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Forecast of Household Electricity Demand

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Context

India is the third-largest producer and consumer of electricity in the world.

As of March 31, 2020, India's national electric grid had an installed capacity of 370.106 GW.

Large hydropower facilities are included in the category of renewable power plants, which make up 35.86% of India's installed capacity.

The gross power produced by utilities in India for the 2018–19 fiscal year was 1,372 TWh, and the nation as a whole (utilities and non–utilities) produced 1,547 TWh.

2018–19 had a gross power consumption of 1,181 kWh per person.

Context

Agriculture had the largest recorded global electric energy use (17.89 percent) in 2015–16.

Despite India's low electricity rate, its per capita electricity usage is low compared to that of the majority of other nations.

Every sector has seen the effects of the lockdown on economic activity as a result of the recent COVID-19 emergency, during which everyone was placed under lockdown for the months of April and May.

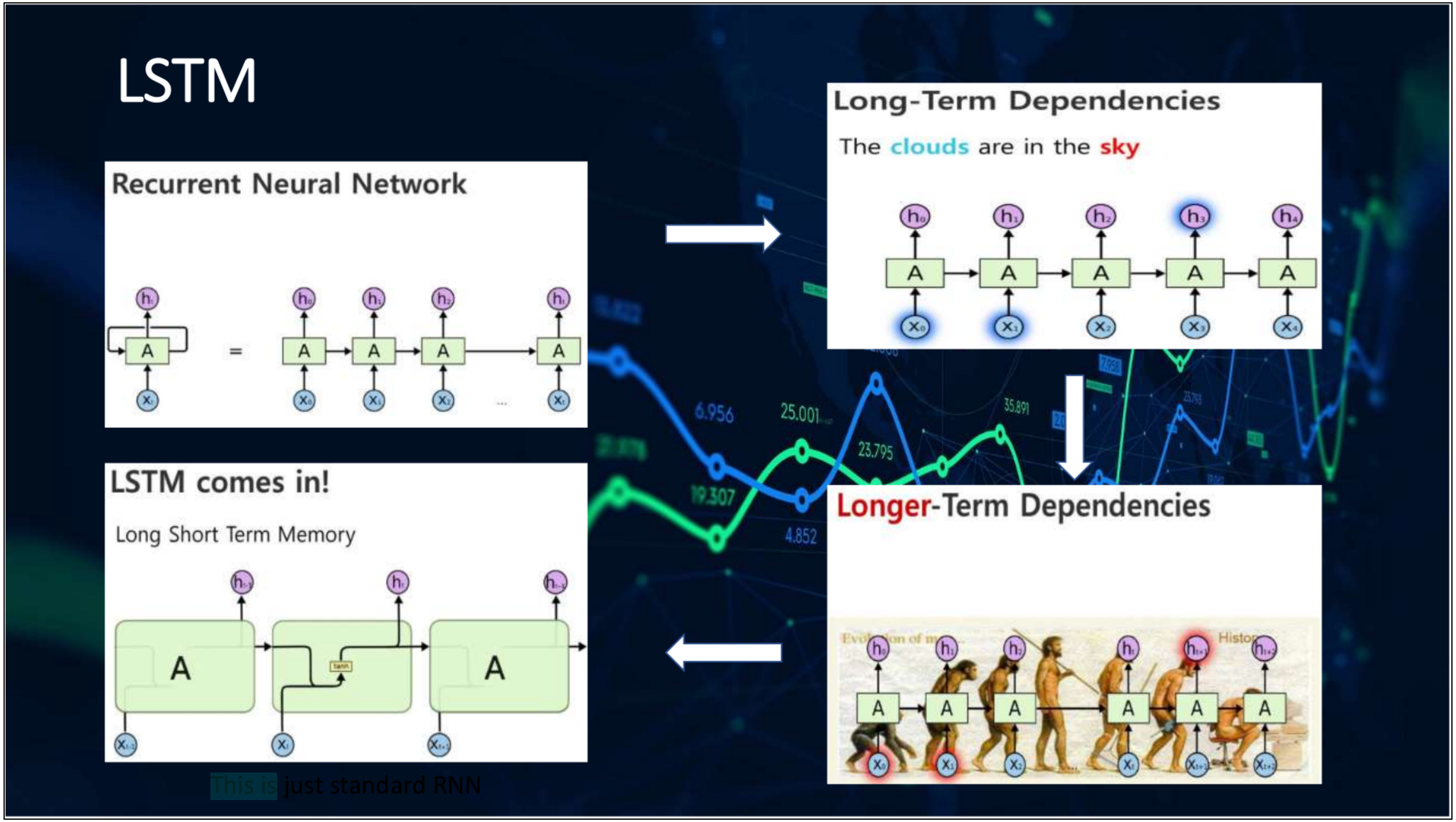
We developed a plan to research the influence on energy consumption state and region-wise due to the importance of power consumption to the nation.

