Problem Statement: Analyzing Air Quality Index (AQI) Trends in a City

Dataset: "City_Air_Quality.csv" Description: The dataset contains information about air quality measurements in a specific city over a period of time. It includes attributes such as date, time, pollutant levels (e.g., PM2.5, PM10, CO), and the Air Quality Index (AQI) values. The goal is to use the matplotlib library to create visualizations that effectively represent the AQI trends and patterns for different pollutants in the city. Tasks to Perform:

1. Import the "City_Air_Quality.csv" dataset.
2. Explore the dataset to understand its structure and content.
3. Identify the relevant variables for visualizing AQI trends, such as date, pollutant levels, and AQI values.
4. Create line plots or time series plots to visualize the overall AQI trend over time.
5. Plot individual pollutant levels (e.g., PM2.5, PM10, CO) on separate line plots to visualize their trends over time.
6. Use bar plots or stacked bar plots to compare the AQI values across different dates or time periods.
7. Create box plots or violin plots to analyze the distribution of AQI values for different pollutant categories.
8. Use scatter plots or bubble charts to explore the relationship between AQI values and pollutant levels.
9. Customize the visualizations by adding labels, titles, legends, and appropriate color schemes.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.impute import SimpleImputer

%matplotlib inline
```

In [2]:
```
aqi = pd.read_csv("City_Air_Quality.csv", encoding = "ISO-8859-1", parse_dat
aqi.head()
```

Out[2]:

	stn_code	sampling_date	state	location	agency	type	so2	no2	rspm	spm
0	150	February - M021990	Andhra Pradesh	Hyderabad	NaN	Residential, Rural and other Areas	4.8	17.4	NaN	NaN
1	151	February - M021990	Andhra Pradesh	Hyderabad	NaN	Industrial Area	3.1	7.0	NaN	NaN
2	152	February - M021990	Andhra Pradesh	Hyderabad	NaN	Residential, Rural and other Areas	6.2	28.5	NaN	NaN
3	150	March - M031990	Andhra Pradesh	Hyderabad	NaN	Residential, Rural and other Areas	6.3	14.7	NaN	NaN
4	151	March - M031990	Andhra Pradesh	Hyderabad	NaN	Industrial Area	4.7	7.5	NaN	NaN

In [3]:
```
sns.set(style="ticks", rc = {'figure.figsize':(20,15)})

# Supressing update warnings

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

Checking the dataset

We can see that there are quite a number of NaNs in the dataset. To proceed with the EDA, we must handle these NaNs by either removing them or filling them. I will be doing both.

In [4]:
```
# checking the original dataset
print(aqi.isnull().sum())
print(aqi.shape)
aqi.info()
```

```
stn_code                      144077
sampling_date                      3
state                              0
location                           3
agency                        149481
type                            5393
so2                            34646
no2                            16233
rspm                           40222
spm                           237387
location_monitoring_station    27491
pm2_5                         426428
date                               7
dtype: int64
(435742, 13)
<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  datetime64[ns]
dtypes: datetime64[ns](1), float64(5), object(7)
memory usage: 43.2+ MB
```

Cleaning the dataset

Removing NaNs Looking at the dataset head, we can conclude that the following columns:

1. stn_code
2. agency
3. sampling_date
4. location_monitoring_agency

do not add much to the dataset in terms of information that can't already be extracted from other columns. Therefore, we drop these columns.

Since date also has missing values, we will drop the rows containing these values as they're of little use as well.

Cleaning values Since the geographical nomenclature has changed over time, we change it here as well to correspond to more accurate insights.

The type column

Currently, the type column has several names for the same type and therefore, it is better to clean it up and make it more uniform.

In [5]:

```
# Cleaning up the data

aqi.drop(['stn_code', 'agency', 'sampling_date', 'location_monitoring_static
aqi = aqi.dropna(subset=['date']) # dropping rows where no date is available

# cleaning up name changes

aqi.state = aqi.state.replace({'Uttaranchal':'Uttarakhand'})
aqi.state[aqi.location == "Jamshedpur"] = aqi.state[aqi.location == 'Jamshed

#changing types to uniform format

types = {
    "Residential": "R",
    "Residential and others": "RO",
    "Residential, Rural and other Areas": "RRO",
    "Industrial Area": "I",
    "Industrial Areas": "I",
    "Industrial": "I",
    "Sensitive Area": "S",
    "Sensitive Areas": "S",
    "Sensitive": "S",
    np.nan: "RRO"
}
aqi.type = aqi.type.replace(types)
```

