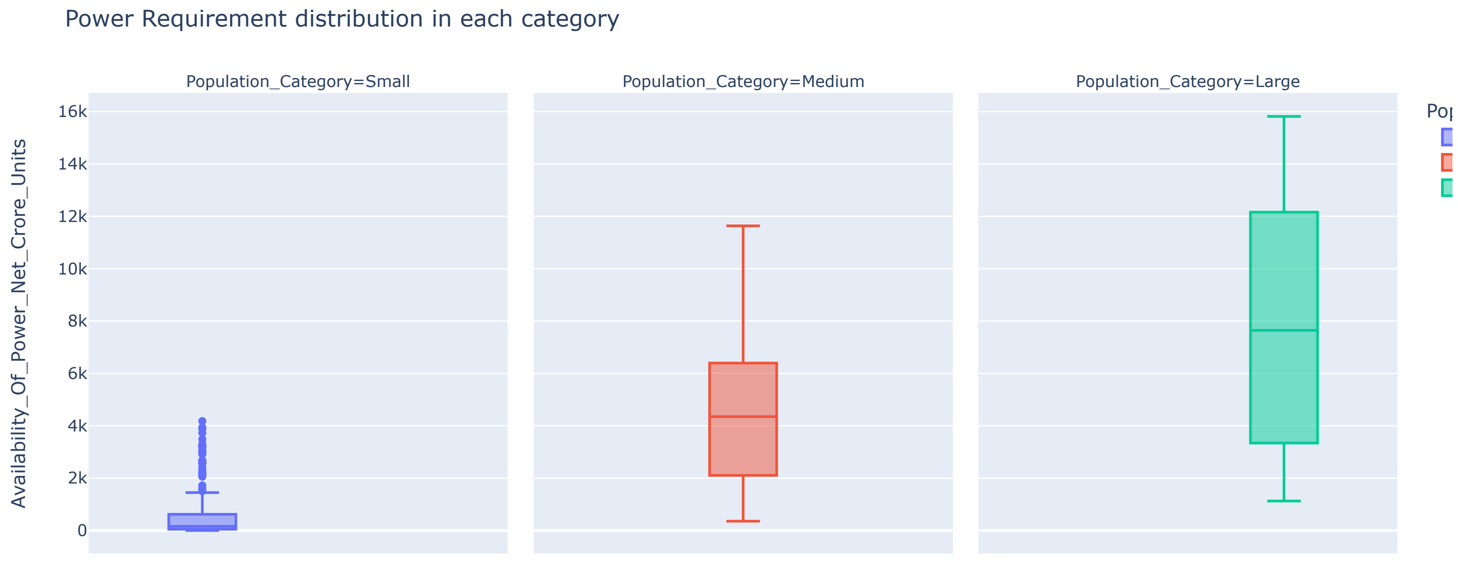
```
Mean: 8042.486486486487
Median: 7645.0
Sample deviation: 4737.811609214953
```

Step 2.c.xvii - Create box plots to visualize the distribution of power requirements and availability within each cluster.

```
# For Power Requirement

px.box(power_infra, y = 'Power_Requirement_Net_Crore_Units', facet_col = 'Population_Category',
       color = 'Population_Category', title = 'Power Requirement distribution in each category')
```




```
# For Power Availability

px.box(power_infra, y = 'Availability_Of_Power_Net_Crore_Units', facet_col = 'Population_Category',
       color = 'Population_Category', title = 'Power Requirement distribution in each category')
```



Step 2.d - Search online for projected population data for the next few years and use it to forecast the expected Power Requirements for each state. If you are making any assumptions for this calculation, state them clearly.

To find the statewise per capita power consumption

```
power_infra['Power_Consumption_Per_Capita'] = power_infra['Power_Requirement_Net_Crore_Units'] / power_infra['Population']

power_consumption_state_grp = power_infra.groupby('State/Union Territory')['Power_Consumption_Per_Capita'].mean()
pd.DataFrame(power_consumption_state_grp.head())
```

	Power_Consumption_Per_Capita
State/Union Territory	
Andaman and Nicobar Islands	0.000718
Andhra Pradesh	0.001045
Arunachal Pradesh	0.000421
Assam	0.000232
Bihar	0.000182

