India Air Quality Analysis and Prediction

1. Importing Required Libraries

In [1]:

```
import pandas as pd # For pandas operations
import matplotlib.pyplot as plt # For visualization
import numpy as np # For array operations
import seaborn as sns # For pair plot
from sklearn.model_selection import train_test_split # For splitting the dataset
import statsmodels.api as sm # For model summary
from sklearn.linear_model import LinearRegression # For linear regression
from sklearn.tree import DecisionTreeRegressor # For decision tree regression
from sklearn.ensemble import RandomForestRegressor # For random forest regression
from sklearn.linear_model import LogisticRegression # For logistic regression
from sklearn.tree import DecisionTreeClassifier # For decision tree classification
from sklearn.ensemble import RandomForestClassifier # For random forest classification
from xgboost import XGBClassifier # For xgboost classification
from sklearn.neighbors import KNeighborsClassifier # For knn classification
from sklearn import metrics # For performance evaluation
from sklearn.metrics import mean_absolute_error, mean_squared_error # For model estimation
from sklearn.metrics import roc_auc_score, roc_curve # For roc_auc curve
import warnings # For disabling system warnings
warnings.filterwarnings("ignore")
```

2. Data Wrangling

In [2]:

```
# Reading the air quality dataset
air_quality_data = pd.read_csv("air_quality_data.csv", index_col=False, encoding='unicode_escape')
air_quality_data
```

Out[2]:

	stn_code	sampling_date	state	location	agency	type	so2	no2	rspm	spm	location_monitoring_station	pm2_5	date
0	150.0	February - M021990	Andhra Pradesh	Hyderabad	NaN	Residential, Rural and other Areas	4.8	17.4	NaN	NaN	NaN	NaN	1990-02-01

	stn_code	sampling_date	state	location	agency	type	so2	no2	rspm	spm	location_monitoring_station	pm2_5	date
1	151.0	February - M021990	Andhra Pradesh	Hyderabad	NaN	Industrial Area	3.1	7.0	NaN	NaN	NaN	NaN	1990-02-01
2	152.0	February - M021990	Andhra Pradesh	Hyderabad	NaN	Residential, Rural and other Areas	6.2	28.5	NaN	NaN	NaN	NaN	1990-02-01
3	150.0	March - M031990	Andhra Pradesh	Hyderabad	NaN	Residential, Rural and other Areas	6.3	14.7	NaN	NaN	NaN	NaN	1990-03-01
4	151.0	March - M031990	Andhra Pradesh	Hyderabad	NaN	Industrial Area	4.7	7.5	NaN	NaN	NaN	NaN	1990-03-01
...	...	...	...	...	...	...	...	...	...	...	...	...	...
435737	SAMP	24-12-15	West Bengal	ULUBERIA	West Bengal State Pollution Control Board	RIRUO	22.0	50.0	143.0	NaN	Inside Rampal Industries,ULUBERIA	NaN	2015-12-24
435738	SAMP	29-12-15	West Bengal	ULUBERIA	West Bengal State Pollution Control Board	RIRUO	20.0	46.0	171.0	NaN	Inside Rampal Industries,ULUBERIA	NaN	2015-12-29
435739	NaN	NaN	andaman-and-nicobar-islands	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
435740	NaN	NaN	Lakshadweep	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
435741	NaN	NaN	Tripura	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

435742 rows × 13 columns

In [3]:

```
# Displaying columns
air_quality_data.columns
```

Out[3]:
```
Index(['stn_code', 'sampling_date', 'state', 'location', 'agency', 'type',
       'so2', 'no2', 'rspm', 'spm', 'location_monitoring_station', 'pm2_5',
       'date'],
      dtype='object')
```

In [4]:
```python
# Dataset description
air_quality_data.describe()
```

Out[4]:

	so2	no2	rspm	spm	pm2_5
count	401096.000000	419509.000000	395520.000000	198355.000000	9314.000000
mean	10.829414	25.809623	108.832784	220.783480	40.791467
std	11.177187	18.503086	74.872430	151.395457	30.832525
min	0.000000	0.000000	0.000000	0.000000	3.000000
25%	5.000000	14.000000	56.000000	111.000000	24.000000
50%	8.000000	22.000000	90.000000	187.000000	32.000000
75%	13.700000	32.200000	142.000000	296.000000	46.000000
max	909.000000	876.000000	6307.033333	3380.000000	504.000000

In [5]:
```python
# Datatype information
air_quality_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 435742 entries, 0 to 435741
Data columns (total 13 columns):
 #   Column                       Non-Null Count   Dtype  
---  ------                       --------------   -----  
 0   stn_code                     291665 non-null  object 
 1   sampling_date                435739 non-null  object 
 2   state                        435742 non-null  object 
 3   location                     435739 non-null  object 
 4   agency                       286261 non-null  object 
 5   type                         430349 non-null  object 
 6   so2                          401096 non-null  float64
 7   no2                          419509 non-null  float64
 8   rspm                         395520 non-null  float64
```

```
 9   spm                          198355 non-null  float64
 10  location_monitoring_station  408251 non-null  object
 11  pm2_5                        9314 non-null    float64
 12  date                         435735 non-null  object
dtypes: float64(5), object(8)
memory usage: 43.2+ MB
```

In [6]:

```python
# Displaying unique entries
air_quality_data.nunique()
```

Out[6]:

```
stn_code                        803
sampling_date                  5485
state                            37
location                        304
agency                           64
type                             10
so2                            4197
no2                            6864
rspm                           6065
spm                            6668
location_monitoring_station     991
pm2_5                           433
date                           5067
dtype: int64
```

In [7]:

```python
# Displaying null values
air_quality_data.isna().sum().sort_values(ascending=False)
```

Out[7]:

```
pm2_5                          426428
spm                            237387
agency                         149481
stn_code                       144077
rspm                            40222
so2                             34646
location_monitoring_station     27491
no2                             16233
type                             5393
date                                7
sampling_date                       3
location                            3
state                               0
dtype: int64
```

In [8]:
```
# Estimating null value percentage
((air_quality_data.isna().sum()/air_quality_data.isna().count())*100).sort_values(ascending=False)
```

Out[8]:
```
pm2_5                          97.862497
spm                            54.478797
agency                         34.304933
stn_code                       33.064749
rspm                            9.230692
so2                             7.951035
location_monitoring_station     6.309009
no2                             3.725370
type                            1.237659
date                            0.001606
sampling_date                   0.000688
location                        0.000688
state                           0.000000
dtype: float64
```

In [9]:
```
# Handling missing categorical data
air_quality_data.state = air_quality_data.state.fillna(air_quality_data['state'].mode()[0])
air_quality_data.location = air_quality_data.location.fillna(air_quality_data['location'].mode()[0])
air_quality_data.agency = air_quality_data.agency.fillna(air_quality_data['agency'].mode()[0])
air_quality_data.type = air_quality_data.type.fillna(air_quality_data['type'].mode()[0])
air_quality_data.isna().sum().sort_values(ascending=False)
```

Out[9]:
```
pm2_5                          426428
spm                            237387
stn_code                       144077
rspm                            40222
so2                             34646
location_monitoring_station     27491
no2                             16233
date                                7
sampling_date                       3
state                               0
location                            0
agency                              0
type                                0
dtype: int64
```