In [6]:

```
aqi.head()
```

Out[6]:

	state	location	type	so2	no2	rspm	spm	pm2_5	date
0	Andhra Pradesh	Hyderabad	RRO	4.8	17.4	NaN	NaN	NaN	1990-02-01
1	Andhra Pradesh	Hyderabad	I	3.1	7.0	NaN	NaN	NaN	1990-02-01
2	Andhra Pradesh	Hyderabad	RRO	6.2	28.5	NaN	NaN	NaN	1990-02-01
3	Andhra Pradesh	Hyderabad	RRO	6.3	14.7	NaN	NaN	NaN	1990-03-01
4	Andhra Pradesh	Hyderabad	I	4.7	7.5	NaN	NaN	NaN	1990-03-01

In [7]:
```
# defining columns of importance, which shall be used reguarly
VALUE_COLS = ['so2', 'no2', 'rspm', 'spm', 'pm2_5']
```

Filling NaNs Since our pollutants column contain a lot of NaNs, we must fill them to have consistent data. If we drop the rows containing NaNs, we will be left with nothing.

I use the SimpleImputer from sklearn.imputer (v0.20.2) to fill the missing values in every column with the mean.

In [8]:
```
# invoking SimpleImputer to fill missing values
imputer = SimpleImputer(missing_values=np.nan, strategy='mean')
aqi[VALUE_COLS] = imputer.fit_transform(aqi[VALUE_COLS])
```

In [9]:
```
# checking to see if the dataset has any null values left over and the forma
print(aqi.isnull().sum())
aqi.tail()
```

```
state       0
location    0
type        0
so2         0
no2         0
rspm        0
spm         0
pm2_5       0
date        0
dtype: int64
```

Out[9]:

	state	location	type	so2	no2	rspm	spm	pm2_5	date
435734	West Bengal	ULUBERIA	RIRUO	20.0	44.0	148.0	220.78348	40.791467	2015-12-15
435735	West Bengal	ULUBERIA	RIRUO	17.0	44.0	131.0	220.78348	40.791467	2015-12-18
435736	West Bengal	ULUBERIA	RIRUO	18.0	45.0	140.0	220.78348	40.791467	2015-12-21
435737	West Bengal	ULUBERIA	RIRUO	22.0	50.0	143.0	220.78348	40.791467	2015-12-24
435738	West Bengal	ULUBERIA	RIRUO	20.0	46.0	171.0	220.78348	40.791467	2015-12-29

Plotting pollutant levels as yearly averages for states

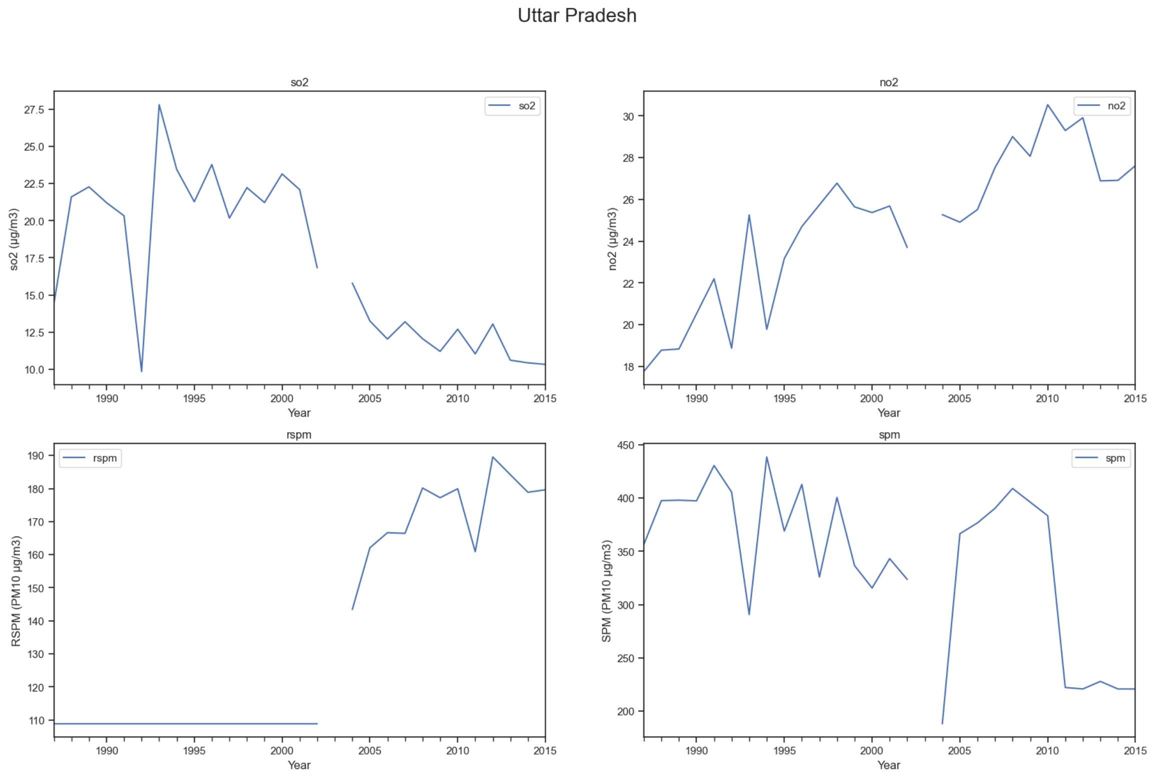
In [10]:
```python
# defining a function that plots SO2, NO2, RSPM and SPM yearly average level
# since data is available monthly, it was resampled to a year and averaged t
# years for which no data was collected has not been imputed
def plot_for_state(state):
    fig, ax = plt.subplots(2,2, figsize=(20,12))
    fig.suptitle(state, size=20)
    state = aqi[aqi.state == state]
    state = state.reset_index().set_index('date')[VALUE_COLS].resample('Y').
    state.so2.plot(legend=True, ax=ax[0][0], title="so2")
    ax[0][0].set_ylabel("so2 (µg/m3)")
    ax[0][0].set_xlabel("Year")

    state.no2.plot(legend=True, ax=ax[0][1], title="no2")
    ax[0][1].set_ylabel("no2 (µg/m3)")
    ax[0][1].set_xlabel("Year")

    state.rspm.plot(legend=True, ax=ax[1][0], title="rspm")
    ax[1][0].set_ylabel("RSPM (PM10 µg/m3)")
    ax[1][0].set_xlabel("Year")

    state.spm.plot(legend=True, ax=ax[1][1], title="spm")
    ax[1][1].set_ylabel("SPM (PM10 µg/m3)")
    ax[1][1].set_xlabel("Year")
```