Dataset

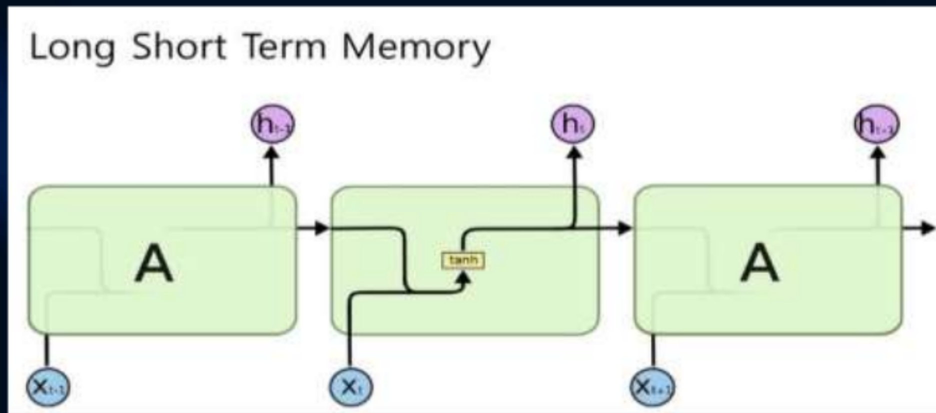
The dataset provides a comprehensive illustration of energy use at the state level. The 17-month time span between the 2nd of January 2019 and the 23rd of May 2020 is represented by content data in the form of a time series. Dates are used to index rows, and states are represented in columns. Together, the rows and columns of each datapoint represent the amount of electricity consumed in Mega Units (MU) by the specified state (column) on the specified date (row).