In [10]:
```
# Handling missing numerical data
air_quality_data.fillna(0, inplace=True)
```

```python
air_quality_data.isna().sum()
```

Out[10]:

```
stn_code                       0
sampling_date                  0
state                          0
location                       0
agency                         0
type                           0
so2                            0
no2                            0
rspm                           0
spm                            0
location_monitoring_station    0
pm2_5                          0
date                           0
dtype: int64
```

In [11]:

```python
coorelation_data = air_quality_data[["state", "location", "so2", "no2", "rspm", "spm", "pm2_5"]]
coorelation_data
```

Out[11]:

	state	location	so2	no2	rspm	spm	pm2_5
0	Andhra Pradesh	Hyderabad	4.8	17.4	0.0	0.0	0.0
1	Andhra Pradesh	Hyderabad	3.1	7.0	0.0	0.0	0.0
2	Andhra Pradesh	Hyderabad	6.2	28.5	0.0	0.0	0.0
3	Andhra Pradesh	Hyderabad	6.3	14.7	0.0	0.0	0.0
4	Andhra Pradesh	Hyderabad	4.7	7.5	0.0	0.0	0.0
...	...	...	...	...	...	...	...
435737	West Bengal	ULUBERIA	22.0	50.0	143.0	0.0	0.0
435738	West Bengal	ULUBERIA	20.0	46.0	171.0	0.0	0.0
435739	andaman-and-nicobar-islands	Guwahati	0.0	0.0	0.0	0.0	0.0
435740	Lakshadweep	Guwahati	0.0	0.0	0.0	0.0	0.0
435741	Tripura	Guwahati	0.0	0.0	0.0	0.0	0.0

435742 rows × 7 columns

In [12]:

```
coorelation_data.corr().abs()
```

Out[12]:

	so2	no2	rspm	spm	pm2_5
so2	1.000000	0.369450	0.097568	0.105536	0.019861
no2	0.369450	1.000000	0.317282	0.191618	0.018202
rspm	0.097568	0.317282	1.000000	0.196845	0.032407
spm	0.105536	0.191618	0.196845	1.000000	0.078646
pm2_5	0.019861	0.018202	0.032407	0.078646	1.000000

In [13]:

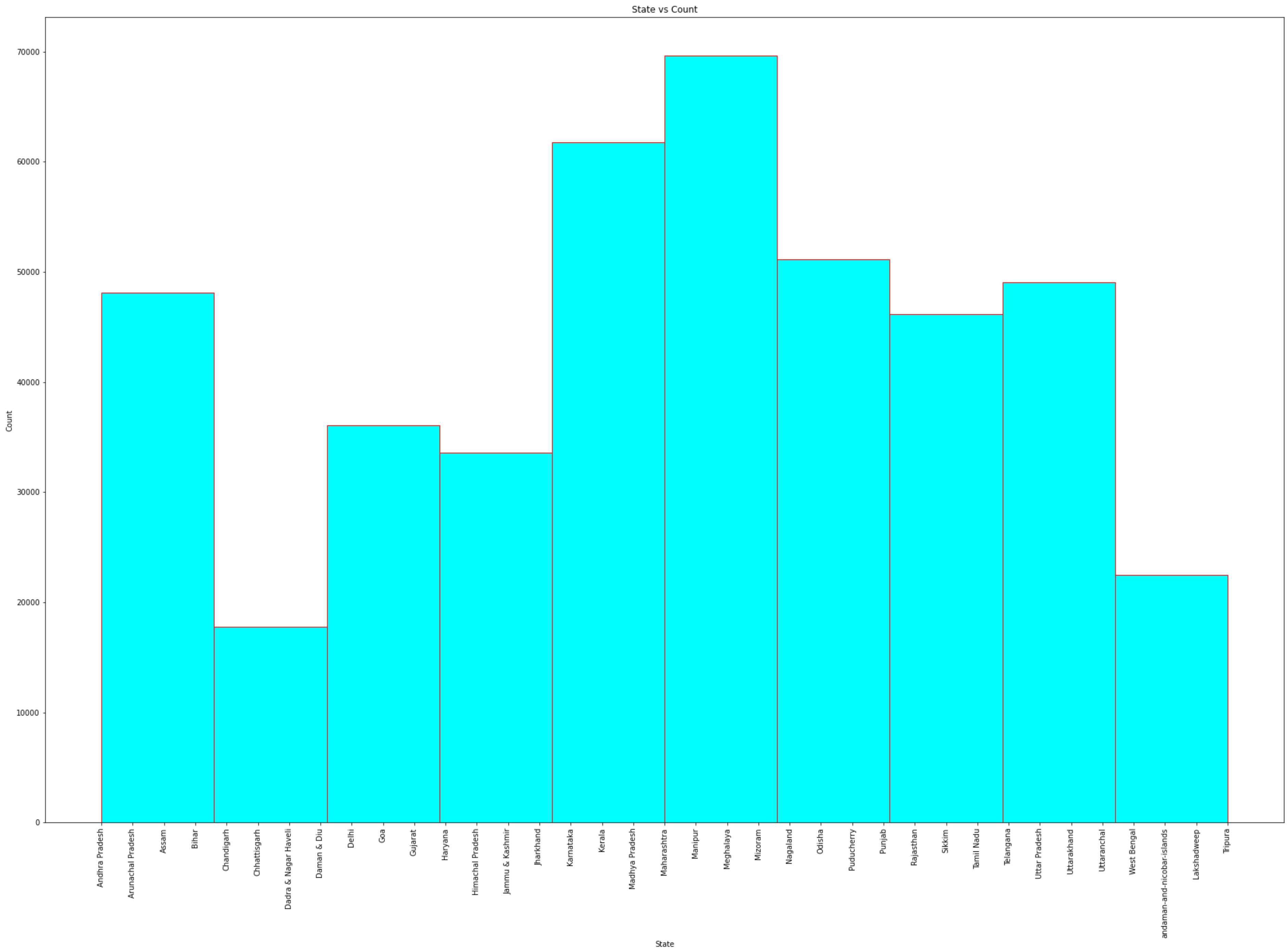
```
# Estimating upper traingular matrix
coorelation_data.corr().abs().where(np.triu(np.ones(coorelation_data.corr().abs().shape),k=1).astype(np.bool))
```

Out[13]:

	so2	no2	rspm	spm	pm2_5
so2	NaN	0.36945	0.097568	0.105536	0.019861
no2	NaN	NaN	0.317282	0.191618	0.018202
rspm	NaN	NaN	NaN	0.196845	0.032407
spm	NaN	NaN	NaN	NaN	0.078646
pm2_5	NaN	NaN	NaN	NaN	NaN