In [11]:
```python
plot_for_state("Uttar Pradesh")
```



Plotting Uttar Pradesh, we see that SO2 levels have fallen in the state while NO2 levels have risen. Information about RSPM and SPM can't be concluded since a lot of data is missing.

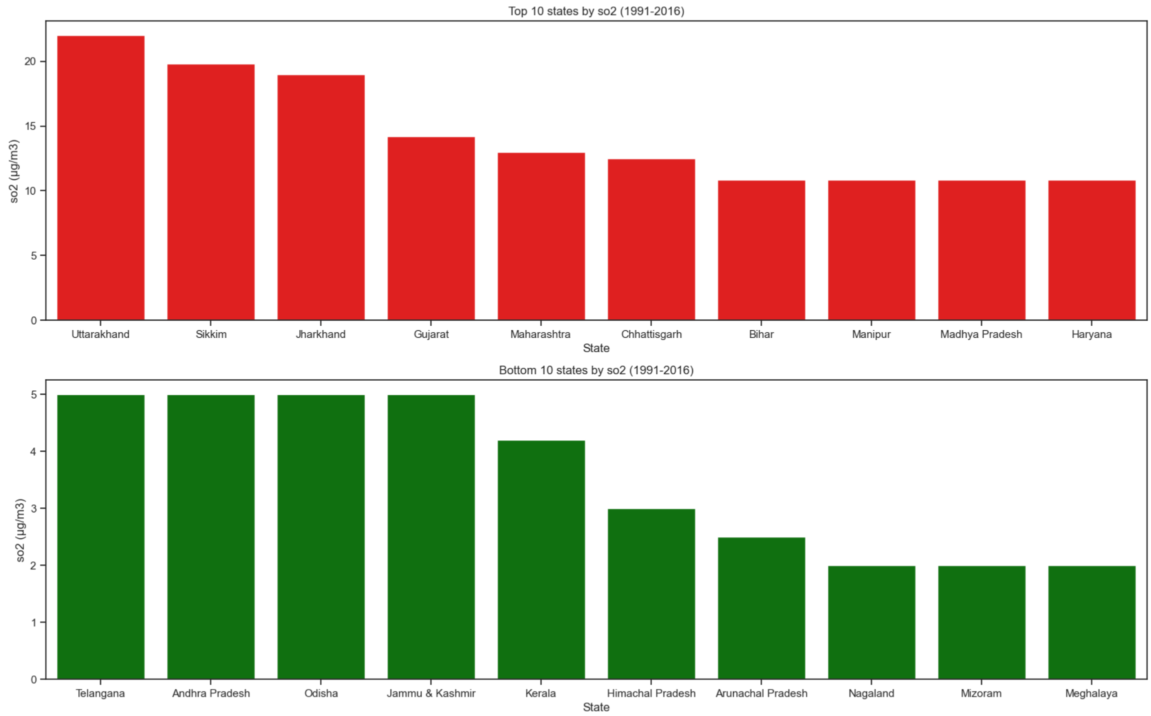
Plotting highest and lowest ranking states