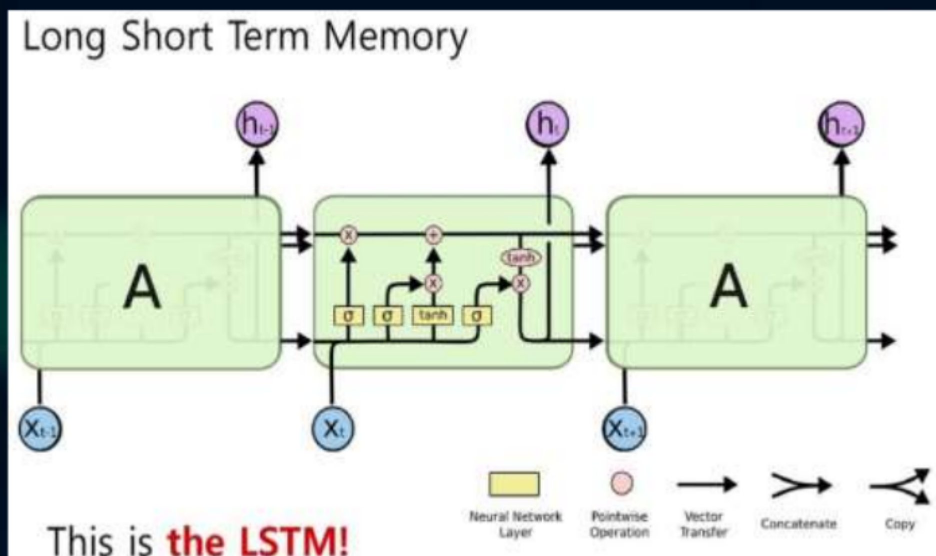
The Dataset

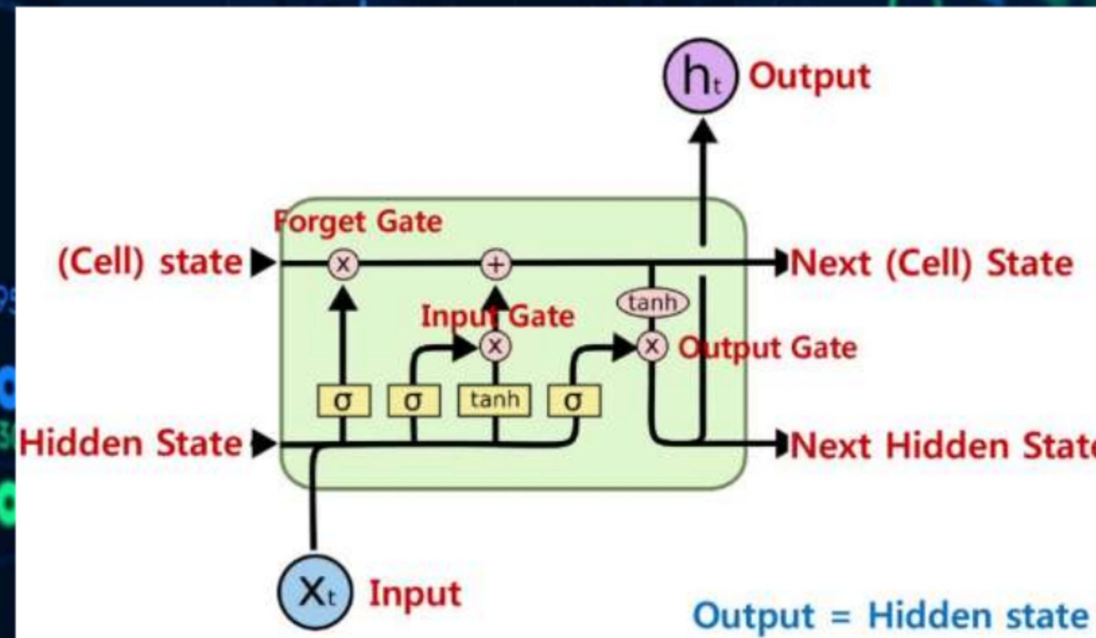
States	Regions	latitude	longitude	Dates	Usage
Punjab	NR	31.51997398	75.98000281	02/01/2019 00:0	119.9
Haryana	NR	28.45000633	77.01999101	02/01/2019 00:0	130.3
Rajasthan	NR	26.44999921	74.63998124	02/01/2019 00:0	234.1
Delhi	NR	28.6699929	77.23000403	02/01/2019 00:0	85.8
UP	NR	27.59998069	78.05000565	02/01/2019 00:0	313.9
Uttarakhand	NR	30.32040895	78.05000565	02/01/2019 00:0	40.7
HP	NR	31.10002545	77.16659704	02/01/2019 00:0	30
J&K	NR	33.45	76.24	02/01/2019 00:0	52.5
Chandigarh	NR	30.71999697	76.78000565	02/01/2019 00:0	5
Chhattisgarh	WR	22.09042035	82.15998734	02/01/2019 00:0	78.7
Gujarat	WR	22.2587	71.1924	02/01/2019 00:0	319.5
MP	WR	21.30039105	76.13001949	02/01/2019 00:0	253
Maharashtra	WR	19.25023195	73.16017493	02/01/2019 00:0	428.6
Goa	WR	15.491997	73.81800065	02/01/2019 00:0	12.8
DNH	WR	20.26657819	73.0166178	02/01/2019 00:0	18.6
Andhra Pradesh	SR	14.7504291	78.57002559	02/01/2019 00:0	164.6
Telangana	SR	18.1124	79.0193	02/01/2019 00:0	204.2
Karnataka	SR	12.57038129	76.91999711	02/01/2019 00:0	206.3
Kerala	SR	8.900372741	76.56999263	02/01/2019 00:0	72.7
Tamil Nadu	SR	12.92038576	79.15004187	02/01/2019 00:0	268.3
Pondy	SR	11.93499371	79.83000037	02/01/2019 00:0	6.3


LSTM
Recurrent Neural Network
Long-Term Dependencies
The clouds are in the sky
Longer-Term Dependencies
LSTM comes in!
Long Short Term Memory
This is just standard RNN