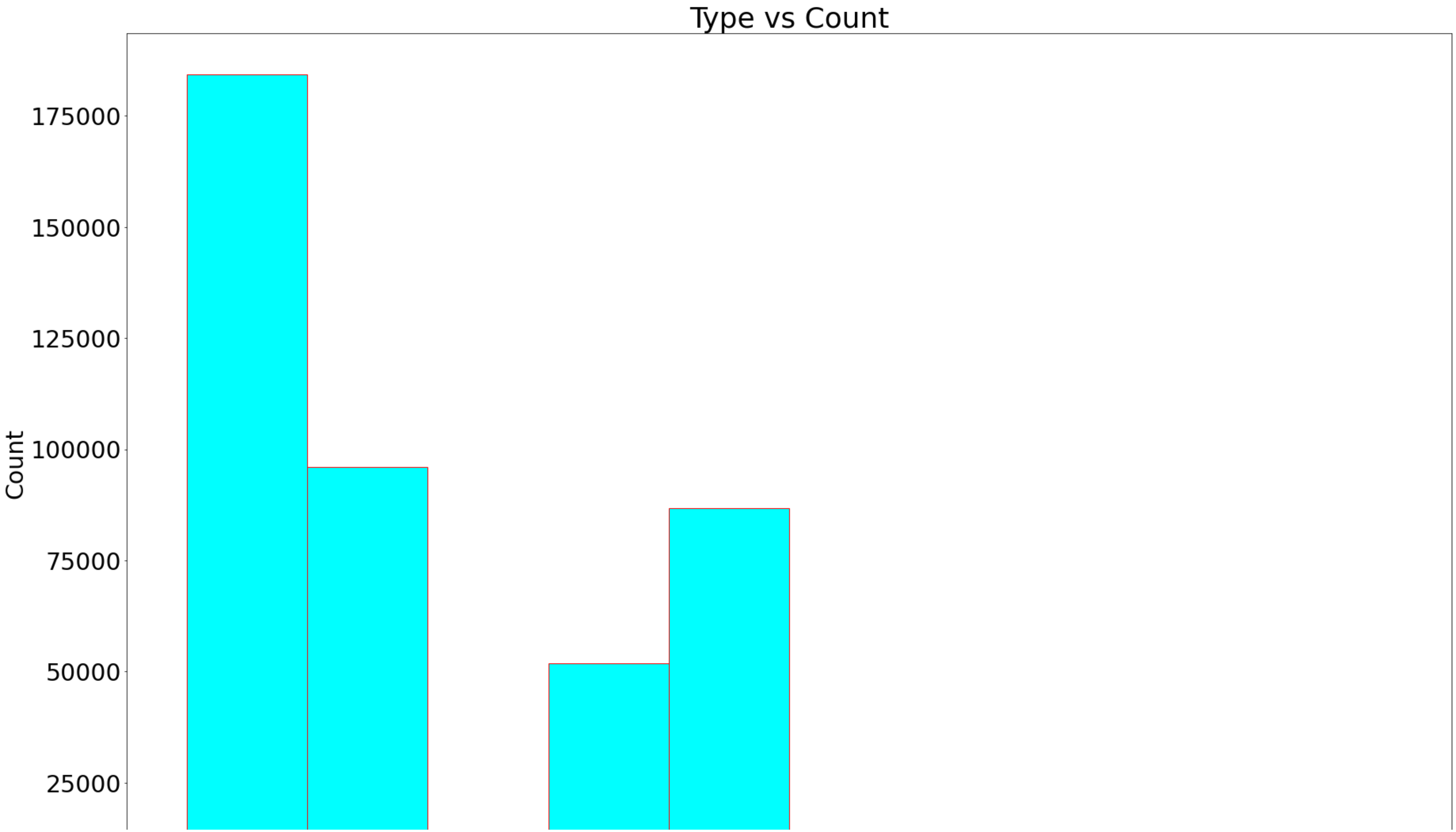
In [14]:

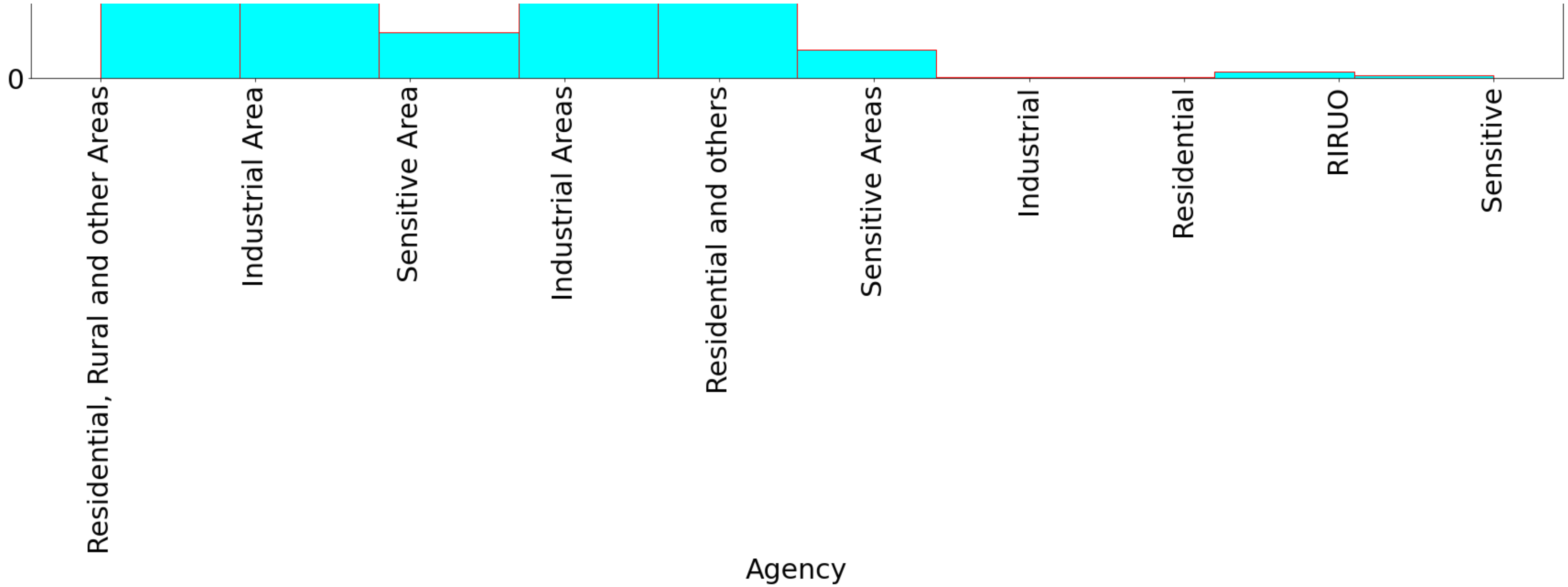
```
# Visualizing state count
plot_state = plt.figure(figsize=(30, 20))
plot_state = plt.xticks(rotation=90)

plot_state = plt.hist(air_quality_data.state, color = "aqua", ec="red")
plot_state = plt.xlabel('State')
plot_state = plt.ylabel('Count')
plot_state = plt.title('State vs Count')
plot_state = plt.rcParams.update({"font.size":30})

plot_state
```


State vs Count
70000
60000
50000
40000
30000
20000
10000
0
Count
Andhra Pradesh
Arunachal Pradesh
Assam
Bihar
Chandigarh
Chhattisgarh
Dadra & Nagar Haveli
Daman & Diu
Delhi
Goa
Gujarat
Haryana
Himachal Pradesh
Jammu & Kashmir
Jharkhand
Karnataka
Kerala
Madhya Pradesh
Maharashtra
Manipur
Meghalaya
Mizoram
Nagaland
Odisha
Puducherry
Punjab
Rajasthan
Sikkim
Tamil Nadu
Telangana
Uttar Pradesh
Uttarakhand
Uttaranchal
West Bengal
andaman-and-nicobar-islands
Lakshadweep
Tripura
State