To generate state-wise projected population dataset

```
state_list = power_infra['State/Union Territory'].unique()
state_list
```

```
['Andaman and Nicobar Islands', 'Andhra Pradesh', 'Arunachal Pradesh', 'Assam', 'Bihar', ..., 'Telangana', 'Tripura', 'Uttar Pradesh',
'Uttarakhand', 'West Bengal']
Length: 36
Categories (36, object): ['Andaman and Nicobar Islands', 'Andhra Pradesh', 'Arunachal Pradesh', 'Assam', ...,
                          'Tripura', 'Uttar Pradesh', 'Uttarakhand', 'West Bengal']
```

```
# Cartesian product to generate year-wise entries for each state

projected_populations = pd.DataFrame(itertools.product(state_list, ['2021-22', '2022-23', '2023-24', '2024-25']), columns = ['State/Union Territory',
projected_populations['Population'] = np.NaN
projected_populations.head(6)
```

	State/Union Territory	Year	Population
0	Andaman and Nicobar Islands	2021-22	NaN
1	Andaman and Nicobar Islands	2022-23	NaN
2	Andaman and Nicobar Islands	2023-24	NaN
3	Andaman and Nicobar Islands	2024-25	NaN
4	Andhra Pradesh	2021-22	NaN
5	Andhra Pradesh	2022-23	NaN

```
projected_populations.to_csv('projected_populations.csv' , index = False)
```

After entering the projected population data in the downloaded csv file

Source of projected population data -

https://main.mohfw.gov.in/sites/default/files/Population%20Projection%20Report%202011-2036%20-%20upload_compressed_0.pdf

```
# Upload dataset to Colab workspace
uploaded = files.upload()
```

Choose files projected_populations.csv

- **projected_populations.csv**(text/csv) - 3748 bytes, last modified: 05/10/2023 - 100% done

```
Saving projected_populations.csv to projected_populations.csv
```

```
# Import the dataset into a DataFrame

projected_populations = pd.read_csv('projected_populations.csv')
```

```
projected_populations['Population'] = projected_populations['Population'] * 100
projected_populations.head()
```

	State/Union Territory	Year	Population
0	Andaman and Nicobar Islands	2021-22	40200
1	Andaman and Nicobar Islands	2022-23	40300
2	Andaman and Nicobar Islands	2023-24	40400
3	Andaman and Nicobar Islands	2024-25	40500
4	Andhra Pradesh	2021-22	5297200

```
projected_populations_state_grp = projected_populations.groupby('State/Union Territory')

for state in state_list:
  # Retrieve the projected population values for a state from the generated dataset grouped by state
  state_population_values = projected_populations_state_grp.get_group(state)['Population'].reset_index()
  indices = state_population_values['index']
  state_population_values.drop('index', axis = 1, inplace = True)

  population_growth_rate = []

  # Find the population growth rate of the state for the years considered for projection
  for pop_ind in range(len(state_population_values) - 1):
    pop_x = state_population_values.iloc[pop_ind]
    pop_y = state_population_values.iloc[pop_ind + 1]
    population_growth_rate.append(float(((pop_y - pop_x)/ pop_x).values))

  # Find the initial forcasted power requirement/demand
  avg_power_consumption_state = power_consumption_state_grp.loc[state]
  first_projected_pop_val = state_population_values.loc[0]
  initial_forcasted_power = float(avg_power_consumption_state * first_projected_pop_val)

  forecasted_power_requirements = [initial_forcasted_power]

  # Find the forcasted power requirement using the population growth rate
  for growth_rate in population_growth_rate:
    prev_forcasted_power_req = forecasted_power_requirements[-1]
    forecasted_power_requirements.append(prev_forcasted_power_req * (1 + growth_rate))

  projected_populations.loc[projected_populations['State/Union Territory'] == state, 'Projected_Power_Req'] = pd.Series(forecasted_power_requirements

projected_populations
```

	State/Union Territory	Year	Population	Projected_Power_Req
0	Andaman and Nicobar Islands	2021-22	40200	28.868118
1	Andaman and Nicobar Islands	2022-23	40300	28.939929
2	Andaman and Nicobar Islands	2023-24	40400	29.011740
3	Andaman and Nicobar Islands	2024-25	40500	29.083551
4	Andhra Pradesh	2021-22	5297200	5536.376312
...	...	...	...	...
139	Uttarakhand	2024-25	1187400	1288.596254
140	West Bengal	2021-22	9860400	4507.482881
141	West Bengal	2022-23	9908400	4529.425113
142	West Bengal	2023-24	9956300	4551.321631
143	West Bengal	2024-25	10004200	4573.218149

144 rows × 4 columns