LSTM

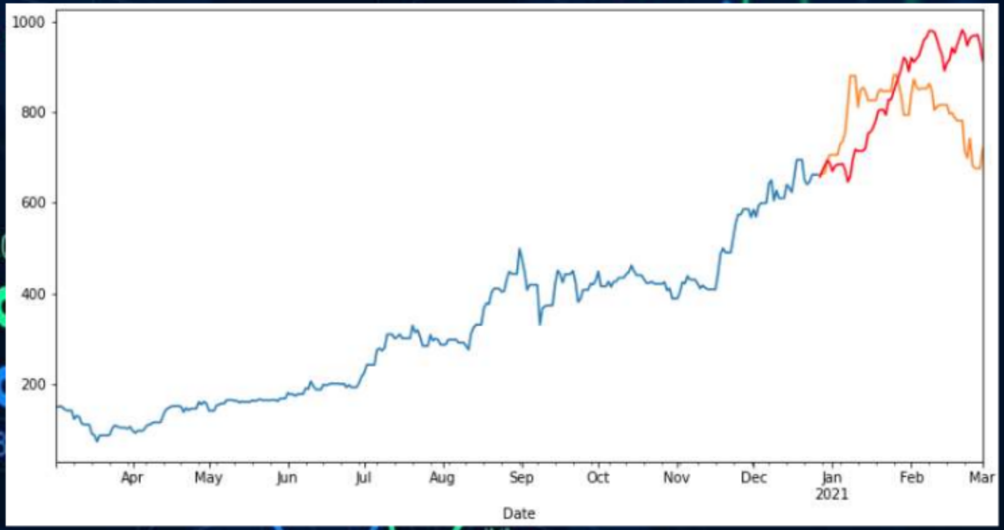

Long Short Term Memory
A
tanh
A


Long Short Term Memory
A
tanh
A
Neural Network Layer
Pointwise Operation
Vector Transfer
Concatenate
Copy
This is the LSTM!


Output
Forget Gate
(Cell) state
Next (Cell) State
Input Gate
tanh
Output Gate
σ
σ
tanh
σ
Hidden State
Next Hidden State
Input
Output = Hidden state