In [15]:

```
plot_type = plt.figure(figsize=(30, 20))
plot_type = plt.xticks(rotation=90)

plot_type = plt.hist(air_quality_data.type.astype(str), color = "aqua", ec="red")
plot_type = plt.xlabel('Agency')
plot_type = plt.ylabel('Count')
plot_type = plt.title('Type vs Count')
plot_type = plt.rcParams.update({"font.size":30})
plot_type
```





In [16]:

```
# Finding states with a large spm count
state_spm = air_quality_data[['spm','state']].groupby(["state"]).mean().sort_values(by='spm')
state_spm
```

Out[16]:

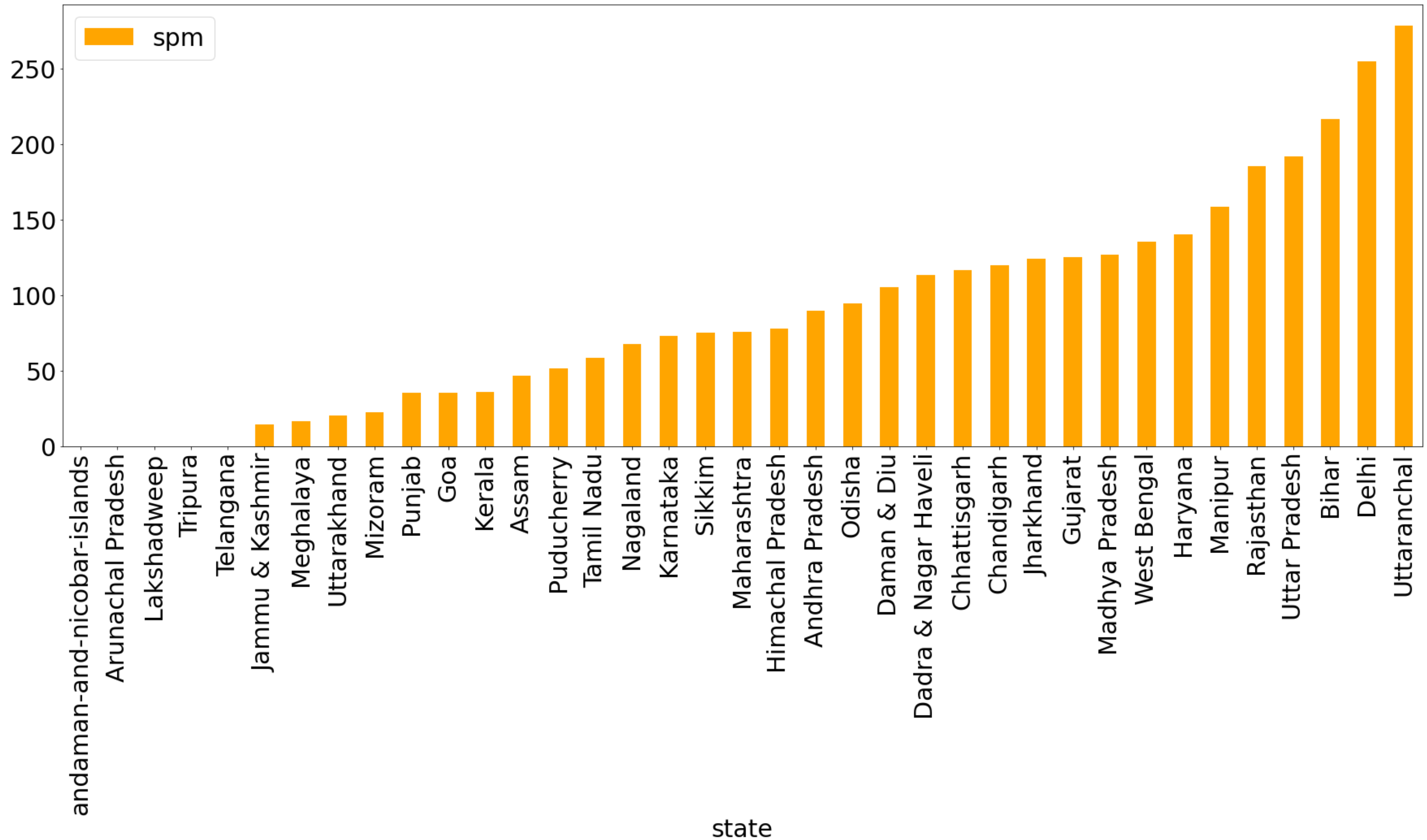
state	spm
andaman-and-nicobar-islands	0.000000
Arunachal Pradesh	0.000000
Lakshadweep	0.000000
Tripura	0.000000
Telangana	0.000000
Jammu & Kashmir	14.461598
Meghalaya	16.560083
Uttarakhand	20.335880

	spm
state	
Mizoram	22.410828
Punjab	35.236834
Goa	35.566913
Kerala	36.034087
Assam	46.693353
Puducherry	51.575033
Tamil Nadu	58.636111
Nagaland	67.602923
Karnataka	73.200829
Sikkim	75.000000
Maharashtra	75.954580
Himachal Pradesh	77.751267
Andhra Pradesh	89.535407
Odisha	94.833144
Daman & Diu	105.255754
Dadra & Nagar Haveli	113.517350
Chhattisgarh	116.428170
Chandigarh	119.739906
Jharkhand	124.253671
Gujarat	125.200207
Madhya Pradesh	126.725988
West Bengal	135.199477
Haryana	140.407602

	spm
state	
Manipur	158.657895
Rajasthan	185.302083
Uttar Pradesh	191.850080
Bihar	216.665055
Delhi	254.980236
Uttaranchal	278.364912

In [17]:

```
# Visualizing spm levels
plt.rcParams['figure.figsize']=(30,10)
state_spm.plot.bar(color='orange')
plt.show()
```



In [18]:

```
# Finding states with a large no2 count
state_no2 = air_quality_data[['no2','state']].groupby(["state"]).mean().sort_values(by='no2')
state_no2
```

Out[18]:

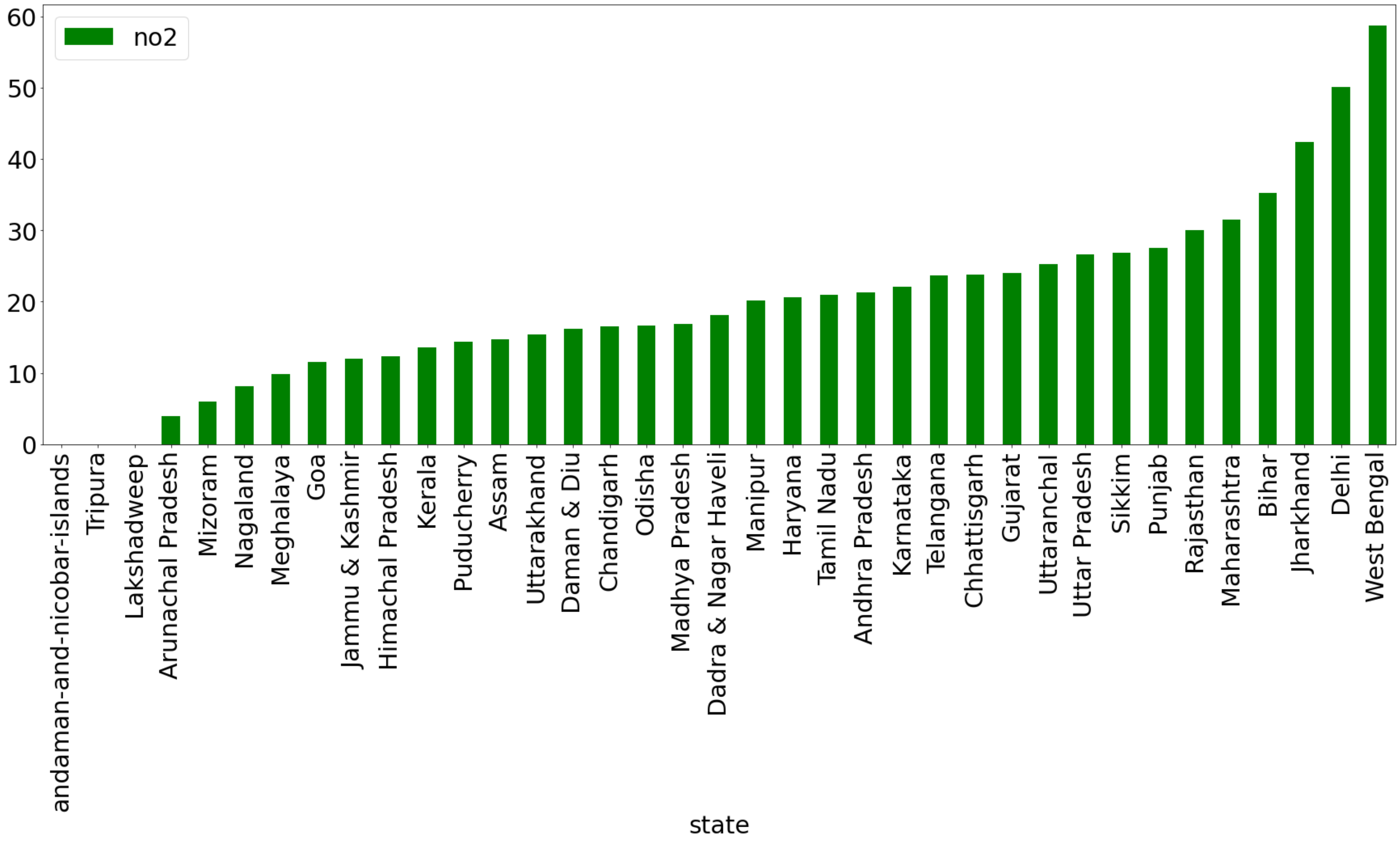
	no2
state	

state	no2
andaman-and-nicobar-islands	0.000000
Tripura	0.000000
Lakshadweep	0.000000
Arunachal Pradesh	4.011111
Mizoram	6.036236
Nagaland	8.140813
Meghalaya	9.826960
Goa	11.607557
Jammu & Kashmir	12.004732
Himachal Pradesh	12.321215
Kerala	13.623459
Puducherry	14.391387
Assam	14.733327
Uttarakhand	15.385345
Daman & Diu	16.168926
Chandigarh	16.578263
Odisha	16.661138
Madhya Pradesh	16.886988
Dadra & Nagar Haveli	18.149685
Manipur	20.173684
Haryana	20.640205
Tamil Nadu	20.955169
Andhra Pradesh	21.250903

	no2
state	
Karnataka	22.128602
Telangana	23.666038
Chhattisgarh	23.751198
Gujarat	24.014738
Uttaranchal	25.256842
Uttar Pradesh	26.662159
Sikkim	26.800000
Punjab	27.578561
Rajasthan	30.012748
Maharashtra	31.468106
Bihar	35.208967
Jharkhand	42.399899
Delhi	50.086259
West Bengal	58.678615

In [19]:

```
# Visualizing no2 levels
plt.rcParams['figure.figsize']=(30,10)
state_no2.plot.bar(color='green')
plt.show()
```



In [20]:

```
# Finding states with a large so2 count
state_so2= air_quality_data[['so2','state']].groupby(["state"]).mean().sort_values(by='so2')
state_so2
```

Out[20]:

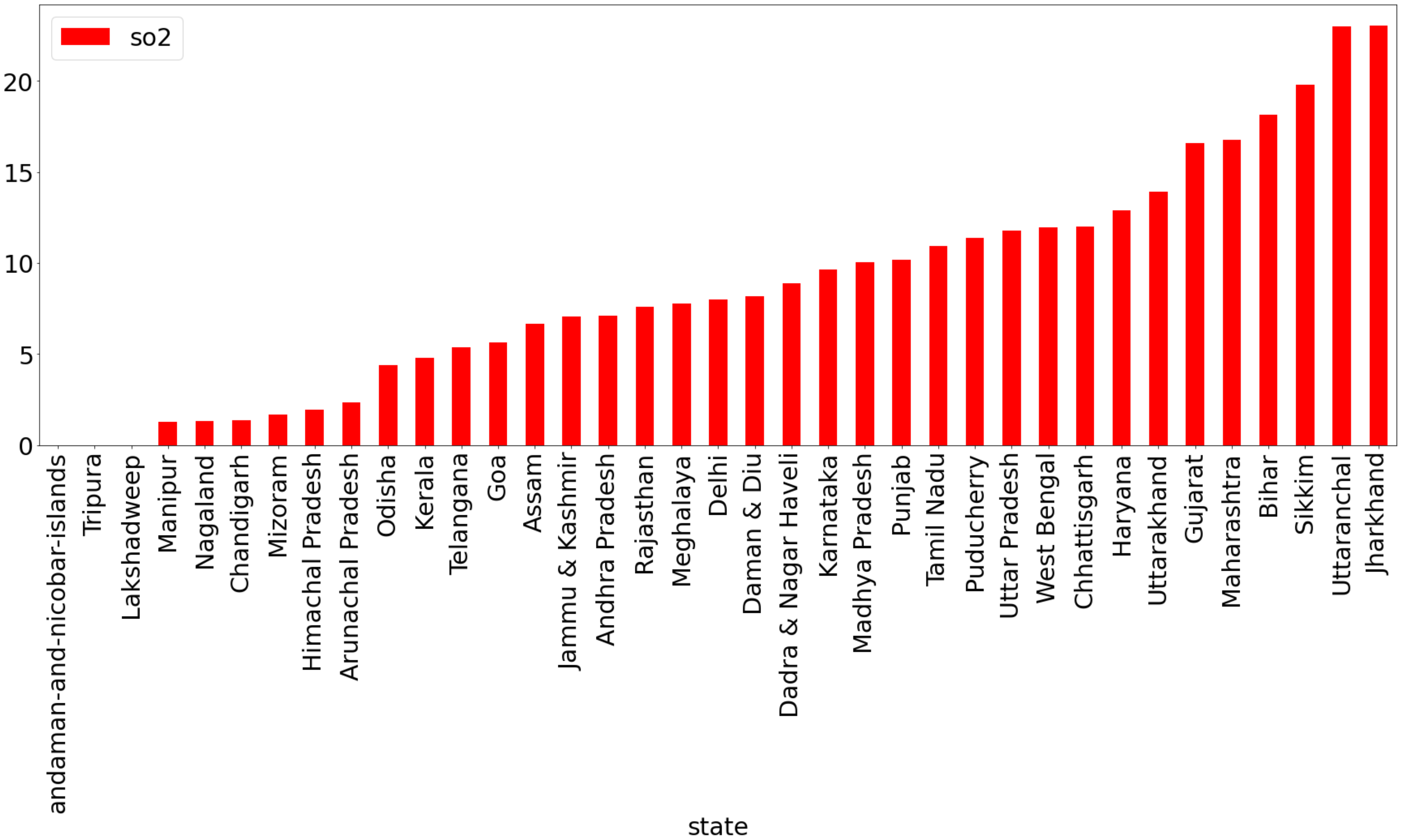
so2

state	so2
state	
andaman-and-nicobar-islands	0.000000
Tripura	0.000000
Lakshadweep	0.000000
Manipur	1.282895
Nagaland	1.331344
Chandigarh	1.388451
Mizoram	1.701052
Himachal Pradesh	1.932816
Arunachal Pradesh	2.366667
Odisha	4.398797
Kerala	4.819990
Telangana	5.376383
Goa	5.656188
Assam	6.677078
Jammu & Kashmir	7.063538
Andhra Pradesh	7.095043
Rajasthan	7.583043
Meghalaya	7.770465
Delhi	7.980131
Daman & Diu	8.182481
Dadra & Nagar Haveli	8.869085
Karnataka	9.645627

	so2
state	
Madhya Pradesh	10.026716
Punjab	10.201116
Tamil Nadu	10.935528
Puducherry	11.363410
Uttar Pradesh	11.789068
West Bengal	11.963817
Chhattisgarh	12.023088
Haryana	12.909327
Uttarakhand	13.932731
Gujarat	16.585112
Maharashtra	16.773817
Bihar	18.120615
Sikkim	19.800000
Uttaranchal	22.964561
Jharkhand	23.021430

In [21]:

```
# Visualizing so2 levels
plt.rcParams['figure.figsize']=(30,10)
state_so2.plot.bar(color='red')
plt.show()
```



In [22]:

```
# Judging from the data, only state, location, type, so2, no2, rspm, spm, and pm2_5 seems significant
air_quality_data = air_quality_data[["so2", "no2", "rspm", "spm", "pm2_5"]]
air_quality_data
```

Out[22]:

	so2	no2	rspm	spm	pm2_5

	so2	no2	rspm	spm	pm2_5
0	4.8	17.4	0.0	0.0	0.0
1	3.1	7.0	0.0	0.0	0.0
2	6.2	28.5	0.0	0.0	0.0
3	6.3	14.7	0.0	0.0	0.0
4	4.7	7.5	0.0	0.0	0.0
...	...	...	...	...	...
435737	22.0	50.0	143.0	0.0	0.0
435738	20.0	46.0	171.0	0.0	0.0
435739	0.0	0.0	0.0	0.0	0.0
435740	0.0	0.0	0.0	0.0	0.0
435741	0.0	0.0	0.0	0.0	0.0

435742 rows × 5 columns

In [23]:

```
# Estimate so2 index
def calculate_so2(value):
    if value <= 40:
        return value * 50 / 40
    elif value <= 80:
        return 50 + (value - 40) * 50 / 40
    elif value <= 380:
        return 100 + (value - 80) * 100 / 300
    elif value <= 800:
        return 200 + (value - 380) * 100 / 420
    elif value <= 1600:
        return 300 + (value - 800) * 100 / 800
    elif value > 1600:
        return 400 + (value - 1600) * 100 / 800
    else:
        return 0
```

```
air_quality_data["so2_index"] = air_quality_data["so2"].apply(calculate_so2)
air_quality_data
```

Out[23]:

	so2	no2	rspm	spm	pm2_5	so2_index
0	4.8	17.4	0.0	0.0	0.0	6.000
1	3.1	7.0	0.0	0.0	0.0	3.875
2	6.2	28.5	0.0	0.0	0.0	7.750
3	6.3	14.7	0.0	0.0	0.0	7.875
4	4.7	7.5	0.0	0.0	0.0	5.875
...	...	...	...	...	...	...
435737	22.0	50.0	143.0	0.0	0.0	27.500
435738	20.0	46.0	171.0	0.0	0.0	25.000
435739	0.0	0.0	0.0	0.0	0.0	0.000
435740	0.0	0.0	0.0	0.0	0.0	0.000
435741	0.0	0.0	0.0	0.0	0.0	0.000

435742 rows × 6 columns

In [24]:

```
# Reference https://www.breeze-technologies.de/blog/what-is-an-air-quality-index-how-is-it-calculated/
# Estimate no2 index
def calculate_no2(x):
    if x <= 40:
        return x * 50 / 40
    elif x <= 80:
        return 50 + (x - 40) * 50 / 40
    elif x <= 180:
        return 100 + (x - 80) * 100 / 100
    elif x <= 280:
        return 200 + (x - 180) * 100 / 100
    elif x <= 400:
        return 300 + (x - 280) * 100 / 120
    elif x > 400:
        return 400 + (x - 400) * 100 / 120
```

```
    else:
        return 0

air_quality_data["no2_index"] = air_quality_data["no2"].apply(calculate_no2)
air_quality_data
```

Out[24]:

	so2	no2	rspm	spm	pm2_5	so2_index	no2_index
0	4.8	17.4	0.0	0.0	0.0	6.000	21.750
1	3.1	7.0	0.0	0.0	0.0	3.875	8.750
2	6.2	28.5	0.0	0.0	0.0	7.750	35.625
3	6.3	14.7	0.0	0.0	0.0	7.875	18.375
4	4.7	7.5	0.0	0.0	0.0	5.875	9.375
...	...	...	...	...	...	...	...
435737	22.0	50.0	143.0	0.0	0.0	27.500	62.500
435738	20.0	46.0	171.0	0.0	0.0	25.000	57.500
435739	0.0	0.0	0.0	0.0	0.0	0.000	0.000
435740	0.0	0.0	0.0	0.0	0.0	0.000	0.000
435741	0.0	0.0	0.0	0.0	0.0	0.000	0.000

435742 rows × 7 columns

In [25]:

```
# Estimate rspm index
def calculate_rspm(x):
    if x <= 30:
        return x * 50 / 30
    elif x <= 60:
        return 50 + (x - 30) * 50 / 30
    elif x <= 90:
        return 100 + (x - 60) * 100 / 30
    elif x <= 120:
        return 200 + (x - 90) * 100 / 30
    elif x <= 250:
        return 300 + (x - 120) * 100 / 130
```

```
    elif x > 400:
        return 400 + (x - 250) * 100 / 130
    else:
        return 0

air_quality_data["rspm_index"] = air_quality_data["rspm"].apply(calculate_rspm)
air_quality_data
```