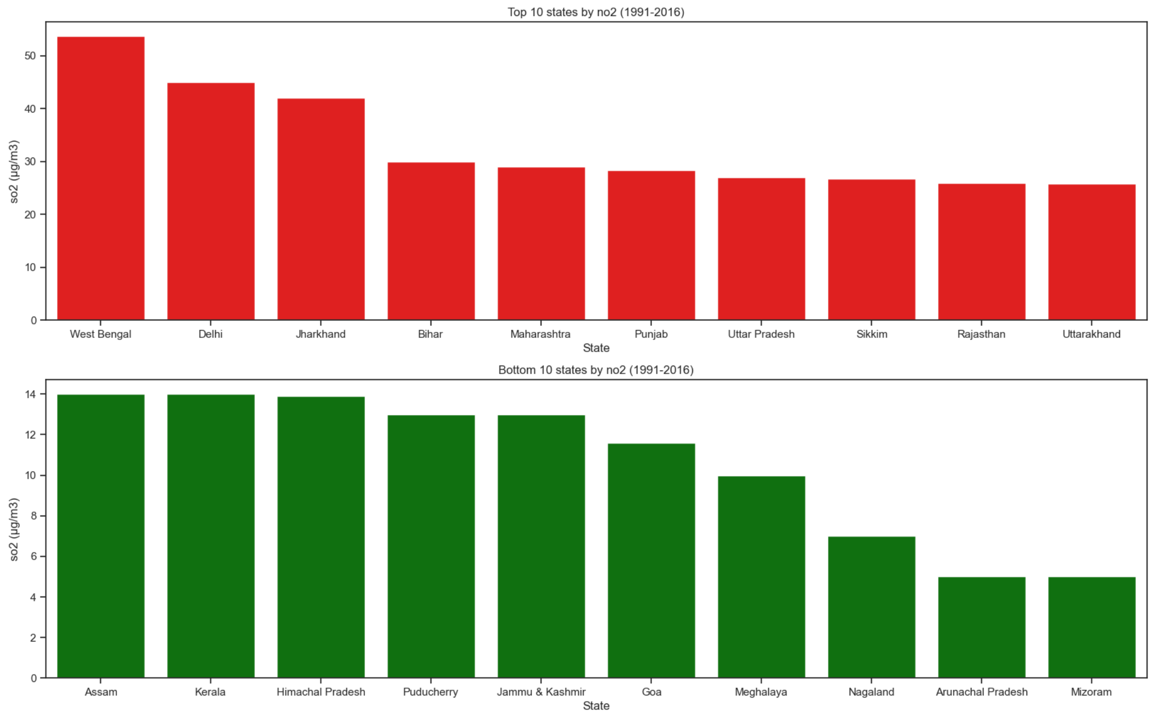
In [12]:
```
# defining a function to find and plot the top 10 and bottom 10 states for c
def top_and_bottom_10_states(indicator="so2"):
    fig, ax = plt.subplots(2,1, figsize=(20, 12))

    ind = aqi[[indicator, 'state']].groupby('state', as_index=False).median(
    top10 = sns.barplot(x='state', y=indicator, data=ind[:10], ax=ax[0], col
    top10.set_title("Top 10 states by {} (1991-2016)".format(indicator))
    top10.set_ylabel("so2 (µg/m3)")
    top10.set_xlabel("State")

    bottom10 = sns.barplot(x='state', y=indicator, data=ind[-10:], ax=ax[1],
    bottom10.set_title("Bottom 10 states by {} (1991-2016)".format(indicator
    bottom10.set_ylabel("so2 (µg/m3)")
    bottom10.set_xlabel("State")
```