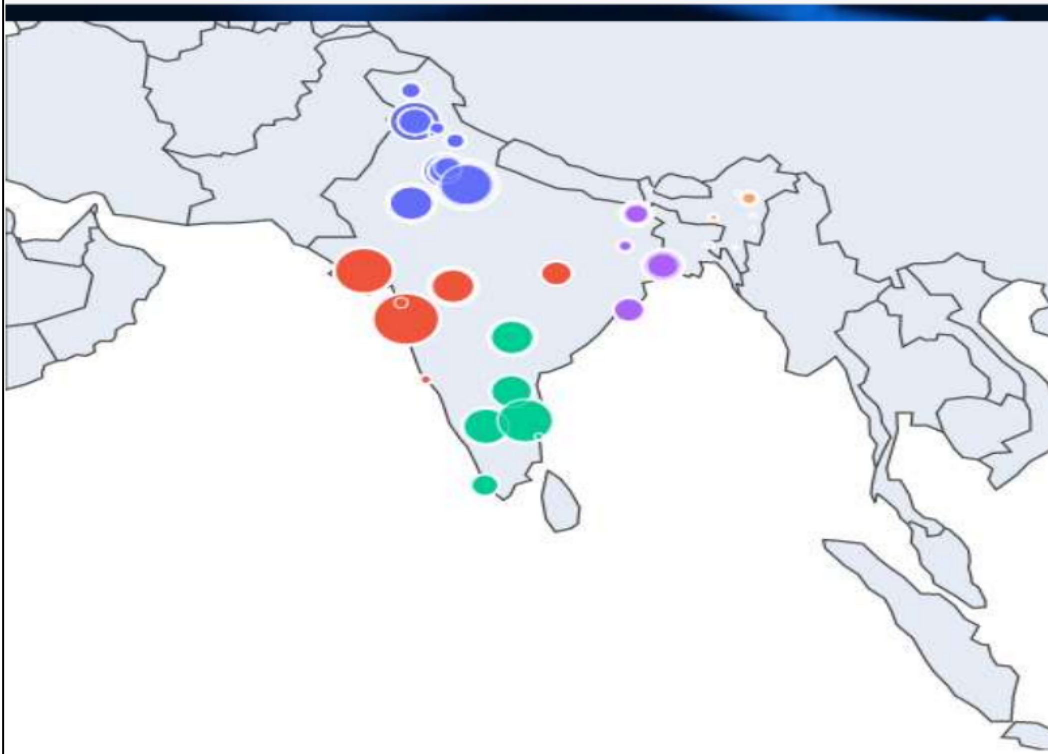
ARIMA

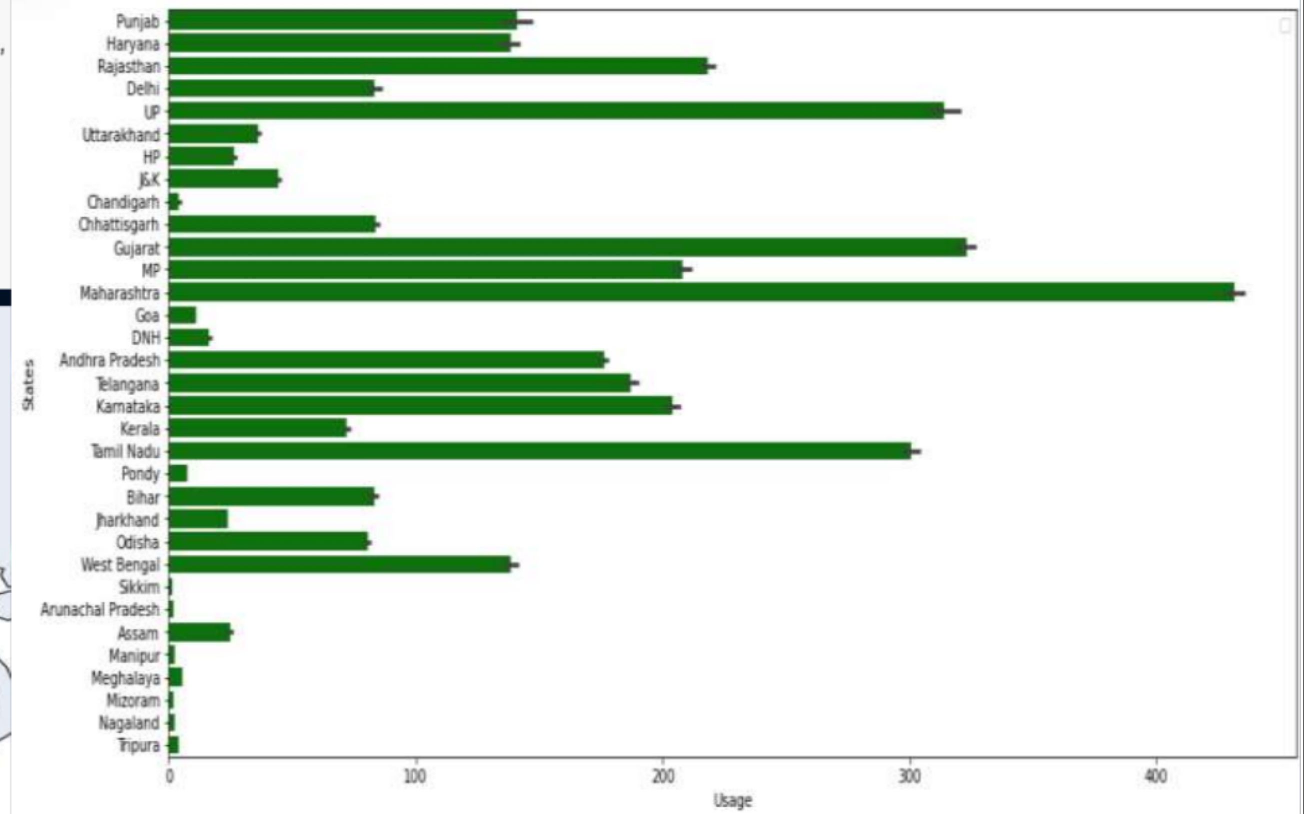
- A simple autoregressive moving average (ARMA) model is generalized into an autoregressive integrated moving average (ARIMA) model. These two models are employed to forecast or predict upcoming time-series data points. Regression analysis in the form of ARIMA shows how strong a dependent variable is in comparison to other varying factors.
- The model's ultimate goal is to forecast future time series movement by focusing on discrepancies between series values rather than actual values. In situations when the data exhibits signs of non-stationarity, ARIMA models are used. Non-stationary data are always converted into stationary data in time series analysis.