Out[25]:

	so2	no2	rspm	spm	pm2_5	so2_index	no2_index	rspm_index
0	4.8	17.4	0.0	0.0	0.0	6.000	21.750	0.000000
1	3.1	7.0	0.0	0.0	0.0	3.875	8.750	0.000000
2	6.2	28.5	0.0	0.0	0.0	7.750	35.625	0.000000
3	6.3	14.7	0.0	0.0	0.0	7.875	18.375	0.000000
4	4.7	7.5	0.0	0.0	0.0	5.875	9.375	0.000000
...	...	...	...	...	...	...	...	...
435737	22.0	50.0	143.0	0.0	0.0	27.500	62.500	317.692308
435738	20.0	46.0	171.0	0.0	0.0	25.000	57.500	339.230769
435739	0.0	0.0	0.0	0.0	0.0	0.000	0.000	0.000000
435740	0.0	0.0	0.0	0.0	0.0	0.000	0.000	0.000000
435741	0.0	0.0	0.0	0.0	0.0	0.000	0.000	0.000000

435742 rows × 8 columns

In [26]:

```
# Estimate spm index
def calculate_spm(x):
    if x <= 50:
        return x * 50 / 50
    elif x <= 100:
        return 50 + (x - 50) * 50 / 50
    elif x <= 250:
        return 100 + (x - 100) * 100 / 150
    elif x <= 350:
        return 200 + (x - 250) * 100 / 100
```

```
    elif x <= 430:
        return 300 + (x - 350) * 100 / 80
    elif x > 400:
        return 400 + (x - 430) * 100 / 430
    else:
        return 0

air_quality_data["spm_index"] = air_quality_data["spm"].apply(calculate_spm)
air_quality_data
```

Out[26]:

	so2	no2	rspm	spm	pm2_5	so2_index	no2_index	rspm_index	spm_index
0	4.8	17.4	0.0	0.0	0.0	6.000	21.750	0.000000	0.0
1	3.1	7.0	0.0	0.0	0.0	3.875	8.750	0.000000	0.0
2	6.2	28.5	0.0	0.0	0.0	7.750	35.625	0.000000	0.0
3	6.3	14.7	0.0	0.0	0.0	7.875	18.375	0.000000	0.0
4	4.7	7.5	0.0	0.0	0.0	5.875	9.375	0.000000	0.0
...	...	...	...	...	...	...	...	...	...
435737	22.0	50.0	143.0	0.0	0.0	27.500	62.500	317.692308	0.0
435738	20.0	46.0	171.0	0.0	0.0	25.000	57.500	339.230769	0.0
435739	0.0	0.0	0.0	0.0	0.0	0.000	0.000	0.000000	0.0
435740	0.0	0.0	0.0	0.0	0.0	0.000	0.000	0.000000	0.0
435741	0.0	0.0	0.0	0.0	0.0	0.000	0.000	0.000000	0.0

435742 rows × 9 columns

In [27]:

```
# Estimate aqi index
def calculate_aqi(so2_index, no2_index, rspm_index, spm_index):
    if(so2_index>no2_index and so2_index>rspm_index and so2_index>spm_index):
        return so2_index
    elif(no2_index>so2_index and no2_index>rspm_index and no2_index>spm_index):
        return no2_index
    elif(rspm_index>so2_index and rspm_index>no2_index and rspm_index>spm_index):
        return rspm_index
```

```
    elif(spm_index>so2_index and spm_index>no2_index and spm_index>rspm_index):
        return spm_index
    else: return 0

air_quality_data["aqi"] = air_quality_data.apply(lambda x:calculate_aqi(x["so2_index"], x["no2_index"], x["rspm_index"], x["spm_in
air_quality_data
```

Out[27]:

	so2	no2	rspm	spm	pm2_5	so2_index	no2_index	rspm_index	spm_index	aqi
0	4.8	17.4	0.0	0.0	0.0	6.000	21.750	0.000000	0.0	21.750000
1	3.1	7.0	0.0	0.0	0.0	3.875	8.750	0.000000	0.0	8.750000
2	6.2	28.5	0.0	0.0	0.0	7.750	35.625	0.000000	0.0	35.625000
3	6.3	14.7	0.0	0.0	0.0	7.875	18.375	0.000000	0.0	18.375000
4	4.7	7.5	0.0	0.0	0.0	5.875	9.375	0.000000	0.0	9.375000
...	...	...	...	...	...	...	...	...	...	...
435737	22.0	50.0	143.0	0.0	0.0	27.500	62.500	317.692308	0.0	317.692308
435738	20.0	46.0	171.0	0.0	0.0	25.000	57.500	339.230769	0.0	339.230769
435739	0.0	0.0	0.0	0.0	0.0	0.000	0.000	0.000000	0.0	0.000000
435740	0.0	0.0	0.0	0.0	0.0	0.000	0.000	0.000000	0.0	0.000000
435741	0.0	0.0	0.0	0.0	0.0	0.000	0.000	0.000000	0.0	0.000000

435742 rows × 10 columns

In [28]:

```
# Assign aqi label
def aqi_label(x):
    if x<=25:
        return "Excellent"
    elif x>25 and x<=50:
        return "Good"
    elif x>50 and x<=120:
        return "Moderate"
    elif x>120 and x<=350:
        return "Poor"
    elif x>350 and x<=500:
```

```python
        return "Very Poor"
    elif x>500:
        return "Severe"

air_quality_data["aqi_label"] = air_quality_data["aqi"].apply(aqi_label)
air_quality_data
```

Out[28]:

	so2	no2	rspm	spm	pm2_5	so2_index	no2_index	rspm_index	spm_index	aqi	aqi_label
0	4.8	17.4	0.0	0.0	0.0	6.000	21.750	0.000000	0.0	21.750000	Excellent
1	3.1	7.0	0.0	0.0	0.0	3.875	8.750	0.000000	0.0	8.750000	Excellent
2	6.2	28.5	0.0	0.0	0.0	7.750	35.625	0.000000	0.0	35.625000	Good
3	6.3	14.7	0.0	0.0	0.0	7.875	18.375	0.000000	0.0	18.375000	Excellent
4	4.7	7.5	0.0	0.0	0.0	5.875	9.375	0.000000	0.0	9.375000	Excellent
...	...	...	...	...	...	...	...	...	...	...	...
435737	22.0	50.0	143.0	0.0	0.0	27.500	62.500	317.692308	0.0	317.692308	Poor
435738	20.0	46.0	171.0	0.0	0.0	25.000	57.500	339.230769	0.0	339.230769	Poor
435739	0.0	0.0	0.0	0.0	0.0	0.000	0.000	0.000000	0.0	0.000000	Excellent
435740	0.0	0.0	0.0	0.0	0.0	0.000	0.000	0.000000	0.0	0.000000	Excellent
435741	0.0	0.0	0.0	0.0	0.0	0.000	0.000	0.000000	0.0	0.000000	Excellent

435742 rows × 11 columns

In [29]:

```python
# Determine aqi label count
air_quality_data["aqi_label"].value_counts().sort_values(ascending=False)
```

Out[29]:

```
Poor         236787
Moderate     110486
Very Poor     51297
Good          24033
Excellent     10412
Severe         2727
Name: aqi_label, dtype: int64
```

3. Regression

In [30]:

```
# Creating training and testing datasets
train = air_quality_data[["so2_index", "no2_index", "rspm_index", "spm_index"]]
test = air_quality_data["aqi"]
```

In [31]:

```
# Splitting the training and testing datasets
test_size = 0.2
X_train, X_test, y_train, y_test = train_test_split(train, test, test_size=test_size, random_state=0)
```