In [13]:
```
top_and_bottom_10_states("so2")
top_and_bottom_10_states("no2")
```





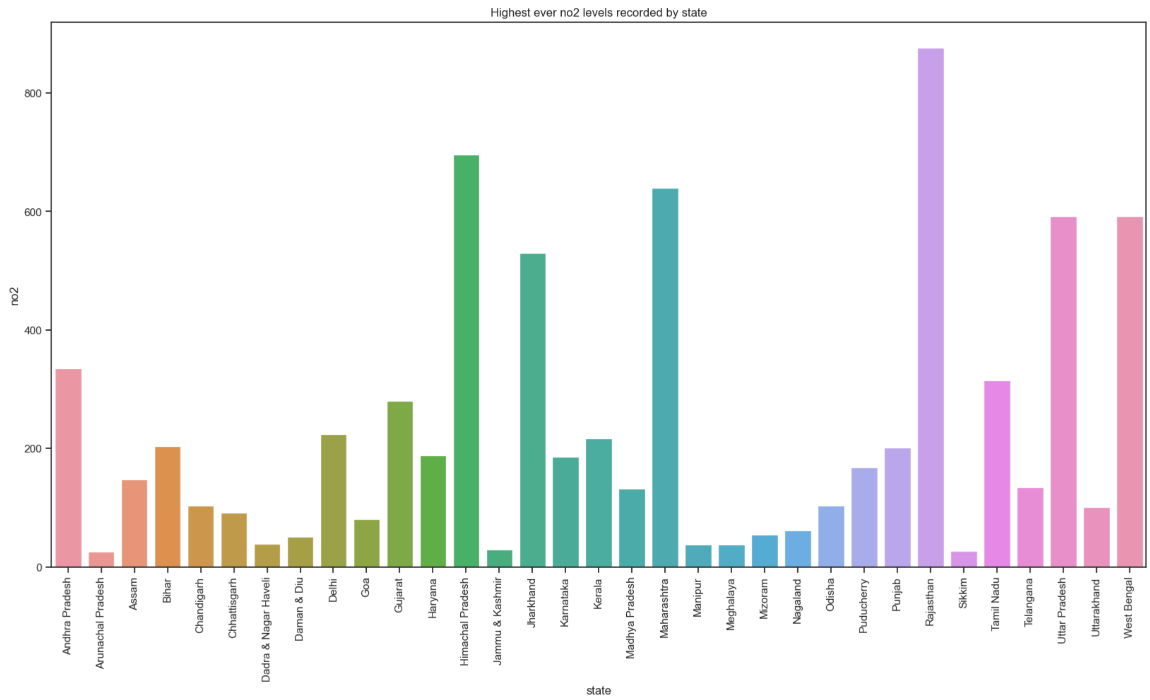
Plotting for SO2, we can see that the top state is Uttarakhand, while the bottom state is Meghalaya.

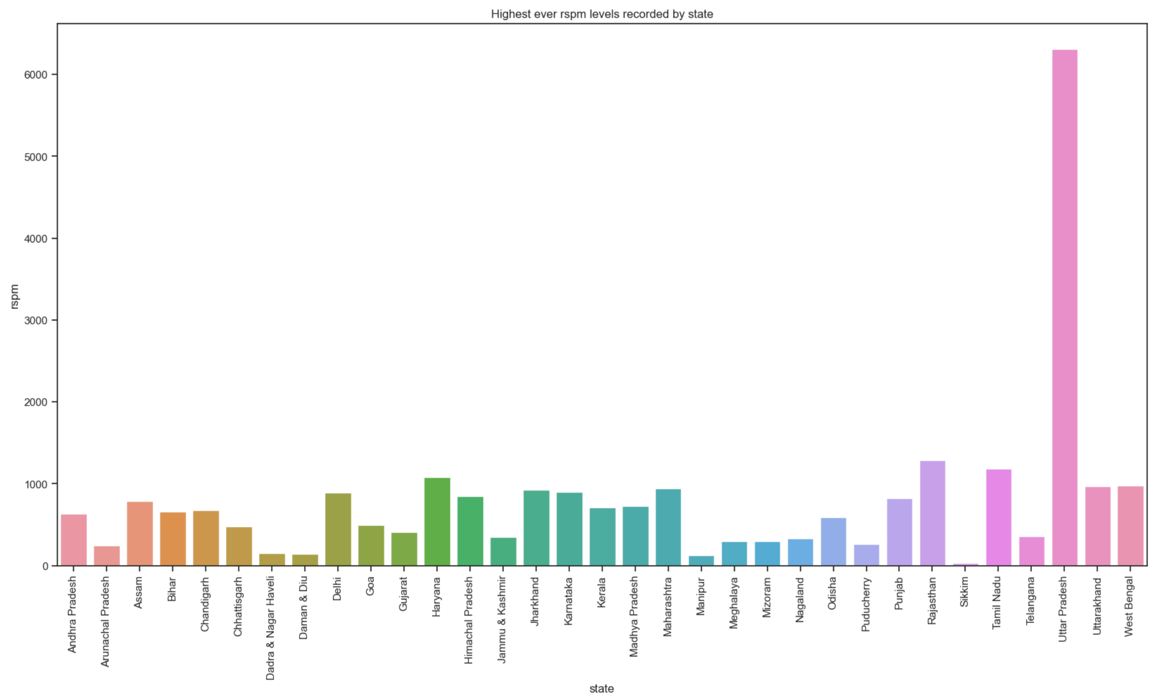
Plotting for NO2, we can see that the top state is West Bengal, while the bottom state is Mizoram.