Visualizations

```
fig = px.scatter_geo(data3,'latitude','longitude', color="Regions",
                    hover_name="States", size="Usage",
                     scope='asia',
                    projection="natural earth")
fig.update_geos(lataxis_range=[5,35], lonaxis_range=[65, 100])
fig.show()
```





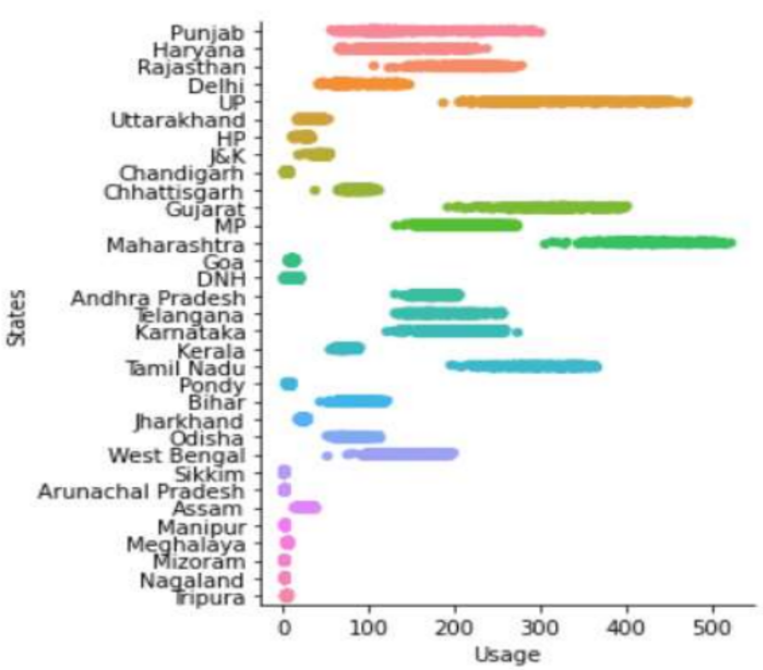

```
plt.figure(figsize=(16,8))
sns.barplot( x=data3["Usage"], y=data3["States"], color="green")
plt.legend()
```

Visualizations

```python
plt.figure(figsize=(16,8))
sns.catplot(x="Usage",y="States",data=data3)
```

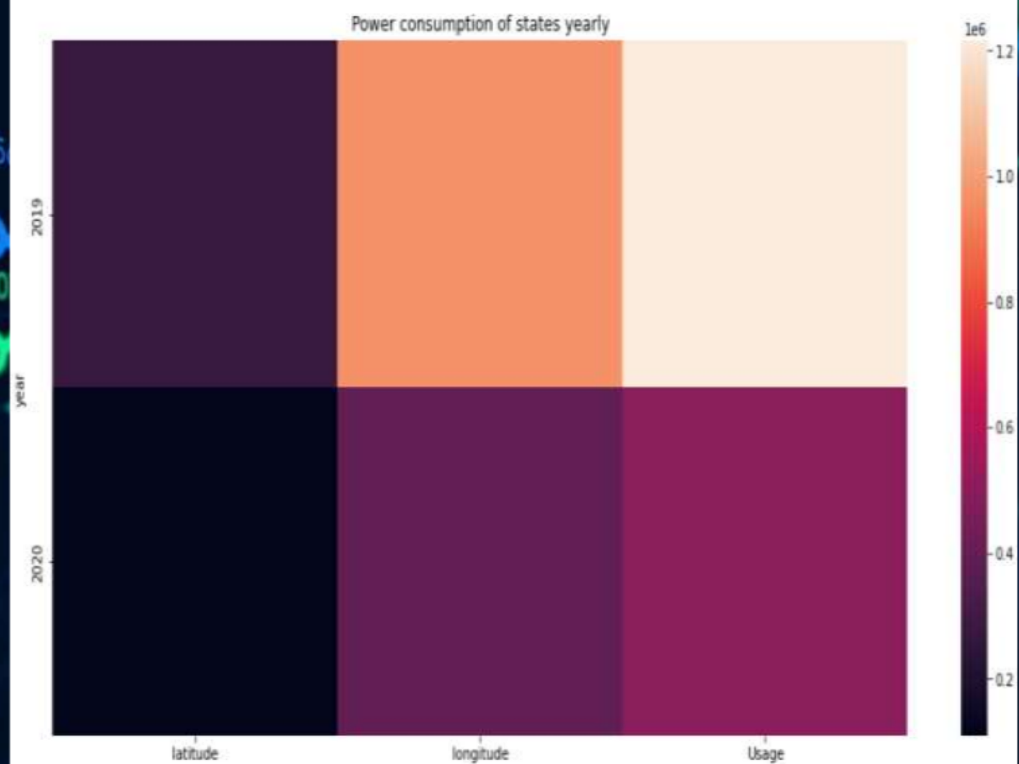
```
<seaborn.axisgrid.FacetGrid at 0x7f18ffec3890>

<Figure size 1152x576 with 0 Axes>
```




```python
plt.figure(figsize=(16,8))
plt.title('Power consumption of states yearly')
sns.heatmap(year1)
```

```
<AxesSubplot:title={'center':'Power consumption of states yearly'}, ylabel='year'>
```