In [32]:

```
# Displaying model summary
ols = sm.OLS(test, train).fit()
print(ols.summary())
```

```
                                 OLS Regression Results
=======================================================================================
Dep. Variable:                    aqi   R-squared (uncentered):                   0.947
Model:                            OLS   Adj. R-squared (uncentered):              0.947
Method:                 Least Squares   F-statistic:                          1.966e+06
Date:                Fri, 24 Jun 2022   Prob (F-statistic):                        0.00
Time:                        23:07:26   Log-Likelihood:                     -2.3575e+06
No. Observations:              435742   AIC:                                  4.715e+06
Df Residuals:                  435738   BIC:                                  4.715e+06
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
so2_index      0.7695      0.007    108.955      0.000       0.756       0.783
no2_index      0.6370      0.004    166.709      0.000       0.629       0.644
rspm_index     0.7606      0.001   1333.574      0.000       0.759       0.762
spm_index      0.4058      0.001    595.548      0.000       0.404       0.407
==============================================================================
Omnibus:                   110089.579   Durbin-Watson:                   0.631
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           516532.757
Skew:                           1.158   Prob(JB):                         0.00
Kurtosis:                       7.805   Cond. No.                         21.3
==============================================================================
```

```
Notes:
[1] R² is computed without centering (uncentered) since the model does not contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

In [33]:

```
# Comparing different regression models
def compare_model(X_train, X_test, y_train, y_test):

    # Linear regression model
    linear_regression = LinearRegression()
    linear_regression.fit(X_train, y_train)
    linear_regression_prediction = linear_regression.predict(X_test)
    print("Linear Regression:")
    print("\nCoefficients: ", linear_regression.coef_)
    print("\nMean Absolute Error: ", metrics.mean_absolute_error(y_test, linear_regression_prediction) )
    print("Mean Square Error: ", metrics.mean_squared_error(y_test, linear_regression_prediction))
    print("Root Mean Square Error: ", np.sqrt(metrics.mean_squared_error(y_test, linear_regression_prediction)))
    print('R-Squared:', linear_regression.score(X_test, y_test))

    # Decision tree model
    descision_tree = DecisionTreeRegressor()
    descision_tree.fit(X_train, y_train)
    descision_tree_prediction = descision_tree.predict(X_test)
    print("\n\nDecision Tree:")
    print("\nMean Absolute Error: ", metrics.mean_absolute_error(y_test, descision_tree_prediction) )
    print("Mean Square Error: ", metrics.mean_squared_error(y_test, descision_tree_prediction))
    print("Root Mean Square Error: ", np.sqrt(metrics.mean_squared_error(y_test, descision_tree_prediction)))
    print('R-Squared:', descision_tree.score(X_test, y_test))

    # Random forest model
    random_forest = RandomForestRegressor()
    random_forest.fit(X_train, y_train)
    random_forest_prediction = random_forest.predict(X_test)
    print("\n\nRandom Forest:")
    print("\nMean Absolute Error: ", metrics.mean_absolute_error(y_test, random_forest_prediction) )
    print("Mean Square Error: ", metrics.mean_squared_error(y_test, random_forest_prediction))
    print("Root Mean Square Error: ", np.sqrt(metrics.mean_squared_error(y_test, random_forest_prediction)))
    print('R-Squared:', random_forest.score(X_test, y_test))


compare_model(X_train, X_test, y_train, y_test)
```

```
Linear Regression:
```

```
Coefficients:  [0.50741117 0.39965858 0.70592265 0.3844146 ]

Mean Absolute Error:  38.603295147132535
Mean Square Error:  2746.8624573816674
Root Mean Square Error:  52.41051857577511
R-Squared: 0.8122961020115025


Decision Tree:

Mean Absolute Error:  0.0891563538388602
Mean Square Error:  13.827355568881572
Root Mean Square Error:  3.7185152371452737
R-Squared: 0.9990551224972415


Random Forest:

Mean Absolute Error:  0.09519401069397564
Mean Square Error:  4.983992600169436
Root Mean Square Error:  2.2324857446732858
R-Squared: 0.9996594242146768
```

4. Classification

In [34]:

```
# Creating training and testing datasets
train = air_quality_data[["so2_index", "no2_index", "rspm_index", "spm_index"]]
test = air_quality_data["aqi_label"]
```

In [35]:

```
# Splitting the training and testing datasets
test_size = 0.2
X_train, X_test, y_train, y_test = train_test_split(train, test, test_size=test_size, random_state=0)
```

In [36]:

```
# Comparing different regression models
def compare_model(X_train, X_test, y_train, y_test):

    # Logistic regression model
    logistic_regression = LogisticRegression()
    logistic_regression.fit(X_train, y_train)
```

```python
    logistic_regression_prediction = logistic_regression.predict(X_test)
    logistic_regression_probability = logistic_regression.predict_proba(X_test)
    print("Logistic Regression:")
    print("\nCoefficients: ", logistic_regression.coef_)
    print('R-Squared:', logistic_regression.score(X_test, y_test))

    # Decision tree model
    descision_tree = DecisionTreeClassifier()
    descision_tree.fit(X_train, y_train)
    descision_tree_prediction = descision_tree.predict(X_test)
    descision_tree_probability = descision_tree.predict_proba(X_test)
    print("\n\nDecision Tree:")
    print('R-Squared:', descision_tree.score(X_test, y_test))

    # Random forest model
    random_forest = RandomForestClassifier()
    random_forest.fit(X_train, y_train)
    random_forest_prediction = random_forest.predict(X_test)
    random_forest_probability = random_forest.predict_proba(X_test)
    print("\n\nRandom Forest:")
    print('R-Squared:', random_forest.score(X_test, y_test))

    # XGBoost model
    xg_boost = XGBClassifier()
    xg_boost.fit(X_train, y_train)
    xg_boost_prediction = xg_boost.predict(X_test)
    xg_boost_probability = xg_boost.predict_proba(X_test)
    print("\n\nXGBoost:")
    print('R-Squared:', xg_boost.score(X_test, y_test))

    # Knn model
    knn = KNeighborsClassifier()
    knn.fit(X_train, y_train)
    knn_prediction = knn.predict(X_test)
    knn_prediction_probability = knn.predict_proba(X_test)
    print("\n\nKNN:")
    print('R-Squared:', knn.score(X_test, y_test))

compare_model(X_train, X_test, y_train, y_test)
```

```
Logistic Regression:

Coefficients:  [[ 0.13586205 -0.0125871  -0.06702125 -0.06087632]
```

```
 [ 0.04619175  0.01846165 -0.00533153 -0.0002483 ]
 [ 0.03713891  0.01043049  0.01156837  0.01053896]
 [ 0.03238136 -0.00848787  0.02304762  0.01849016]
 [-0.24787077  0.0086987   0.01617101  0.01072339]
 [-0.0037033  -0.01651586  0.02156578  0.0213721 ]]
R-Squared: 0.6274197064797071


Decision Tree:
R-Squared: 0.9992197271339889


Random Forest:
R-Squared: 0.9990131843165154
[23:09:40] WARNING: ..\src\learner.cc:1115: Starting in XGBoost 1.3.0, the default evaluation metric used with the objective 'mult
i:softprob' was changed from 'merror' to 'mlogloss'. Explicitly set eval_metric if you'd like to restore the old behavior.


XGBoost:
R-Squared: 0.9993344731436964


KNN:
R-Squared: 0.9944118693272441
```

In [ ]:

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