Plotting the highest ever recorded levels

In [14]:
```
# defining a function to find the highest ever recorded levels for a given i
# sidenote: mostly outliers
def highest_levels_recorded(indicator="so2"):
    plt.figure(figsize=(20,10))
    ind = aqi[[indicator, 'location', 'state', 'date']].groupby('state', as_
    highest = sns.barplot(x='state', y=indicator, data=ind)
    highest.set_title("Highest ever {} levels recorded by state".format(indi
    plt.xticks(rotation=90)
```

In [15]:
```
highest_levels_recorded("no2")
highest_levels_recorded("rspm")
```





Plotting for NO2, we can see that Rajasthan recorded the highest ever NO2 level. Plotting for RSPM, we can see that Uttar Pradesh recorded the highest ever RSPM level.

Plotting yearly trends

In [16]:
```
# defining a function to plot the yearly trend values for a given indicator
def yearly_trend(state="", indicator="so2", ):
    plt.figure(figsize=(20,12))
    aqi['year'] = aqi.date.dt.year
    if state is "":
        year_wise = aqi[[indicator, 'year', 'state']].groupby('year', as_inc
        trend = sns.pointplot(x='year', y=indicator, data=year_wise)
        trend.set_title('Yearly trend of {}'.format(indicator))
    else:
        year_wise = aqi[[indicator, 'year', 'state']].groupby(['state','year
        trend = sns.pointplot(x='year', y=indicator, data=year_wise)
        trend.set_title('Yearly trend of {} for {}'.format(indicator, state)
```

In [17]:
```
yearly_trend()
yearly_trend("West Bengal", "no2")
```

Plotting for SO2, we can see the yearly trend for sulphur dioxide levels in the country.
Plotting for NO2 in West Bengal, we can see the yearly trend.

Plotting a heatmap for a particular indicator

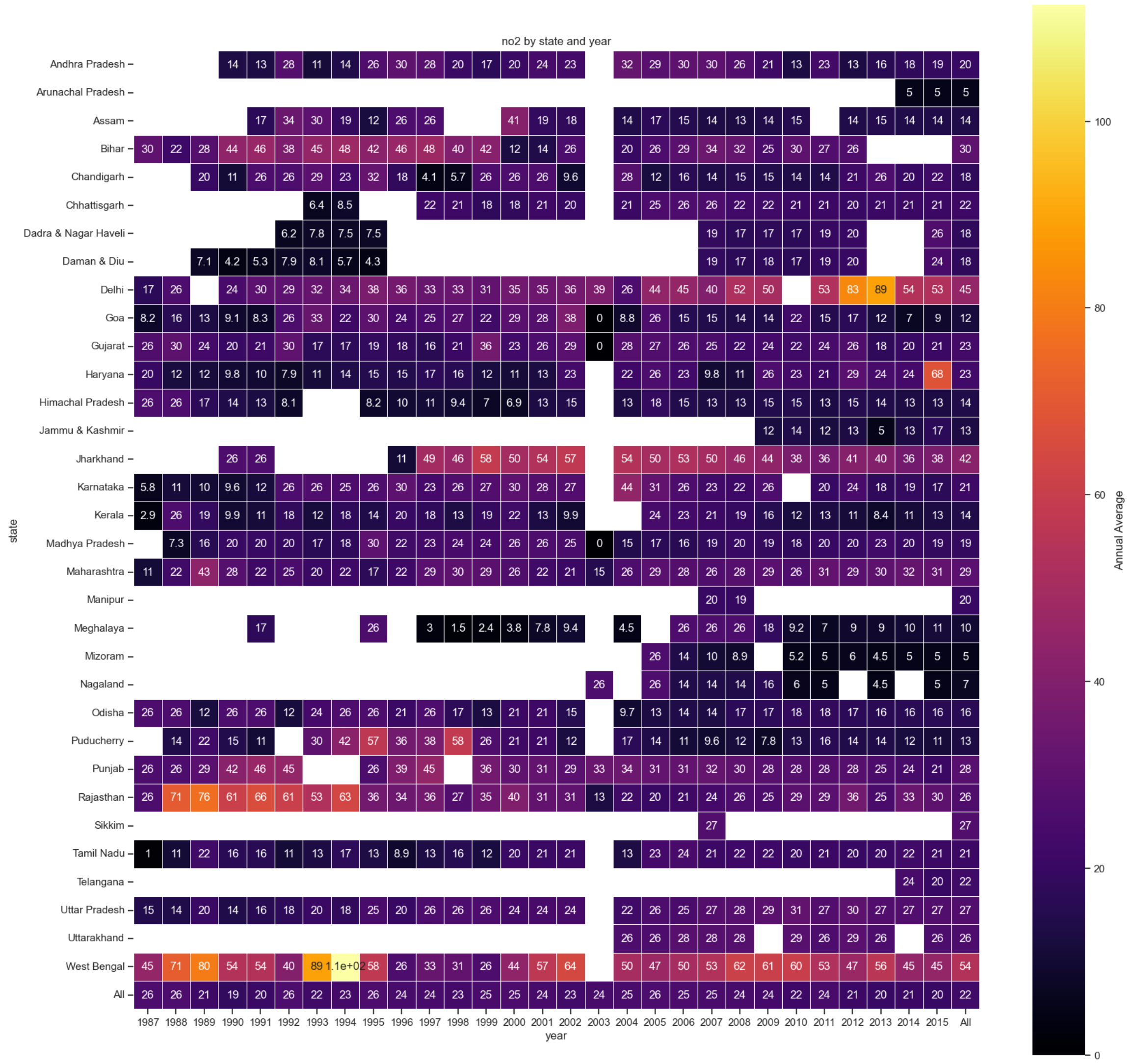
In [18]:

```python
# defining a function to plot a heatmap for yearly median average for a give
def indicator_by_state_and_year(indicator="so2"):
    plt.figure(figsize=(20, 20))
    hmap = sns.heatmap(
        data=aqi.pivot_table(values=indicator, index='state', columns='year'
                 annot=True, linewidths=.5, cbar=True, square=True, cmap='infe

    hmap.set_title("{} by state and year".format(indicator))
```