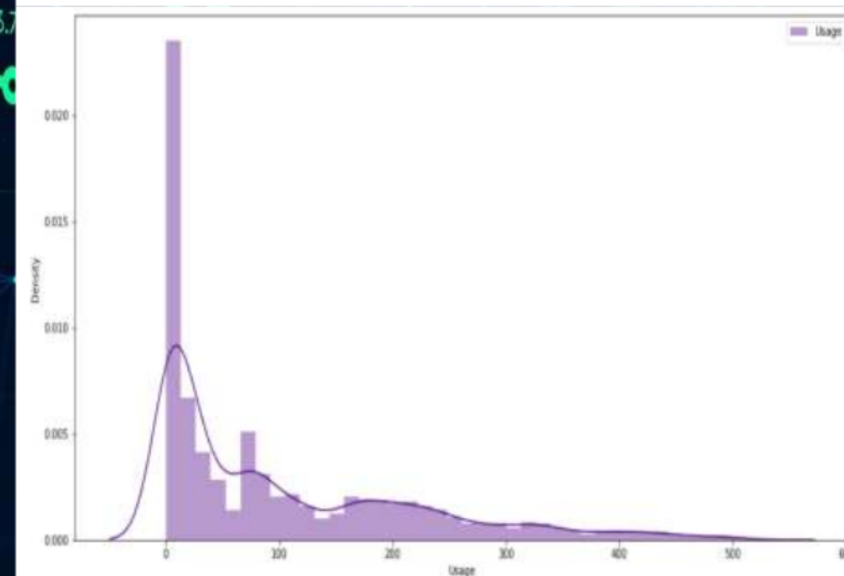


Visualizations

```python
pie_df.sort_values('Usage', inplace=True, ascending=False)
labels = pie_df["States"]
sizes = pie_df['Usage']/pie_df['Usage'].sum()
#colors
colors = ['#ff9999','#66b3ff','#99ff99','#ffcc99']

fig1, ax1 = plt.subplots()
patches, texts, autotexts = ax1.pie(sizes, colors = colors, labels=labels, autopct='%1.1f%%', startangle=90)
for text in texts:
    text.set_color('grey')
for autotext in autotexts:
    autotext.set_color('grey')
# Equal aspect ratio ensures that pie is drawn as a circle
ax1.axis('equal')
plt.tight_layout()
plt.show()
```

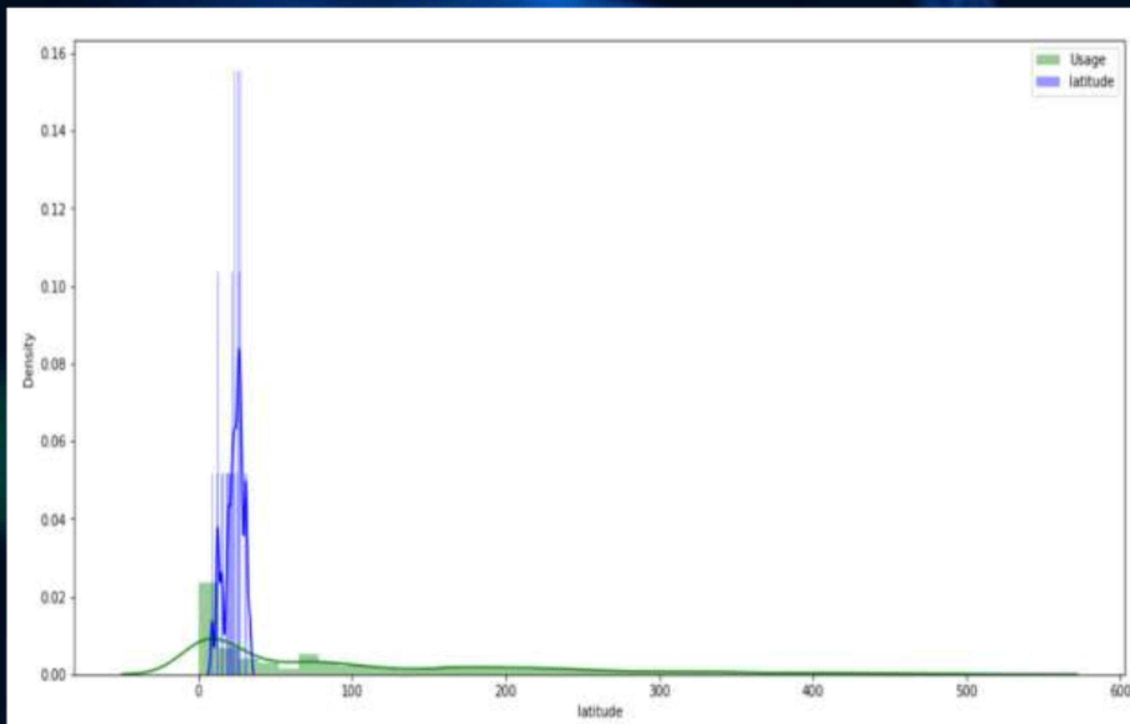
```python
plt.figure(figsize=(16,8))
sns.distplot( data3["Usage"] , color="indigo", label="Usage")
plt.legend()
```

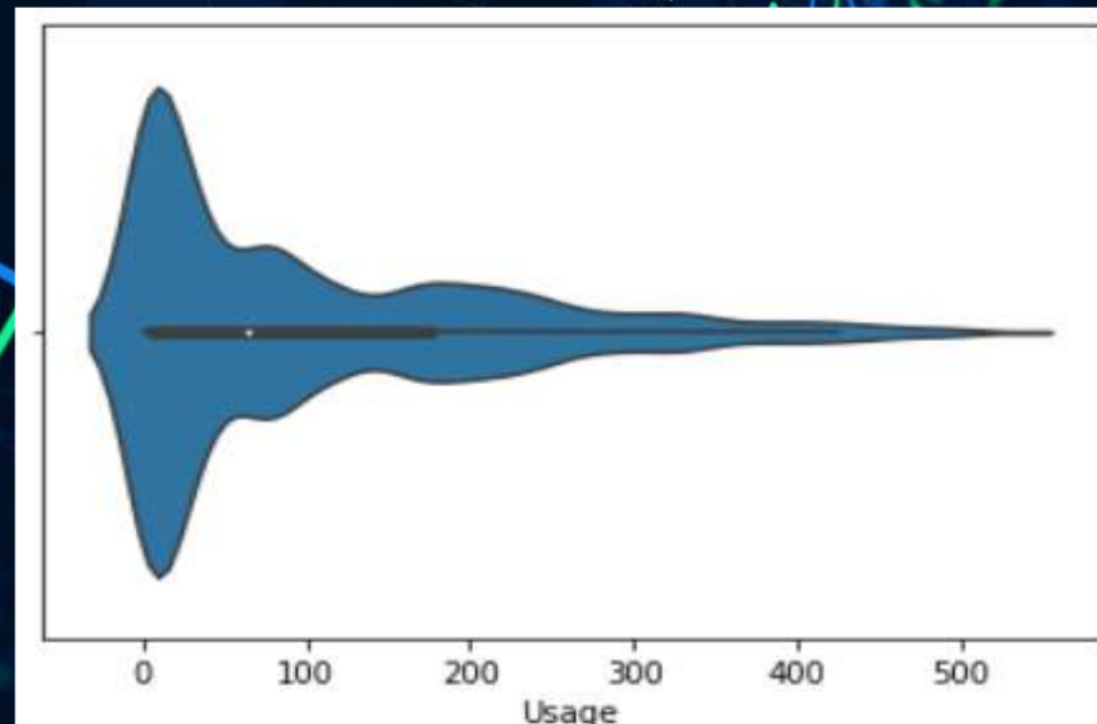


Visualizations

```python
plt.figure(figsize=(16,8))
sns.distplot( data3["Usage"] , color="green", label="Usage")
sns.distplot( data3["latitude"] , color="blue", label="latitude")
plt.legend()
```

```python
sns.violinplot(data3['Usage'])
```





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Thank You!

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