In [19]:

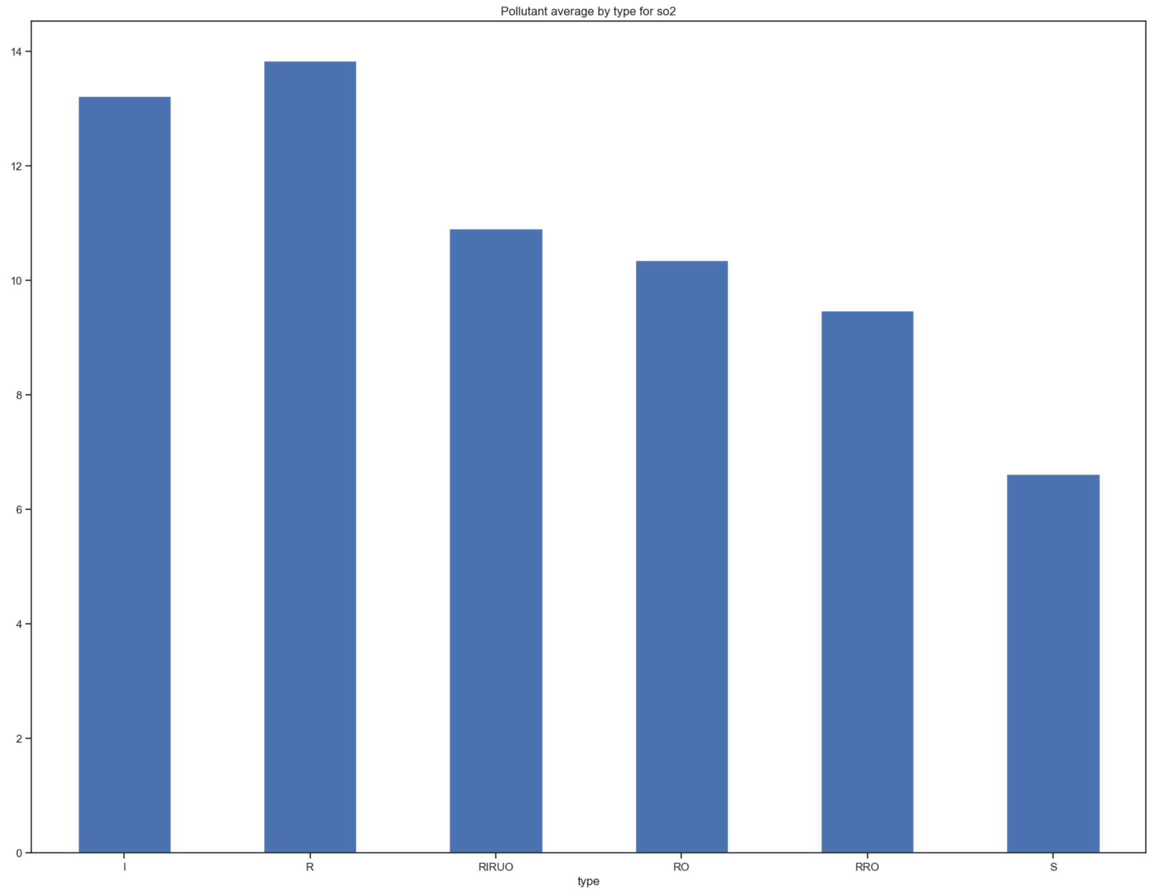
```python
indicator_by_state_and_year('no2')
```



Plotting pollutant average by type

In [20]:
```
# defining a function to plot pollutant averages by type for a given indicat
def type_avg(indicator=""):
    type_avg = aqi[VALUE_COLS + ['type', 'date']].groupby("type").mean()
    if indicator is not "":
        t = type_avg[indicator].plot(kind='bar')
        plt.xticks(rotation = 0)
        plt.title("Pollutant average by type for {}".format(indicator))
    else:
        t = type_avg.plot(kind='bar')
        plt.xticks(rotation = 0)
        plt.title("Pollutant average by type")
```

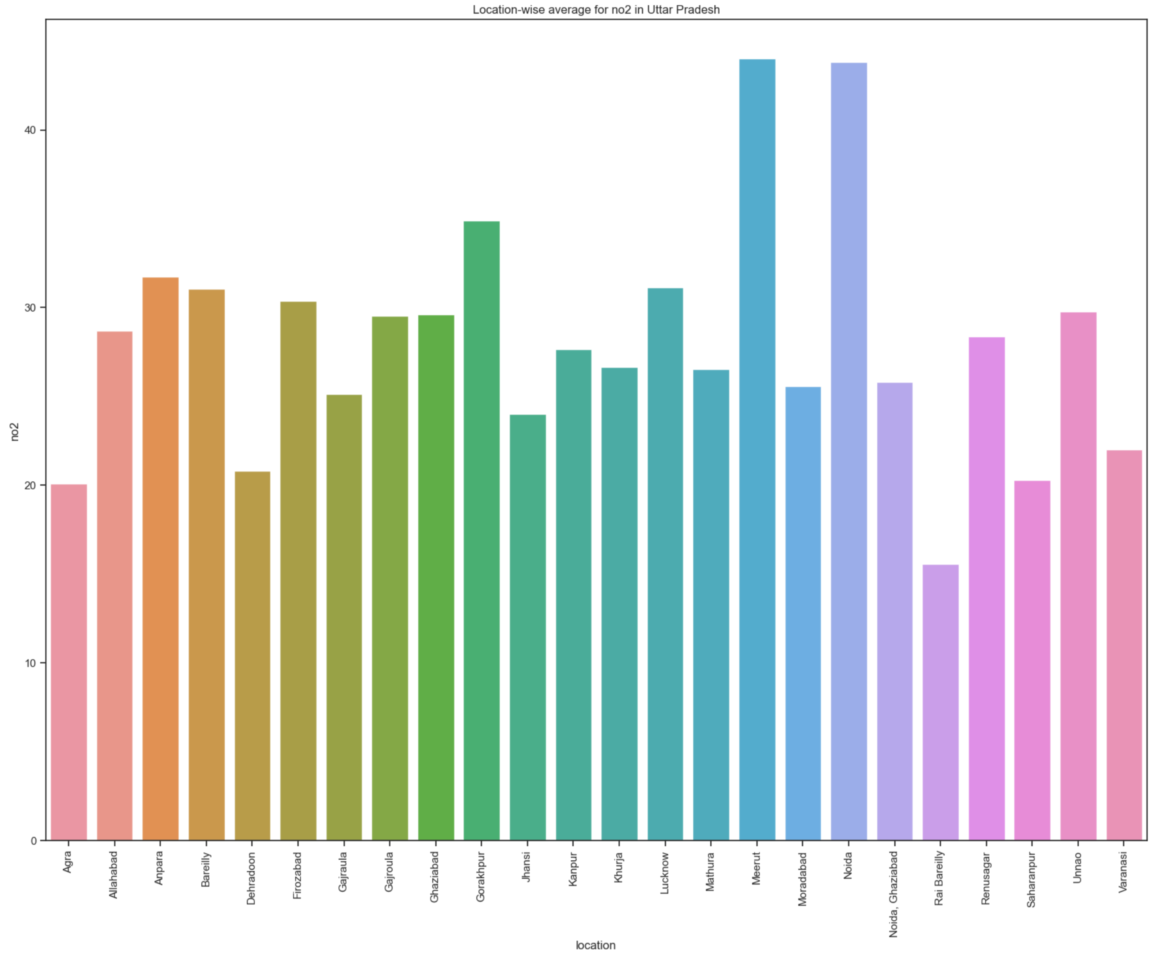
In [21]:
```
type_avg('so2')
```



Plotting pollutant averages by locations/state

In [22]:
```
# defining a function to plot pollutant averages for a given indicator (defa
def location_avgs(state, indicator="so2"):
    locs = aqi[VALUE_COLS + ['state', 'location', 'date']].groupby(['state',
    state_avgs = locs.loc[state].reset_index()
    sns.barplot(x='location', y=indicator, data=state_avgs)
    plt.title("Location-wise average for {} in {}".format(indicator, state))
    plt.xticks(rotation = 90)
```

In [23]:
```
location_avgs("Uttar Pradesh", "no2")
```



In [ ]: