Model development and analysis of impact of community mobility during COVID-19

Project report submitted to Visvesvaraya National Institute of Technology, Nagpur in partial fulfillment of the requirements for the award of the degree

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CHAPTER 1:
INTRODUCTION

1.1 INTRODUCTION

In March’20, after the lockdown was imposed, the United Nations (UN) and the World Health Organization (WHO) praised India's response to the pandemic as 'comprehensive and robust', terming the lockdown restrictions as 'aggressive but vital' for containing the spread and building necessary healthcare infrastructure. However, the implementation of such restrictions was not as smooth as perceived. The lockdown implementation had its own virtues leading to adverse effects on the local economy and psychologies of the individual. The pandemic has left a severe impact on Indian economy, leading to a negative growth rate for the first time in decades. Nevertheless, the economy started to rebound after the lockdown was eased. However, this untimely relaxation led to spikes in number of cases and reimplementation of lockdown in a hasty manner. Due to the lack of analysis and a prudent structure to follow, the implementation of restrictions and their consequences have been varied in different regions. This deficiency led to the emergence of need to develop a model and analyse the different structures of restrictions imposed across the nation. Thus devising a model to standardize a set of practices to follow in order to minimize the spread of disease is necessary. The project aims to analyse community mobility and its relation with respect to the number of cases to provide a structured guideline for restrictions and a model to follow in future pandemics. The analysis is based on the community mobility during the phases of lockdown and its repercussions on the spread of disease while considering the different aspects of analysis namely economic, psychological and its impact on the population of India.

1.2 OBJECTIVE

The following are the objectives of the project:

- Identifying the parameters that affect the spread of disease
- Analysing the regions affected the most during the pandemic
- Economic impact on local businesses in different regions

- Devising a structured lockdown implementation
- Impact of community mobility on variation in number of cases
- Developing a model from COVID19 to handle future outbreaks

1.3 METHODOLOGY

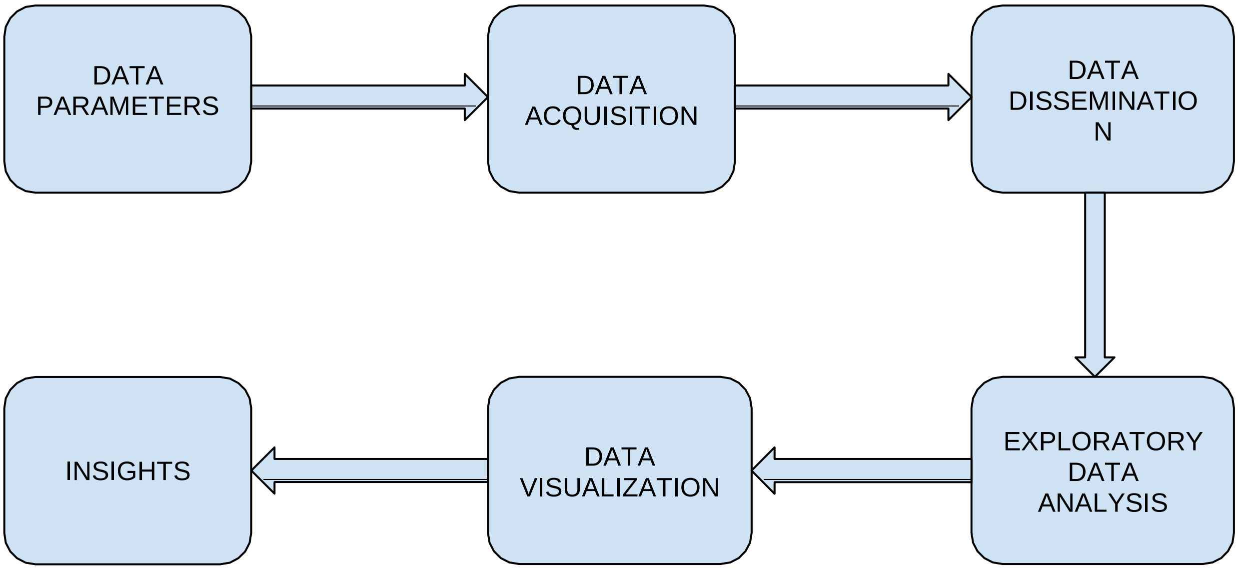


Figure 1: Methodology Flow Chart

The approach of analysis is as follows-

1. Identifying the parameters that affect the spread of disease
2. Based on the parameters, acquiring the necessary data (Community mobility, Number of cases and phases of lockdown)
3. Organizing the data (cases and mobility) of different regions based on the phases of lockdown
4. Comparing the lockdown protocols in different states to devise an ideal implementation to be followed.
5. Exploratory analysis of data to gain insights into the adverse impact in different regions and developing a model.
6. Visualizing the acquired insights.

The flow depicts the analysis process being opted in the project. Firstly, the data parameters need to be identified on the basis of which the datasets are formed. Secondly, the aspects (economic, psychological, and impact) are decided in exploratory analysis. Later, the same are utilized to acquire region-wise analysis and based on the it a theoretical model is devised. Lastly, to provide a comprehensive solution to the correlation among parameters, a mathematical base is provided. This relation is later translated in form of causa loop diagram.

CHAPTER 2:
LITERATURE SURVEY

2. LITERATURE SURVEY

As per different papers available in literature, a few studies focus on the trend analysis and forecasting for Indian region. The studies on Indian region presents long term and short-term trend, respectively. In addition, the studies in Indian region from the past are more focused on presenting time series analysis based on the overall data for Indian region rather than covering other sources of information. Considering the number of infected patients, the need to analyse the patient's background and information is required for the authorities to get better insight on the situation.

The [1] paper studies lockdown imposition in various region in the country based on the community mobility data and provides theoretical insights & its implementations. It analyses the impact of lockdown for COVID-19 on community mobility using spatial time-series change over different states and union territories (UTs) of India.

The [2] paper studies strategies for continuation of lockdown based on discussion and database. It suggests that only essential services should be open for the citizens of India and the national lockdown and provides future strategies for the same.

The [3] paper studies and analyses the COVID-19 spread in India since the day of outbreak and pattern of spreading of virus in India and to understand why National and local authorities are having a difficult time in dealing with the COVID-19. It suggests the implementation strategies to be followed for minimal spread of disease.

The [4] paper studies and presents the outcomes of a city-scale simulation experiments that suggest how the disease may evolve once restrictions are lifted. It studies the impact of case isolation, home quarantine, social distancing of the elderly, school and college closures, closure of offices, odd-even strategies, etc., as components of various post-lockdown restrictions that might remain in force for some time after the lockdown is lifted.

CHAPTER 3:
DATA RESOURCES

3.1 DATA RESOURCES

We needed data that would help us track

- Community mobility on a timeline in different regions
- Number of cases on a timeline in different regions

3.1.1 Community Mobility Data

We needed data that would show us how population of a region was moving during the lockdown phases, that showed mobility data of people to and from different places such as **Grocery shops, Retail shops, Parks, Workplaces, Residential &Transit Spots.** This data was obtained by Google [5], which keeps a track of its users' movement with the help of Google Maps, tracking their movement from their home to the aforementioned spots. They have made this data available for a population.

Table 1: Community Mobility Dataset

	A	B	C	D	E	F	G	H	I	J
1	Country	State	Region	Date	Retail & Recreation	Grocery & Pharmacy	Parks	Transit Station:	Workplace	Residential
99046	India	Maharashtra	Nagpur	18-06-20	-64	8	-77	-50	-38	20
99047	India	Maharashtra	Nagpur	19-06-20	-63	11	-76	-50	-37	21
99048	India	Maharashtra	Nagpur	20-06-20	-65	3	-78	-52	-33	20
99049	India	Maharashtra	Nagpur	21-06-20	-71	-8	-80	-56	-20	20
99050	India	Maharashtra	Nagpur	22-06-20	-64	4	-77	-52	-38	20
99051	India	Maharashtra	Nagpur	23-06-20	-64	6	-77	-51	-39	21
99052	India	Maharashtra	Nagpur	24-06-20	-63	9	-77	-47	-35	20
99053	India	Maharashtra	Nagpur	25-06-20	-61	14	-76	-49	-36	19
99054	India	Maharashtra	Nagpur	26-06-20	-63	13	-76	-48	-35	19
99055	India	Maharashtra	Nagpur	27-06-20	-63	6	-77	-52	-35	20
99056	India	Maharashtra	Nagpur	28-06-20	-67	5	-79	-51	-17	16
99057	India	Maharashtra	Nagpur	29-06-20	-62	5	-76	-49	-35	18
99058	India	Maharashtra	Nagpur	30-06-20	-59	15	-74	-47	-35	17
99059	India	Maharashtra	Nagpur	01-07-20	-59	11	-74	-47	-33	18
99060	India	Maharashtra	Nagpur	02-07-20	-61	8	-75	-49	-34	19
99061	India	Maharashtra	Nagpur	03-07-20	-61	10	-74	-49	-35	20
99062	India	Maharashtra	Nagpur	04-07-20	-62	4	-76	-51	-31	20
99063	India	Maharashtra	Nagpur	05-07-20	-69	-10	-79	-57	-18	19
99064	India	Maharashtra	Nagpur	06-07-20	-63	-2	-77	-52	-34	21
99065	India	Maharashtra	Nagpur	07-07-20	-56	20	-74	-46	-35	18
99066	India	Maharashtra	Nagpur	08-07-20	-57	14	-75	-44	-32	18
99067	India	Maharashtra	Nagpur	09-07-20	-57	16	-73	-47	-33	18
99068	India	Maharashtra	Nagpur	10-07-20	-59	15	-73	-47	-32	19
99069	India	Maharashtra	Nagpur	11-07-20	-59	10	-75	-50	-32	19
99070	India	Maharashtra	Nagpur	12-07-20	-64	7	-76	-51	-17	16
99071	India	Maharashtra	Nagpur	13-07-20	-61	4	-75	-51	-33	19
99072	India	Maharashtra	Nagpur	14-07-20	-59	12	-74	-48	-34	19

in a specific region in a generalized manner, wherein the data shows how visits to places, such as grocery stores and parks, are changing in each geographic region. These datasets show how visits and length of stay at different places change compared to a baseline. They calculate these changes using the same kind of aggregated and anonymized data used to show popular times for places in Google Maps. Changes for each day are compared to a baseline value for that day of the week:

- **The baseline is the median value, for the corresponding day of the week, during the 5-week period Jan 3–Feb 6, 2020.**
- The datasets show trends over several months with the most recent data representing approximately 2-3 days ago—this is how long it takes to produce the datasets.

The data shows how visitors to (or time spent in) categorized places change compared to our baseline days. A baseline day represents a normal value for that day of the week. To make the reports useful, they use categories to group some of the places with similar characteristics for purposes of social distancing guidance. For example, they combine grocery and pharmacy as these tend to be considered essential trips.

3.1.2 COVID-19 Cases Data

Table 2: Covid-19 Cases Dataset

Date	State	District	Confirmed	Recovered	Deceased
26-04-2020	Andaman and Nicobar Islands	Unknown	33	11	0
26-04-2020	Andhra Pradesh	Anantapur	53	14	4
26-04-2020	Andhra Pradesh	Chittoor	73	13	0
26-04-2020	Andhra Pradesh	East Godavari	39	12	0
26-04-2020	Andhra Pradesh	Guntur	214	29	8
26-04-2020	Andhra Pradesh	Krishna	177	29	8
26-04-2020	Andhra Pradesh	Kurnool	279	31	9
26-04-2020	Andhra Pradesh	Prakasam	56	23	0
26-04-2020	Andhra Pradesh	S.P.S. Nellore	72	23	2
26-04-2020	Andhra Pradesh	Srikakulam	3	0	0
26-04-2020	Andhra Pradesh	Visakhapatnam	22	19	0
26-04-2020	Andhra Pradesh	West Godavari	51	10	0
26-04-2020	Andhra Pradesh	Y.S.R. Kadapa	58	28	0
26-04-2020	Arunachal Pradesh	Lohit	1	1	0
26-04-2020	Assam	Unknown	36	27	1
26-04-2020	Bihar	Arwal	4	0	0
26-04-2020	Bihar	Aurangabad	2	0	0
26-04-2020	Bihar	Banka	2	0	0
26-04-2020	Bihar	Begusarai	9	1	0
26-04-2020	Bihar	Bhagalpur	5	1	0
26-04-2020	Bihar	Bhojpur	2	1	0
26-04-2020	Bihar	Buxar	25	1	0
26-04-2020	Bihar	East Champaran	5	0	0
26-04-2020	Bihar	Gaya	6	5	0
26-04-2020	Bihar	Gopalganj	12	3	0
26-04-2020	Bihar	Jehanabad	1	0	0
26-04-2020	Bihar	Kaimur	14	0	0
26-04-2020	Bihar	Lakhisarai	1	1	0

A collection of data for the cases of COVID-19 was necessary to understand the causality of movement restriction and number of infected people. The data needed to be based on a timeline with the number of cases being detected in every region of India. This data was collected from various sources and compiled to give a more accurate dataset.

We have collected and reorganized this data region wise and sorted it with the dates they were reported.

3.2 MERGING DATA SETS

The two datasets of Community Mobility Data & COVID-19 Cases were ineffective to our research individually. This was done by merging them to create a single dataset that provided us with data of all the States and Districts considered on a given timeline. This was done with the help of Tableau Prep by the following steps:

Table 3: Merged Dataset

State	District	Date	Retail	Grocery/ Pharma	Parks	Transit Spots	Workplaces	Residential	Confirmed	Recovered	Deceased	Active
Andhra Pradesh	Chittoor	26-04-2020	-83	-48	-57	-68	-33	23	73	13	0	60
Andhra Pradesh	East Godavari	26-04-2020	-87	-43	-74	-57	-27	22	39	12	0	27
Andhra Pradesh	Guntur	26-04-2020	-86	-54	-70	-61	-35	25	214	29	8	177
Andhra Pradesh	Krishna	26-04-2020	-88	-58	-68	-73	-40	24	177	29	8	140
Andhra Pradesh	Kurnool	26-04-2020	-85	-47	-72	-62	-34	27	279	31	9	239
Andhra Pradesh	Prakasam	26-04-2020	-78	-34	-59	-48	-20	22	56	23	0	33
Andhra Pradesh	Srikakulam	26-04-2020	-82	-40	-46	-56	-22	20	3	0	0	3
Andhra Pradesh	West Godavari	26-04-2020	-84	-42	-58	-55	-24	22	51	10	0	41
Bihar	Aurangabad	26-04-2020	-78	-35	9	-54	-23	17	2	0	0	2
Bihar	Banka	26-04-2020	-73	9	-37	-54	-2	15	2	0	0	2
Bihar	Begusarai	26-04-2020	-77	15	-68	-68	-19	16	9	1	0	8
Bihar	Bhagalpur	26-04-2020	-73	-27	-77	-64	-23	17	5	1	0	4
Bihar	Bhojpur	26-04-2020	-78	-1	-56	-68	-21	15	2	1	0	1
Bihar	Buxar	26-04-2020	-81	-6	-58	-81	-17	15	25	1	0	24
Bihar	Gaya	26-04-2020	-77	-26	-59	-69	-23	15	6	5	0	1
Bihar	Gopalganj	26-04-2020	-73	13	-46	-43	-18	13	12	3	0	9
Bihar	Jehanabad	26-04-2020	-75	-27	-13	-41	-15	14	1	0	0	1
Bihar	Kaimur	26-04-2020	-70	-9	24	-50	-13	15	14	0	0	14
Bihar	Lakhisarai	26-04-2020	-76	-28	-27	-72	-15	17	1	1	0	0
Bihar	Madhepura	26-04-2020	-79	23	44	-47	-13	14	1	0	0	1
Bihar	Munger	26-04-2020	-70	-22	-66	-67	-17	18	68	11	1	56
Bihar	Nalanda	26-04-2020	-82	-34	-77	-50	-23	15	34	6	0	28
Bihar	Nawada	26-04-2020	-79	16	85	-48	-19	13	3	2	0	1
Bihar	Patna	26-04-2020	-88	-54	-91	-76	-48	20	33	5	0	28
Bihar	Rohtas	26-04-2020	-78	-36	-17	-67	-22	16	15	0	0	15
Bihar	Saran	26-04-2020	-77	-19	-5	-63	-21	15	3	1	0	2
Bihar	Siwan	26-04-2020	-76	-27	48	-59	-21	14	30	18	0	12
Bihar	Vaishali	26-04-2020	-80	-8	-1	-57	-20	15	2	0	1	1
Chhattisgarh	Bilaspur	26-04-2020	-90	-75	-84	-83	-42	26	1	1	0	0
Chhattisgarh	Durg	26-04-2020	-78	-29	-68	-73	-23	22	1	1	0	0
Chhattisgarh	Korba	26-04-2020	-78	-32	-82	-66	-18	26	28	24	0	4

- States, Districts and Dates were first matched from both the datasets to build a common framework of the main dataset required. Only the districts in consideration were filtered.
- Datasets were cleaned for N/A values and any errors presented during the first step of merging to obtain an accurate final dataset. Errors presented were mainly due to case-sensitivity, spelling errors, missing value points in individual datasets.

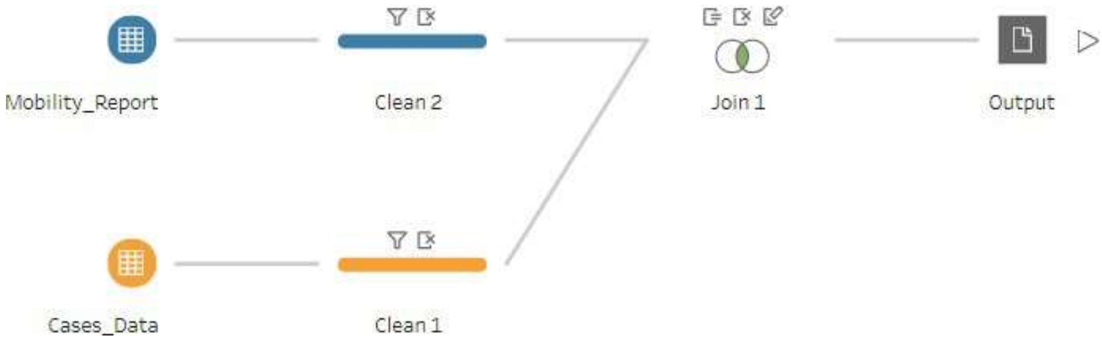


Figure 2: Data cleaning & joining process in Tableau Prep

- Once the datasets were precise, they were merged to get the main dataset used for analysis of the project. This was done by loading the cleaned datasets in Tableau Prep and joining them with Inner Join option.

CHAPTER 4:
ANALYSIS

4.1 ASSUMPTIONS

The following assumptions are made to justify and provide a basis to the process of the project:

- Novel Coronavirus is an airborne virus, spread through contact between the infected and the vulnerable. This was the reason for lockdown restrictions to be implemented, which imposed restrictions on movement of the population. The assumption is that this restriction on mobility of communities led to severe impact on local economy, and we want to analyse the trend between mobility restrictions and economic impact in different regions around India.
- Lockdown procedures were implemented in different fashions in different regions of the country, with varying outcomes in all of the said regions. The aim is to study the protocols implemented and find out a success rate of the restrictions imposed based on the economic aspect in various regions.
- As the restrictions imposed are varying region wise, we think there is a certain set of guidelines that can be followed for a successful lockdown to be implemented, wherein spread of the virus is minimal and local economy does not take a huge hit. This can determined by finding a relation between the lockdown procedures that were implemented in different regions and compare them with the number of cases, which can point to a direct relation between spread of the disease and the success of the restrictions implemented.
- Airborne disease with similar contagiousness may return in the future, so from this project the motive is to introduce a certain set of guidelines, a theoretical model that can be followed in any future circumstances that can help minimalize the damage and help prevent the spread effectively.
- As days passed, the virus mutated over time which increased its immunity to traditional medical procedures that were being followed to curb its spread in an individual, also the new strain had new characteristics which furthered its spread. The mutated virus was brought into India around mid-January 2021, and along with it brought disparities in the data analysis. So only data upto 19th January 2021 is considered for model preparation.

4.2 ASPECTS OF ANALYSIS

4.2.1 Economic Impact

The **economic impact of the 2020 coronavirus pandemic in India** has been largely disruptive. India's growth in the fourth quarter of the fiscal year 2020 went down to 3.1% according to the Ministry of Statistics. The Chief Economic Adviser to the Government of India said that this drop is mainly due to the coronavirus pandemic effect on the Indian economy. Notably India had also been witnessing a pre-pandemic slowdown, and according to the World Bank, the current pandemic has "magnified pre-existing risks to India's economic outlook".

- Largest GDP contraction ever in Q1 (April–June) FY2020–2021 at -24%
- Sharp rise in unemployment
- Stress on supply chains
- Decrease in government income
- Collapse of the tourism industry
- Collapse of the hospitality industry
- Reduced consumer activity
- Plunge in fuel consumption. Rise in LPG sales.
- Trade tensions with China

4.2.2 Psychological Impact

COVID-19 pandemic has caused a lot of uncertainty in the lives of Indian public, just like their global counterparts. Our survey is one of the first mental health related data from India, during the initial phase of COVID-19 pandemic and indicated that a significant proportion of them have had a psychological impact during the crisis. The factors that predicted higher impact were younger age, being female and having a known physical comorbidity. There is a need for considering mental health issues by the policy makers; while planning interventions to fight the pandemic.

4.2.3 Impact Analysis

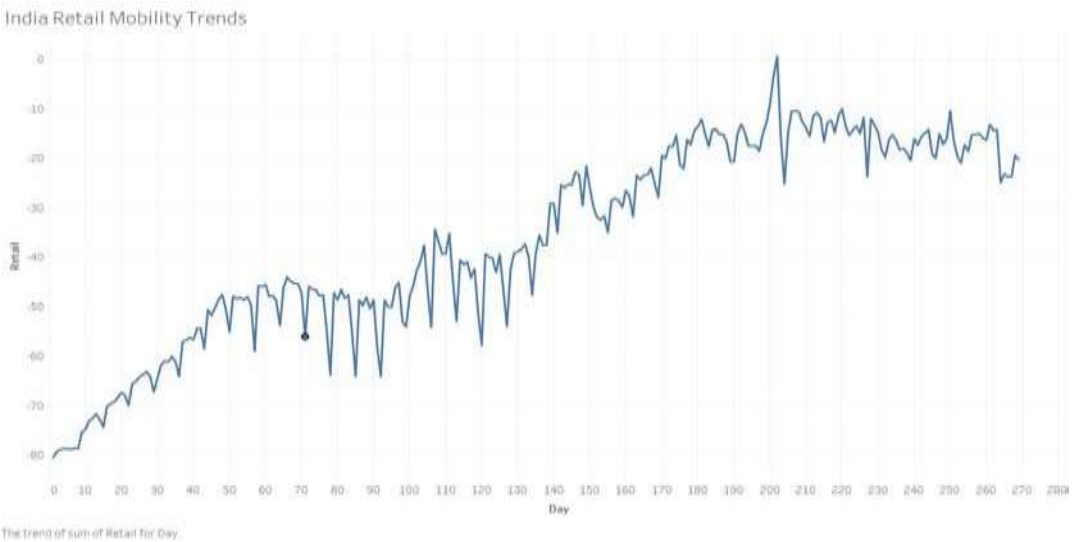
Lockdown dates were almost the same in all parts of India with minor variations here and there but lockdown implementation is different in different places.

Apart from lockdown implementation contract tracing, testing also placed a crucial role in spread of COVID-19. Due to this growth of COVID-19 cases varied from region to region.

4.3 ANALYSIS PARAMETERS

- **Retail & recreational mobility:**

Mobility towards places like restaurants, cafes, shopping centers, museums, libraries, and picture theatres are named as retail &



recreational mobility

Figure 3: India Retail & Recreational Mobility vs Time

- **Grocery & pharmacy mobility:**

Daily or sometimes weekly mobility trends for places viz. grocery, food warehouses, markets, local hats, farmer’s markets, specialty food shops, different drug or medicine stores, and pharmacies

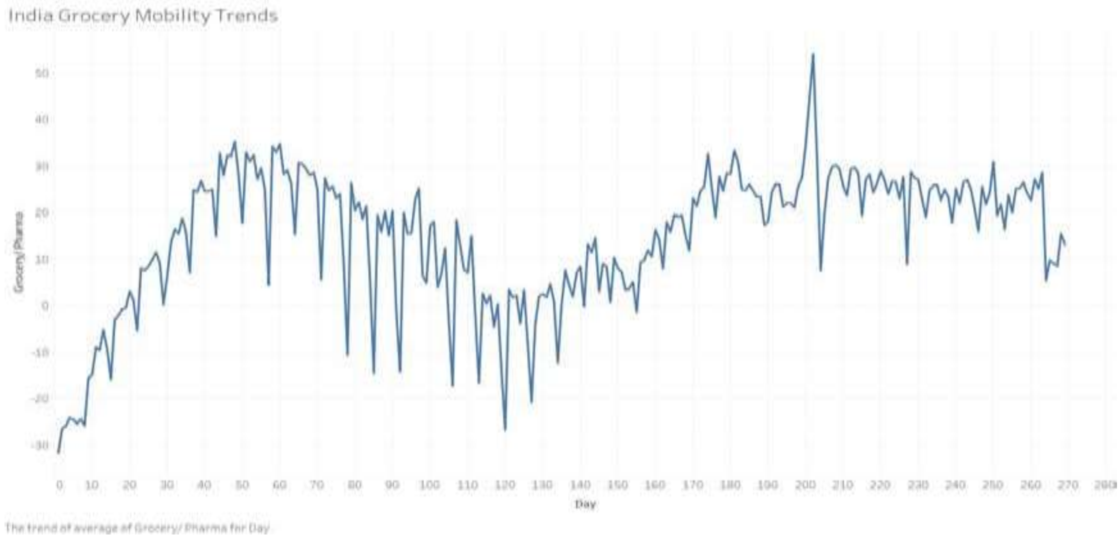


Figure 4: India Grocery & Pharmacy Mobility vs Time

- **Parks mobility:**

Mobility trends for places of attraction like local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens.

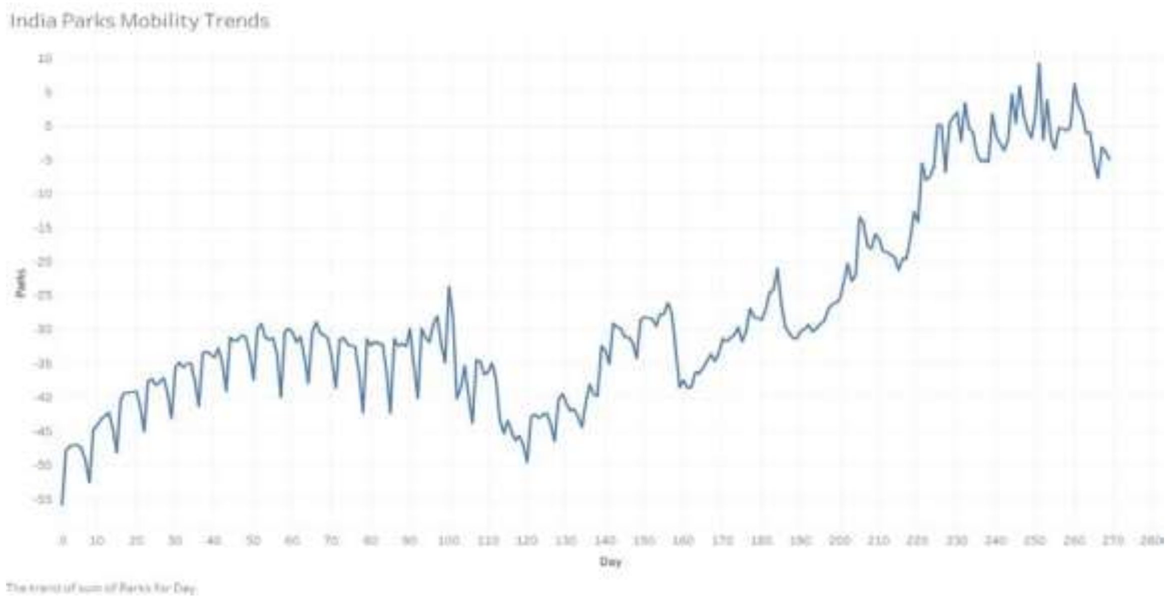


Figure 5: India Parks Mobility vs Time

- **Transit stations mobility**:

This mobility refers to the process by which a person moves from one place to another place like public transport hubs such as subway, bus, and train stations.

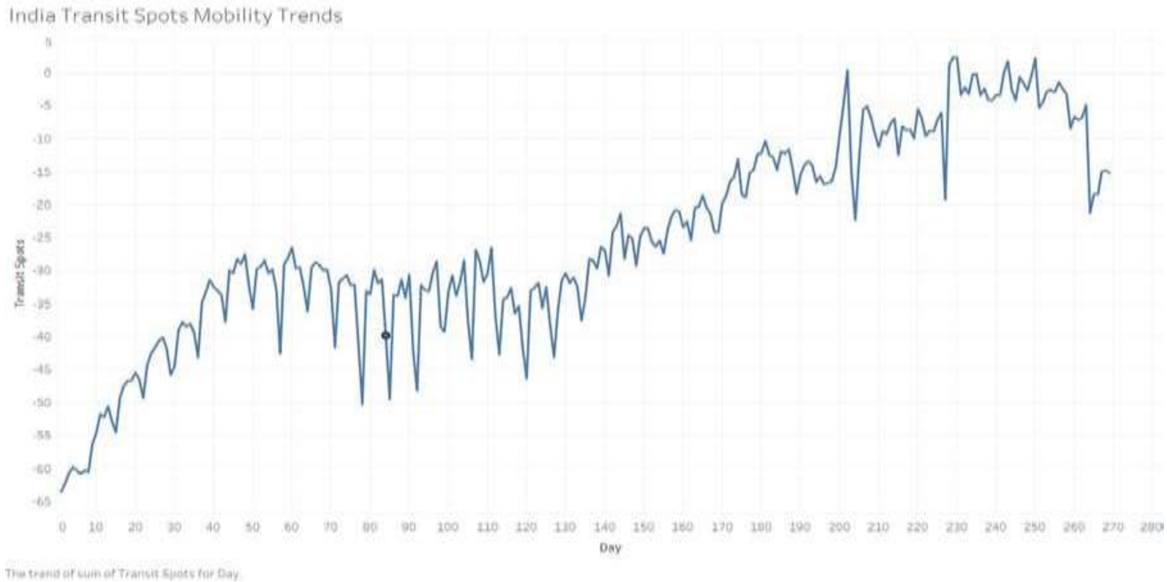


Figure 6: India Transit Spots Mobility vs Time

- **Workplace's mobility:**

This type of mobility trends for going places of work from a native place

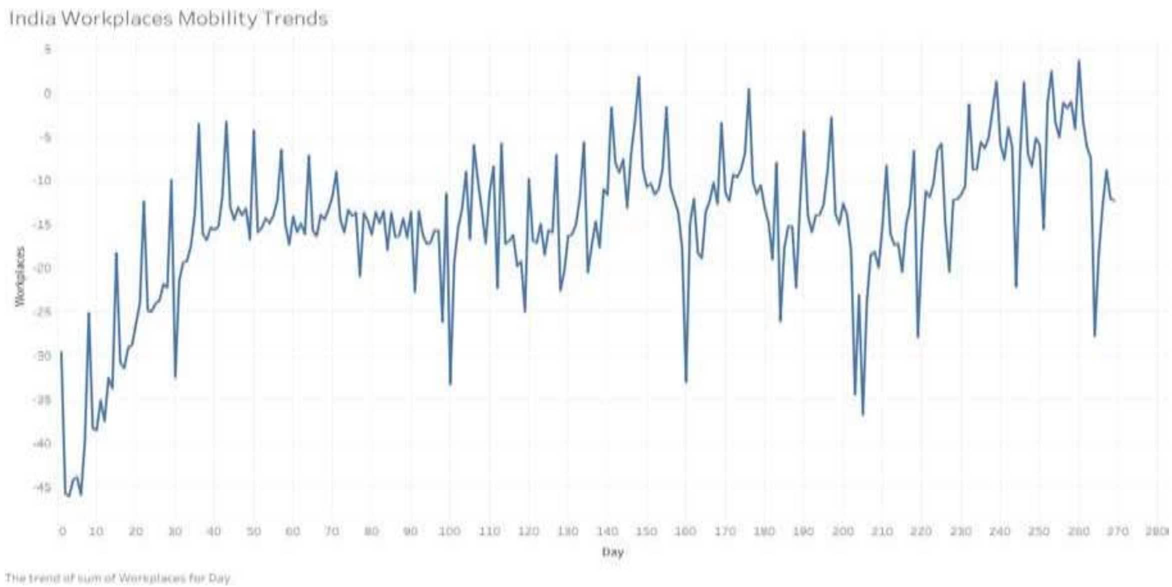


Figure 7: India Workplaces Mobility vs Time

- **Residential mobility:**

Mobility in the direction of places of residence where a person lived

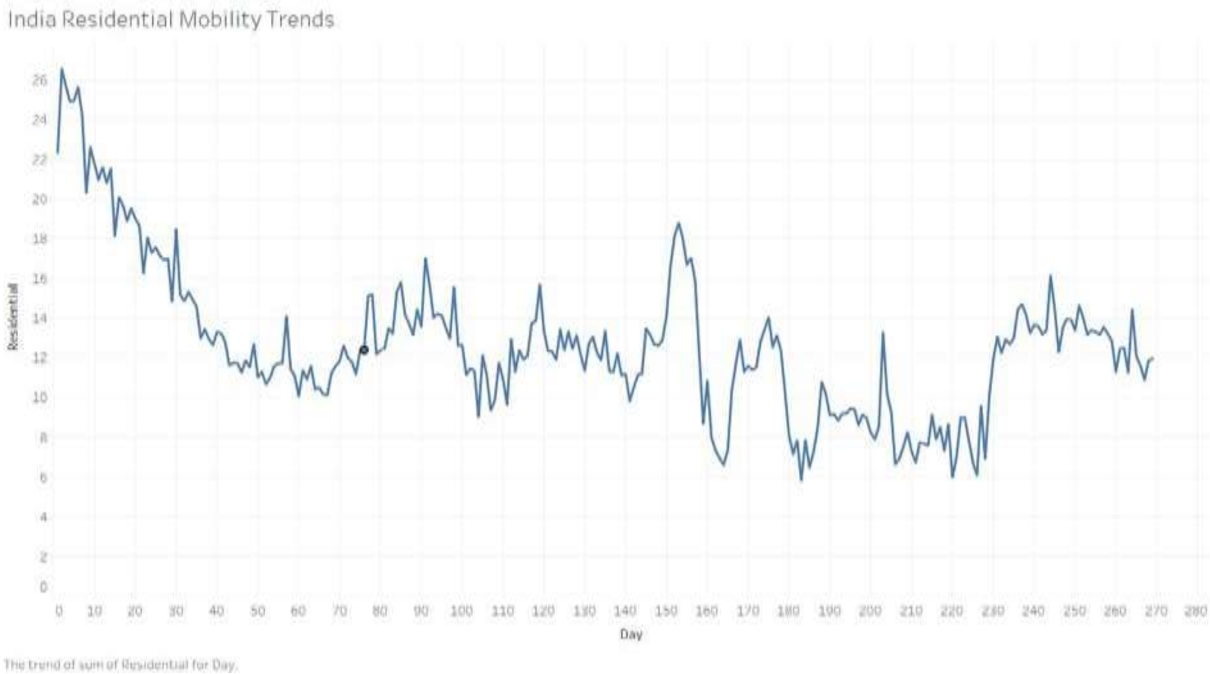


Figure 8: India Residential Mobility vs Time

Nationwide lockdown:

- Phase 1: 25 March 2020 – 14 April 2020 (21 days)
- Phase 2: 15 April 2020 – 3 May 2020 (19 days)
- Phase 3: 4 May 2020 – 17 May 2020 (14 days)
- Phase 4: 18 May 2020 – 31 May 2020 (14 days)

Unlock:

- Unlock 1.0: 1 June 2020 – 30 June 2020 (30 days)
- Unlock 2.0: 1 July 2020 – 31 July 2020 (31 days)
- Unlock 3.0: 1 August 2020 – 31 August 2020 (31 days)
- Unlock 4.0: 1 September 2020 - 30 September 2020 (30 days)
- Unlock 5.0: 1 October 2020 - 31 October 2020 (31 days)
- Unlock 6.0: 1 November 2020 - 30 November 2020 (30 days)
- Unlock 7.0: 1 December 2020 - 31 December 2020 (4 days)

Number of COVID-19 cases in a region also placed a role in community mobility of the region.

Some terms involved with number of COVID-19 cases-

Total Confirmed cases: Number of people infected with COVID-19 from beginning.

Total recovered cases: Number of people cured from COVID-19 from beginning. **Total active cases:** Number of people who are currently suffering from COVID-19 **Total deaths:** number of people who deceased while suffering from COVID-19.

Total Confirmed cases =Total recovered cases + Total active cases + Total deaths

4.4 EXPLORATORY ANALYSIS

4.4.1 Maharashtra Analysis:

The movement of people in a particular region determines the spread of disease in a proportional manner. A region being divided into- grocery, retail shops, transit spots, workplaces, parks and residential areas. In the first stage of analysis, the state of Maharashtra is considered and then the same process can be applied on the entire nation.

The variations from baseline give an insight to most affected business/ places in a region. The colour coded representation of average no. of people visiting a spot on the map of Maharashtra is as follows-

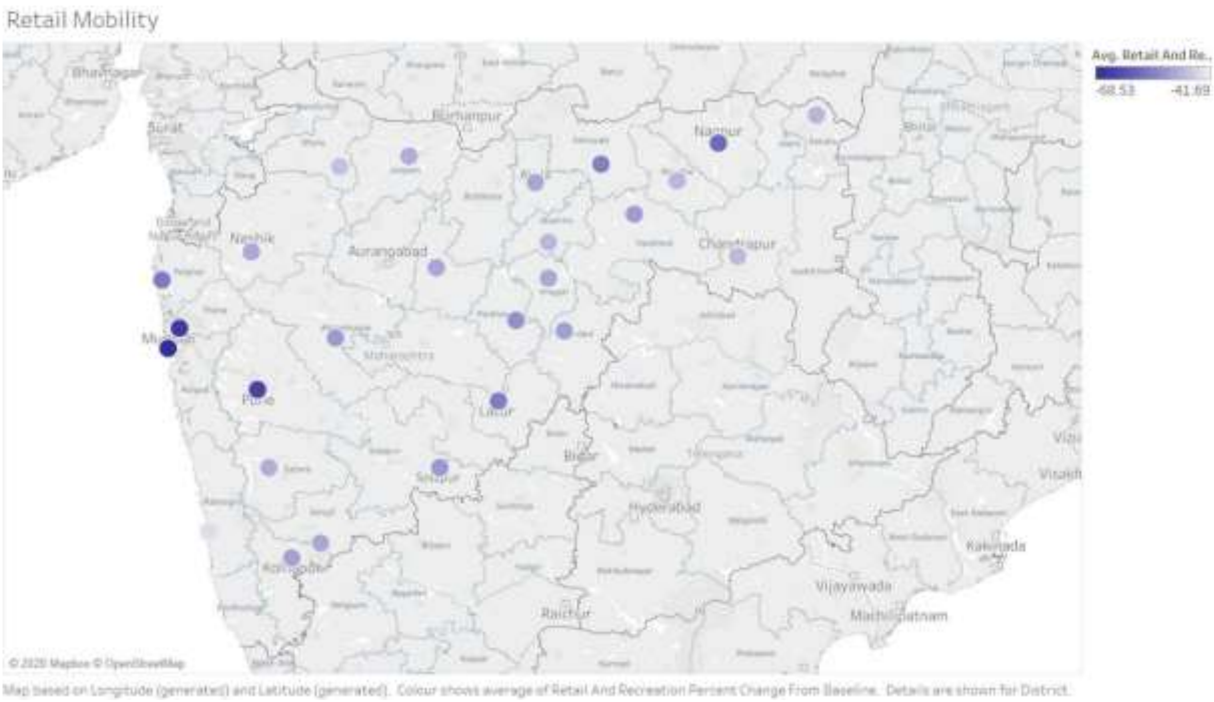


Figure 9: Average Retail Mobility in Maharashtra

Figure 10: Average Residential Mobility in Maharashtra

Figure 11: Average Transit Mobility in Maharashtra

The regions with dark blue colour represent a negative deviation from baseline i.e. less people visiting a particular region than the usual number and vice versa or the light shades with a linear variation. The average value being considered is based on the timeline from March to September of all the spots in a region.

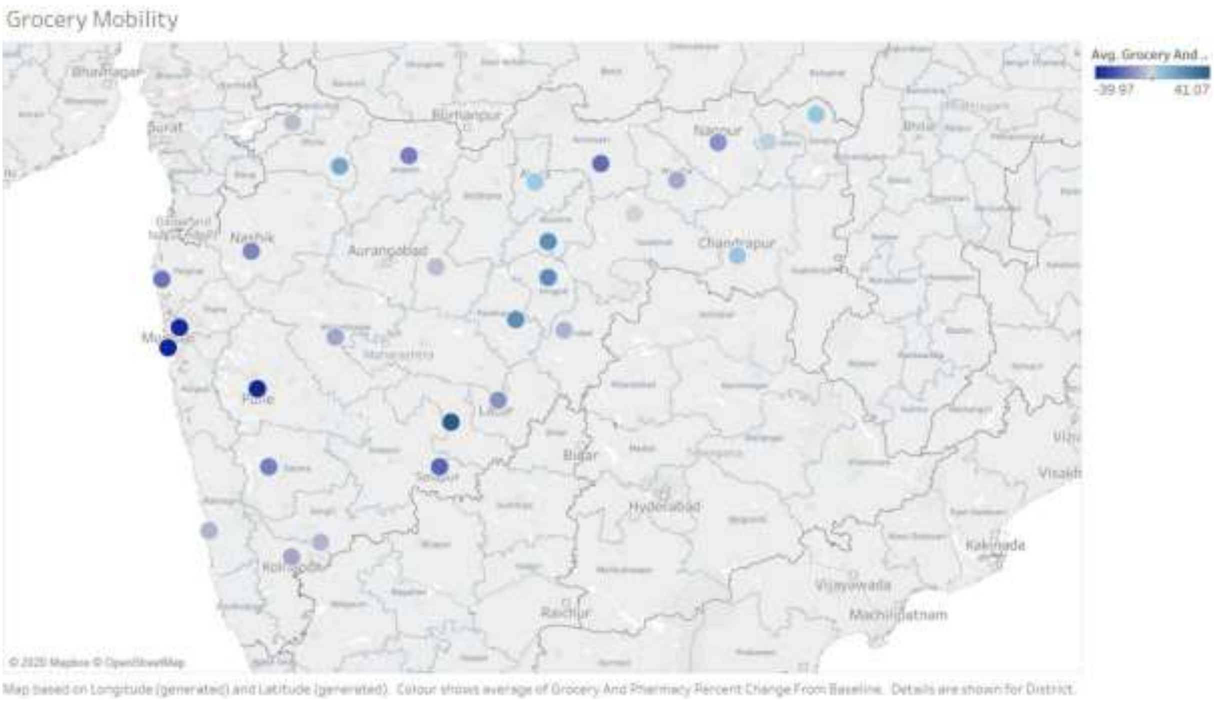


Figure 12: Average Workplace Mobility in Maharashtra

From the above visualization, it is evident that all the spots in the districts of Mumbai and Pune are affected the most in terms of mobility. The restrictions in these regions have resulted in less people visiting the shops, transit spots and places. Thus, resulting in loss of local businesses and ultimately the economy. Whereas in the districts of Chandrapur and Sangli the trend seems somewhat stabilized with a few people visiting shops and places.

The earlier maps represented the variation for a tenure of 7 months, wherein the values were averaged out from all the spots. Now, to gain quarterly insights of all the districts in the state of Maharashtra can be viewed in details to check the implementation of lockdown in different phases.

Figure 13: Average Park Mobility in Maharashtra

Figure 14: Average Grocery Mobility in Maharashtra

Quarter-2: Phase Lockdown
Quarter-3: Phase Unlock 1-2
Quarter-4: Phase Unlock 3-4

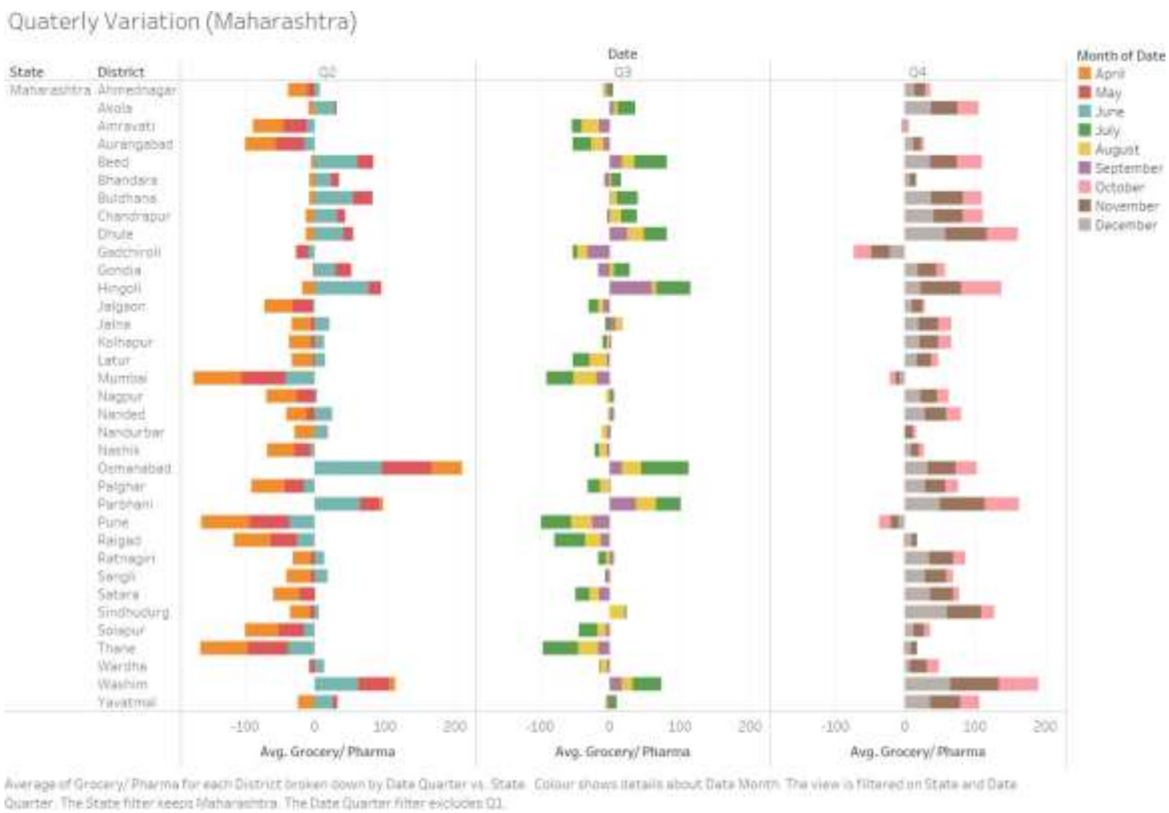


Figure 15: Average change in Grocery & Pharmacy w.r.t Baseline for each district in Maharashtra

From the above visualization, it is evident that in quarter-1 the restrictions imposed were strictly followed and resulted in less mobility. Whereas, in the other two quarters the fluctuation observed tend to result in failure of social distancing and thus spikes in number of cases in those particular region (currently the districts of Maharashtra in consideration) can be observed as its repercussions.

4.4.2 India Analysis:

4.4.2.1 Economic Aspect:

The economic aspect in India can be observed with mobility at Groceries/ Pharma, Workplaces, and Retail stores. The fall in percentage of people visiting a business point directly impact the sales. With this assumption, we can proceed with observing the trends at the above economic points-

A. Workplaces:

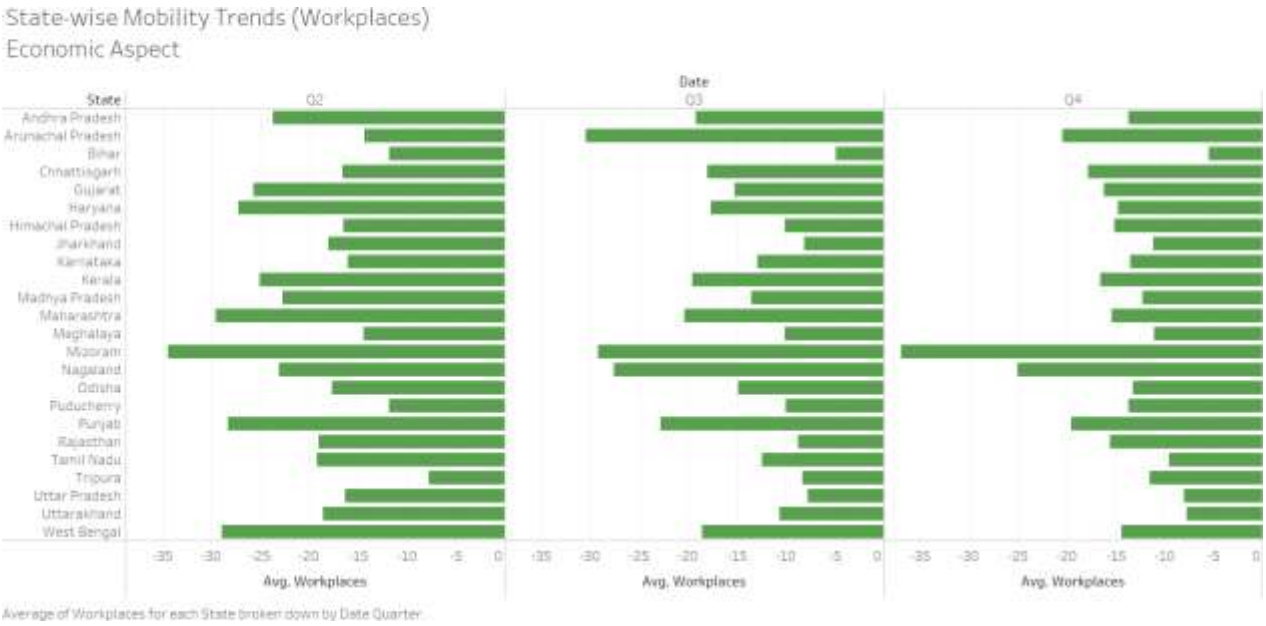


Figure 16: Average of Workplace for each state at each quarter

Mobility trends in the second quarter shows more negative deviation than other quarters. As the emergence of lockdown paved way to work from home and implement online working culture. Moreover, in quarter-2 the trends seems to be comparatively less negative, this may be due to migration of workers and unstable restriction on industries and workplaces. Later, as the restrictions were relaxed, the industries started working in partial capacities leading to positive deviation in mobility. This trend can be seen in quarter-3 and quarter-4.

B. Groceries/ Pharma:

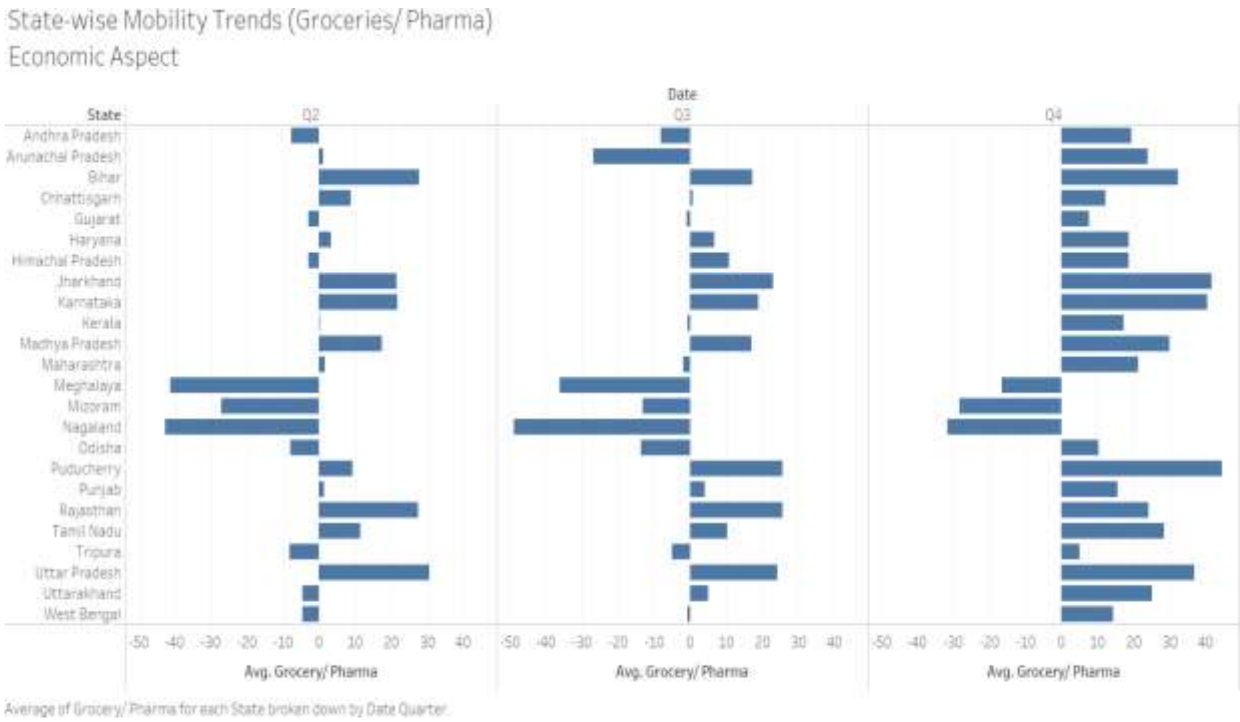


Figure 17: Average of Grocery & Pharma for each state at each Quarter

Initially, in quarter-2, due to sudden imposition of lockdown and emergence of the pandemic, people panicked and reached out to grocery and pharmaceutical stores to stock up their inventories. This resulted in the positive trend of mobility in the first quarter. However, as time went on, people assessed the situation and reduced their movement and along with restrictions and spread of disease, the trend deviated to negative values in quarter-3. Finally, with loosened restrictions in quarter-4, things started to normalize as before, and Groceries and Pharmacies were conducting business as usual.

Groceries and pharmaceutical stores did not take much of an economic impact as they were deemed to be essential services. However, this was only applicable to select stores which means small local vendors lost some business in the earlier stages of lockdown.

C. Retail:

Any business outlet that is not a Grocery or a Pharmacy comes under the group Retail. Quarter 2 was the period of total lockdown being imposed throughout the country during which no retail stores were in business as they were not considered as an essential service required. This can be understood from the trends as mobility is seen to be more towards the negative side indicating almost minimal movement to Retail establishments. Same was the situation during Quarter 3 as most regions only allowed essential services to be opened. As Quarter 4 came about, businesses were allowed to open and as compared to previous quarters, the trends can be said to be less negative indicating people started moving for purchases. Overall, this implies that Retail stores took the worst hit during this pandemic with business being almost minimal and their loses increasing over time being closed.

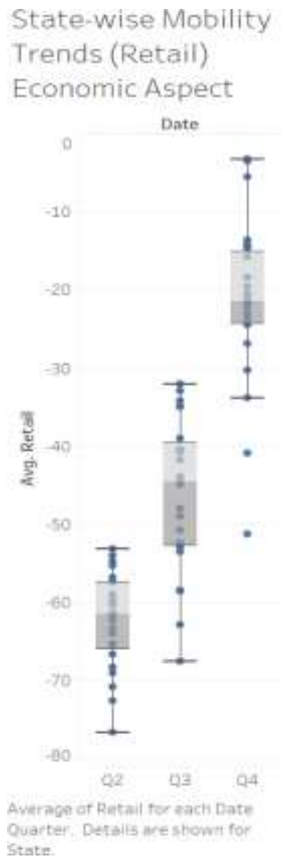


Figure 18: Average of Retail at each Quarter

4.4.2.2 Psychological Aspect:

A. Parks/Recreational

This is the average mobility data of the entire country illustrating the patterns during the various lockdown and unlock phases that were followed throughout the country.

The rise and fall around the month of December indicates the presence of the new mutated COVID-19 strain entering India.

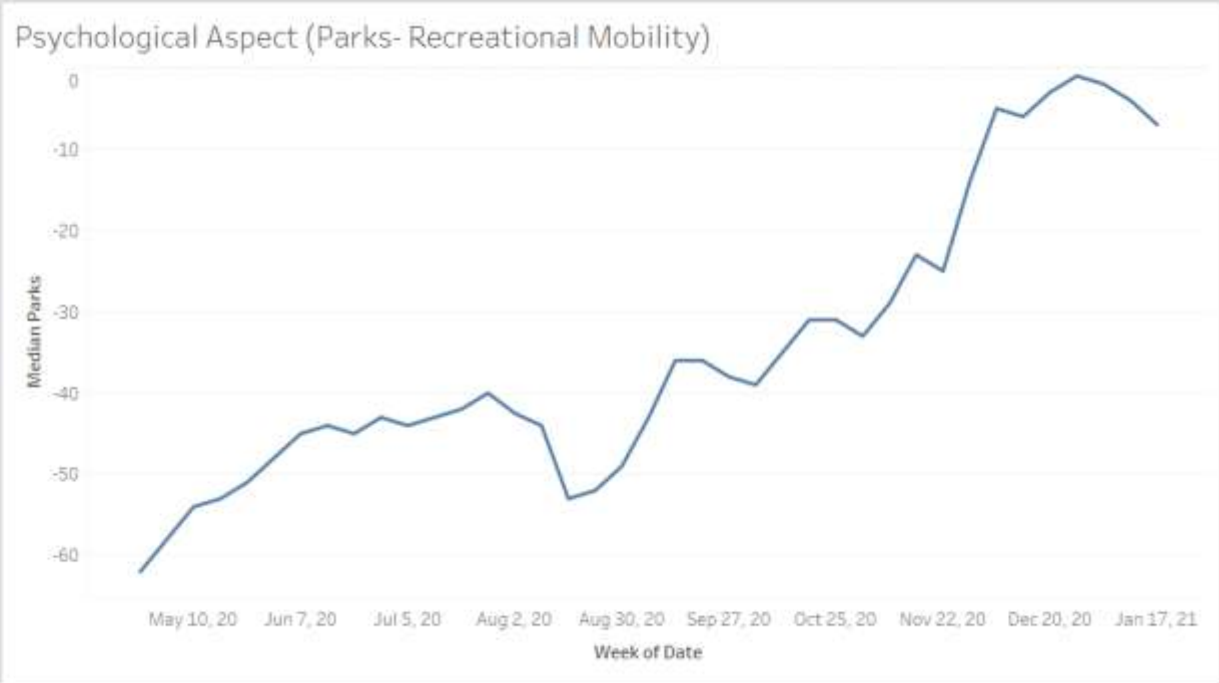


Figure 19: Avg of Parks mobility vs

Time Fall during Month of August:

This fall occurred during Unlock Phase 3 – Phase 4, wherein the public transit modes were being opened up. The general populace had recognized the possibility of increased foot traffic in recreational places so they stopped going to recreational spots to avoid the increased risk of infection that was brought in by public transit reopening.

Fall during Month of December:

The fall in mobility indicates the understanding the general public showed in suppressing the spread by reducing movement to recreational places like malls, parks etc. People were already familiar with the necessary precautions to be followed. The fall in mobility shows that people were accepting of the new strain being fatal and were taking the necessary steps before being intimated by the governing bodies

4.4.2.3 Impact Analysis:

- The impact of this pandemic has brought about various changes in different aspects of our society. One that is majorly observed is the mobility of employee's workplaces and offices. As the unlock phases were initiated there

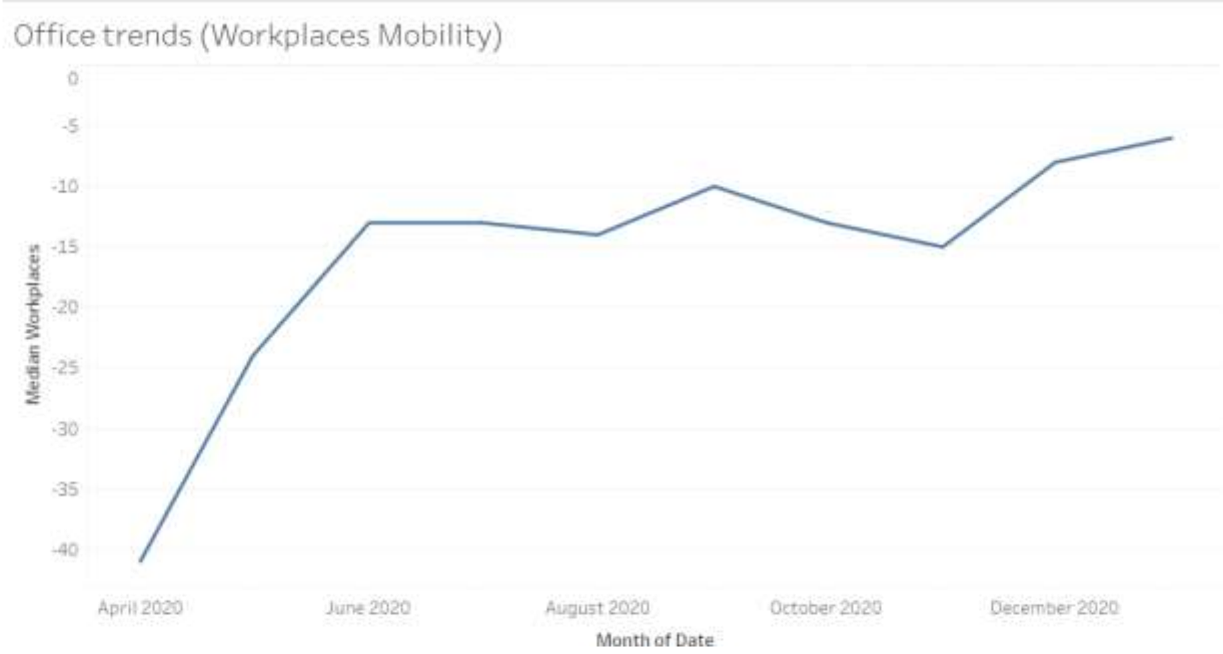


Figure 20: Avg of Office Mobility vs Time

was still reduced foot traffic to workplaces as people were aware of the dangers of travelling with the virus not as under control. Corporations have faced this situation by making work from home a preferred method for their employees, which ensures work and safety. The flattening of the curve indicates that most corporations are starting to accept WFH as a norm in the industry.

From the graphs below, it can be perceived that during Quarter 2 the curve started to flatten in terms of COVID cases due to lockdown being strictly imposed.

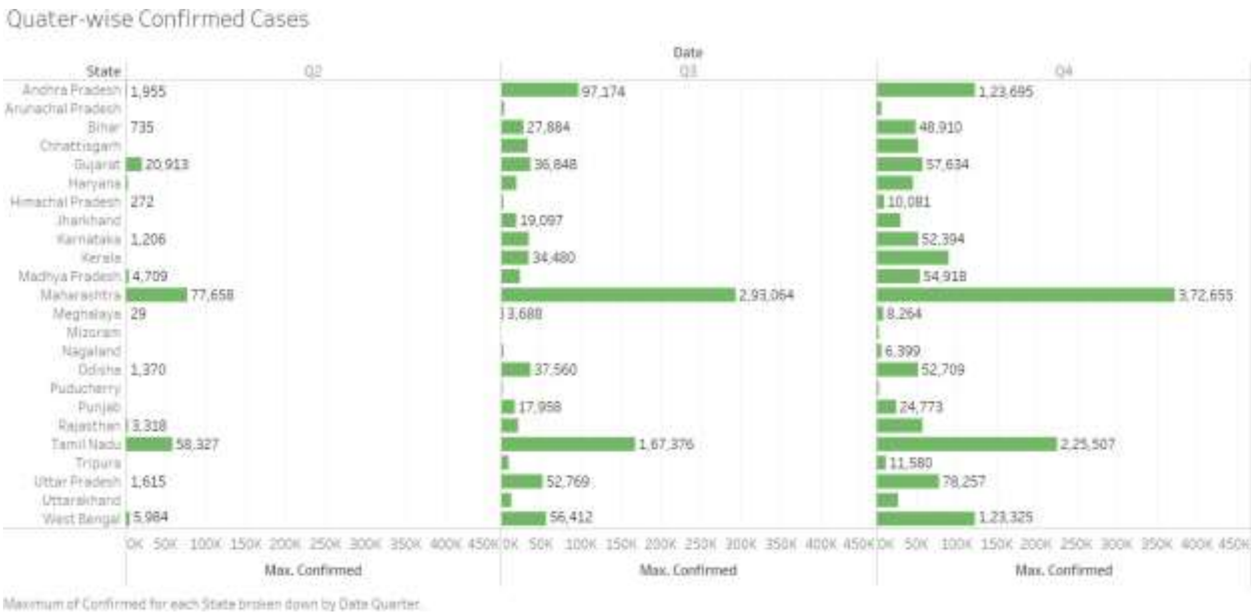
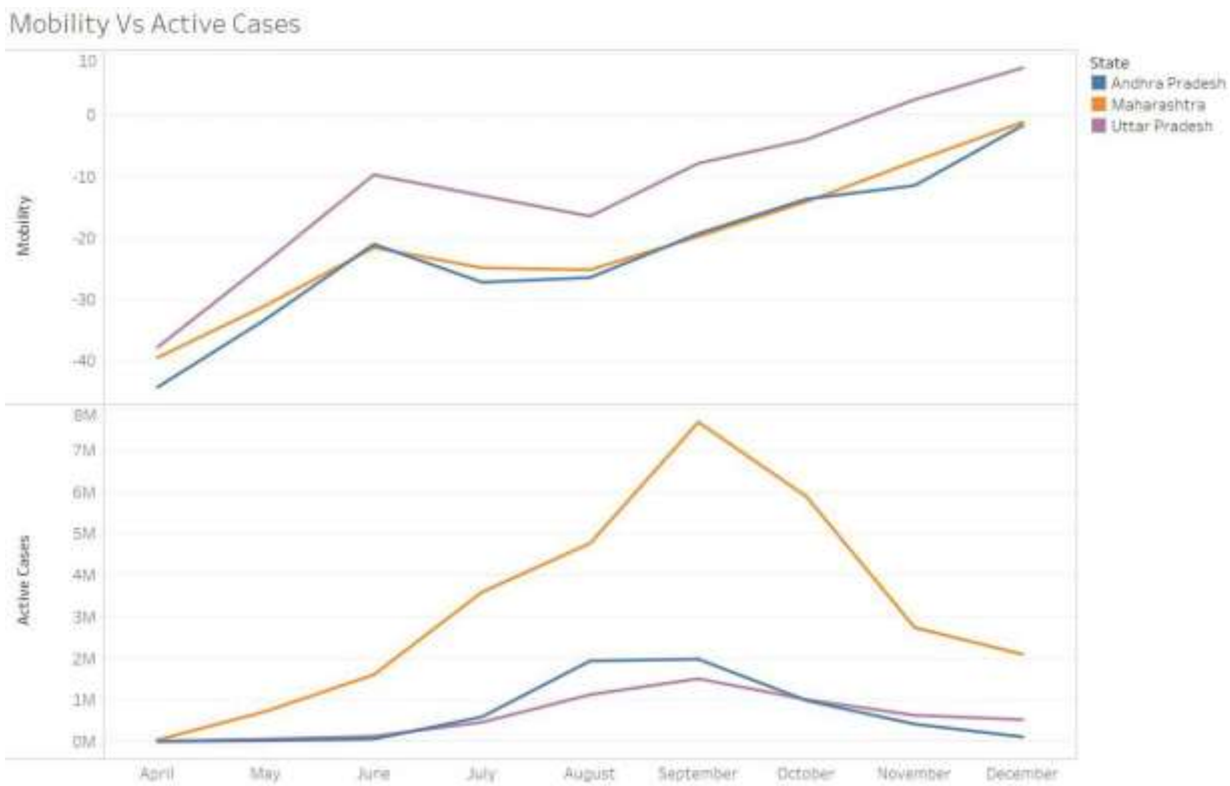


Figure 21: Confirmed cases of each state in each Quarter

In the following months, as lockdown was being relaxed the seriousness amongst the public abated, which led to even more spread of the virus. These trends can be observed in Quarter 3 and Quarter 4 as the cases keep rising. It can be concluded that relaxation in terms of restrictions did no good towards the wellbeing of the nation as due to mass negligence of the people, all the work achieved in Quarter 2 in terms of curbing the spread of disease was undone in the following quarters.

4.5 CASE STUDY: RELATION BETWEEN MOBILITY AND ACTIVE CASES

We have considered 3 states here to showcase that even if mobility trends are similar, the varying conditions present were the reason some states were able to handle the pandemic better than the others.



The trends of average of AvG Mobility and sum of Active for Date Month. Colour shows details about State. The view is filtered on State and Date Month. The State filter keeps Andhra Pradesh, Maharashtra and Uttar Pradesh. The Date Month filter excludes January.

Figure 22: Graphs of Mobility vs Time & Active Cases vs Time

The lockdown restrictions imposed in each state were according to the guidelines proposed by the central government, but the understanding and reaction to the laws among the people majorly affected the spread of the virus. According to the mobility trends seen above, it can be said that implementation of the guidelines laid were done with the same severity by the authorities in the state of Andhra Pradesh and Maharashtra, whereas in Uttar Pradesh the Mobility trends suggest that some leniency was shown. However, looking at the trend of active cases for these states, a spike in cases of Maharashtra is observed

whereas the trends of Andhra Pradesh and Uttar Pradesh have flattened out over time. This suggests that despite the authorities' efforts to curb mobility, people of Maharashtra showed carelessness when it came to following the basic measures such as wearing masks, using of sanitizers, and maintaining social distancing. Maharashtra and Uttar Pradesh being densely populated states were expected to have same trends of COVID-19 cases, but such was not the case. It can be said that people of Uttar Pradesh were more accepting of the consequences from spread of the virus and followed the precautions mentioned earlier.

Another reason that can explain to rise of cases in Maharashtra as compared to the other states in consideration is failure to control celebrations of festivals and occasions. Ganesh Chaturthi is one such festival which is celebrated with great enjoyment and vigor throughout the nation. Due to the scenario at the time authorities of Uttar Pradesh and Andhra Pradesh implemented strict actions and restrictions on their public to celebrate the festival, which helped in flattening the curve, whereas in Maharashtra, authorities had suggested the same restrictions but failed to act when people started gathering in crowds. The rise in cases due to this can be seen in the following months of August and September.

4.6 THEORETICAL MODEL

According to the community guidelines laid out by the Government of India, the following was the list for institutions that were deemed to be necessary and unnecessary to function:

Table 4: List of Essential and Non-Essential services

Essential/ Open	**Essential/ Open**
Selective Shops, including ration shops (under PDS), prioritizing Home deliveries	Banks, ATM's, Insurance Offices, Capital & debt market services (NSE, BSE)
Hospitals and pharmacies, including all manufacturing and distribution units	Telecommunication, internet, broadcasting, cable & IT services
E-commerce stores offering home deliveries (Intra City)	Gas stations, Printing presses, LPG and gas stores and Electronic Media
Cold storage & warehouse services	Power distribution, transmission & distribution units and services
Non-Essential/Closed/Restricted	**Non-Essential/Closed/Restricted**
Services like hospitality, retail, alcohol stores, education & training, any commercial stores	Places of worship
Functions/gatherings like social gatherings, marriage functions, cultural, sports or entertainment events	Transport- Air, road, rail
Funerals- Only congregation of upto 20 people	Offices of government and private Institutions

From the analysis of community mobility done so far, some guidelines can be put forward to help suppress the spread of the virus:

Table 5: Theoretical Model: Proposed Scenarios

Label	Policy	Description
CI	Case isolation at home	Individuals showing symptoms stay at home for 7 days, non-household contacts reduced by 75% during this period, household contacts remain unchanged. 70% of the households are estimated to comply.
HQ	Voluntary home quarantine	If a symptomatic individual has been identified, all members of the household remain at home for 14 days. Household contact rates double, while contact with community reduce by 75%. 50% of household expected to comply.
SDO	Social distancing of those aged 65 and over	Workplace contacts reduce by 50%, household contacts increase by 25%, other contacts reduce by 75%. 75% of households are estimated to comply.
LD	Lockdown	Closure of schools and colleges. Only essential workplaces active. For a compliant household, household, contact rate doubles, community contact rate reduces by 75%, workspace contact rate reduces by 75%. For a non- compliant household, household contact rate increases by 25%, workspace contact rate reduces by 75%, and no change to community contact rate. 90% of the household comply with LD
LD26-CI	Lockdown for 26 days	Lockdown for 26 days and then normal activity, but with CI. 90% of the household comply with the lockdown.
LD40-CI	Lockdown for 40 days	Lockdown for 40 days and then normal activity, but with CI. 90% of the household comply with the lockdown.

LD26-PE- CI	Phased emergence (PE) from lockdown, scenario 1	Lockdown for 26 days, then CI, HQ and SDO for 14 days. Schools and colleges remain closed during this period. Normal activity resumes after this period with reopening of schools and colleges, but with CI. In all interventions, 90% of the household comply with the lockdown.
LD26-PE-SCCI	Phased emergence from lockdown, scenario 2	Lockdown for 26 days, then CI, HQ and SDO for 14 days. Schools and colleges remain closed during this period. Non-essential services remain closed for another 28 days. CI remains in place throughout. In all interventions, 90% of the household comply with the lockdown.
LD26 - PEOE -CI	Phased emergence from lockdown, scenario 3	Lockdown for 26 days, then CI, HQ and SDO for 14 days. Schools and colleges remain closed and an odd-even workplace strategy is in place during this period. Normal activity resumes only after reduction in trends in cases and spread of virus. CI remains in force throughout. In all interventions, 90% of the household expected to comply with the lockdown.

For containment zones within districts where spread of virus could not be controlled or people were not following the cited precautions sincerely, policies LD26-CI & LD40-CI are recommended to follow as per the severity of disease in the locality and the population density present.

Policies LD26-PE- CI, LD26-PE- SCCI & LD26- PEOE-CI are recommended for states to be followed in case of another outbreak of a disease that is similar in fashion to COVID-19. Selection of policies must be done on the basis of spread of virus, population density & mainly trend of cases.

LD26-PE- CI is recommended for states where the virus did not spread to or the authorities were able to contain the spread.

LD26-PE- SCCI is recommended for states where facilities require a buffer period to prepare to handle the outbreak, if population density is as compared to that of states in the earlier scenario, and if compliance of people is a concern which is contributing to spread of the virus.

LD26- PEOE-CI is recommended for states which are densely populated, spread of the virus is proving difficult to be managed, public is non complacent or trends of cases don’t seem to lower or be affected by the previous scenarios.

4.7 INDIA AVERAGE DATASET

Table 6: India Average Dataset

Day	Retail	Grocery/ Pharma	Parks	Transit Spots	Workplaces	Residential	Lockdown	Active Cases
1	-80.4589	-31.61392405	-55.8323	-63.5443038	-29.64557	22.34493671	-100	16564
2	-79.3834	-26.47852761	-47.8067	-62.3159509	-45.726994	26.54907975	-100	17249
3	-78.955	-25.9009009	-47.2222	-60.7327327	-46	25.6996997	-100	18405
4	-78.6964	-24.11011905	-47.0119	-59.8244048	-44.169643	24.92261905	-100	19209
5	-78.6912	-24.49117647	-46.9647	-60.3058824	-43.85	24.96764706	-100	20179
6	-78.9104	-25.43352601	-47.5549	-60.8439306	-45.884393	25.63583815	-100	21404
7	-78.6196	-24.3832853	-49.3487	-60.3112392	-39.685879	24.23342939	-100	22592
8	-78.6657	-25.78571429	-52.4943	-60.4942857	-25.088571	20.31714286	-100	24202
9	-75.4545	-15.64204545	-44.8011	-56.3267046	-38.275568	22.59659091	-100	26311
10	-74.7744	-14.93593315	-44.1086	-54.5988858	-38.473538	21.78830084	-100	27490
11	-73.1602	-8.988950276	-43.2099	-51.8121547	-35.077348	20.9640884	-100	29252
12	-72.6152	-9.536585366	-42.7669	-52.2601626	-37.444444	21.59349593	-100	30707
13	-71.6	-5.216	-42.232	-50.584	-32.549333	20.81066667	-100	32360
14	-72.8624	-9.388888889	-44.6085	-52.8280423	-33.685185	21.52380952	-100	33828
15	-74.3013	-15.79480519	-48.0961	-54.5220779	-18.288312	18.15584416	-100	35650
16	-70.1886	-3.07751938	-40.323	-49.3565892	-30.741602	20.0878553	-100	37016
17	-69.557	-2.141772152	-39.3089	-47.4632911	-31.410127	19.67341772	-100	38288
18	-69.2399	-0.712121212	-39.3207	-46.7550505	-29.10101	18.90909091	-100	39939
19	-68.3609	-0.418546366	-39.208	-46.7017544	-28.75188	19.53132832	-100	42103
20	-67.3424	3.136476427	-39.129	-45.4813896	-26.354839	19.01736973	-100	43581
21	-67.9525	1.215	-41.3625	-46.55	-23.985	18.6575	-100	44404
22	-69.9181	-5.379652605	-45.0546	-49.2729529	-12.401985	16.28039702	-100	46692
23	-65.6432	8.041262136	-37.6311	-44.4223301	-24.839806	18.04854369	-100	48549
24	-65.1718	7.52	-37.2565	-42.5435294	-24.917647	17.31294118	-100	50289
25	-64.2266	8.488317757	-38.2664	-41.7196262	-24.03271	17.58411215	-100	52029
26	-63.6912	9.870967742	-37.7143	-40.6290323	-23.675115	17.15898618	-100	54112
27	-63.1359	11.4516129	-37.1175	-40.1474654	-21.829493	16.94239631	-100	56585
28	-64.0926	9.138888889	-39.3704	-41.8402778	-22.212963	16.99537037	-100	59682

Earlier the dataset was merged, and now to analyse the nationwide situation, irrespective of States & Districts, a new dataset was formulated from the earlier dataset. This contains the average of all the aspects of mobility parameters on a given day. Dataset was for a total of 269 Days, starting from 26th April 2020 to 19th Jan 2021. Active cases denote the total number of cases on the given date throughout the country.

A Lockdown parameter was added that denotes if lockdown was active (-100) or not (100). The first 90 days were assigned -100 to denote lockdown was present, after which 100 was assigned to denote no restrictions in districts.

4.8 PYTHON CODE TO IMPLEMENT INDIA AVG. DATASET

The jupyter notebook is intended to analyze the trends in the country over the tenure of 269 days. It fits a polynomial regression model and calculates the R-Square values for different degrees, finally obtaining the optimal model. It also builds correlation among the parameters, thus analyzing the trends.

In [1]:

```
# pandas is a software library written for the Python programming language
for data man ipulation and analysis. To import the data into a pandas
dataframe (df) and display the first five rows using head()

import os, types import pandas as pd
```

In [2]:

```
# To import the .csv data into a pandas dataframe and display the first
five rows

df = pd.read_csv(body) df.head()
```

Out [2]:

	Day	Retail	Grocery/ Pharma	Parks	Transit Spots	Workplaces	Residential	Lockdown
0	1	-80.458861	-31.613924	-55.832278	-63.544304	-29.645570	22.344937	-100
1	2	-79.383436	-26.478528	-47.806748	-62.315951	-45.726994	26.549080	-100
2	3	-78.954955	-25.900901	-47.222222	-60.732733	-46.000000	25.699700	-100
3	4	-78.696429	-24.110119	-47.011905	-59.824405	-44.169643	24.922619	-100
4	5	-78.691176	-24.491176	-46.964706	-60.305882	-43.850000	24.967647	-100

In [3]:

```
# describe() gives a outline of the dataset by providing the primary
analysis

df.describe()
```

Out[3]:

	Day	Retail	Grocery/ Pharma	Parks	Transit Spots	Workplaces	Residential
count	269.000000	269.000000	269.000000	269.000000	269.000000	269.000000	269.000000
mean	135.000000	-36.396433	14.754259	-27.794377	-25.391497	-14.919641	12.664699
std	77.797815	19.839180	14.745239	14.531587	15.338305	8.832184	3.767260
min	1.000000	-80.458861	-31.613924	-55.832278	-63.544304	-46.000000	5.823529
25%	68.000000	-49.750567	5.596330	-37.644144	-33.907449	-17.649746	10.667421
50%	135.000000	-36.814732	18.972789	-31.309417	-28.258503	-13.990909	12.359375
75%	202.000000	-17.334842	25.697517	-22.031746	-12.782313	-9.779221	13.941176
max	269.000000	0.552036	54.128959	9.216704	2.321267	3.706818	26.549080

In [4]:

```
# Scikit-Learn (formerly scikits.learn and also known as sklearn) is a free
software ma chine learning library for the Python programming language. It
features various classif ication, regression and clustering algorithms
including support vector machines, random forests, gradient boosting, k-
means and DBSCAN, and is designed to interoperate with th e Python numerical
and scientific libraries NumPy and SciPy.

from sklearn.linear_model import
LinearRegression lm =
LinearRegression()
import numpy as np
from sklearn.preprocessing import PolynomialFeatures
```

In [5]:

```
# To divide the dataframe into X (independent parameters) and Y (dependent
variable)

X = df[['Day','Retail','Grocery/ Pharma','Parks','Transit
Spots','Workplaces','Resident ial','Lockdown']]
Y = df[['Active Cases']]
```

In [6]:

```
from sklearn.model_selection import train_test_split
```

In [7]:

```
# To divide the dataset into training and testing dataset for enhanced
performance on u nknown data

x_train,x_test,y_train,y_test = train_test_split(X,Y,test_size =
0.3,random_state = 0)
```

In [8]:

```
# To perform polynomial regression model on th training dataset and test
the model on t esting dataset to acquire the R-Square values (for degress
1-10)

Rsqu_test = []
order = [1,2,3,4,5,6,7,8,9,10]
for n in order:
    pr = PolynomialFeatures(degree = n) x_train_pr =
    pr.fit_transform(x_train) x_test_pr = pr.fit_transform(x_test)
    lm.fit(x_train_pr,y_train)
    Rsqu_test.append(lm.score(x_test_pr,y_test))
```

In [9]:

```
Rsqu_test
```

Out[9]:

```
[0.7944078411592574,
 0.9387280284911631,
 0.7136552621851047,
 -1.73178676097953,
 -0.8298959485811157,
 -3.1166831057268523,
 -6.522839699995473,
 -12.631432941436103,
 -24.586469679210026,
 -51.920133125050114]
```

In [10]:

```
# Maximum Value of R-Square value to select the optimum model

i = Rsqu_test.index(max(Rsqu_test)) Rsqu_test[i]
```

Out[10]:

```
0.9387280284911631
```

In [11]:

```
# To get the model with highest R-Square Value

pr = PolynomialFeatures(degre = i+1) x_train_pr =
pr.fit_transform(x_train) x_test_pr = pr.fit_transform(x_test)
lm.fit(x_train_pr,y_train)
```

Out[11]:

```
LinearRegression()
```

In [12]:

```
# To get the coefficients and intercept value of the model

print("Coefficients: \n", lm.coef_, "\n\n","Intercept:", lm.intercept_)
```

```
Coefficients:
 [[-1.11798364e-07 -4.94347012e+04  1.99025112e+05 -1.00830928e+05
     -7.57518668e+03  6.43188869e+04  4.87807190e+04  9.78053409e+04
      8.68516399e+02  4.58245963e+01 -7.86466197e+02  3.72544947e+02
     -3.24574723e+01 -1.52780799e+02 -1.98503050e+02 -5.26617035e+02
      4.22897183e+01  9.87127867e+02 -1.05988099e+03 -2.48677124e+02
   1.15795767e+03  9.18324482e+02  1.77793853e+03  9.56482130e+01
   2.82060423e+02  1.09705404e+02 -4.41637692e+02 -8.38579028e+01
     -1.34643872e+02 -6.10247687e+00 -3.47387412e+01  4.08557679e+02
      3.98722956e+02  1.19748533e+03  6.65472553e+01 -2.61277736e+02
     -5.65658327e+02 -3.74594871e+02 -9.11141526e+01  1.77217839e+02
      1.13002656e+03  4.92741455e+01  3.03401819e+03  5.44491440e+01
   0.00000000e+00]]

 Intercept: [8341002.99426599]
```

In [13]:

```
# Seaborn is a Python data visualization library based on matplotlib. It
provides a hig h-level interface for drawing attractive and informative
statistical graphics.

import seaborn as sns
```

In [14]:

```
# Select a dataframe of all parameters (dependent and independent)

D = df[['Retail','Grocery/ Pharma','Parks','Transit
Spots','Workplaces','Residential', 'Active Cases']]
```

In [15]:

```
# To find pearson correlation among the parameters

corr = D.corr()
```

In [16]:

```
# To visualize the correlation in form of a heatmap

sns.heatmap(corr,annot = True)
```

Out[16]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fac50638510>
```

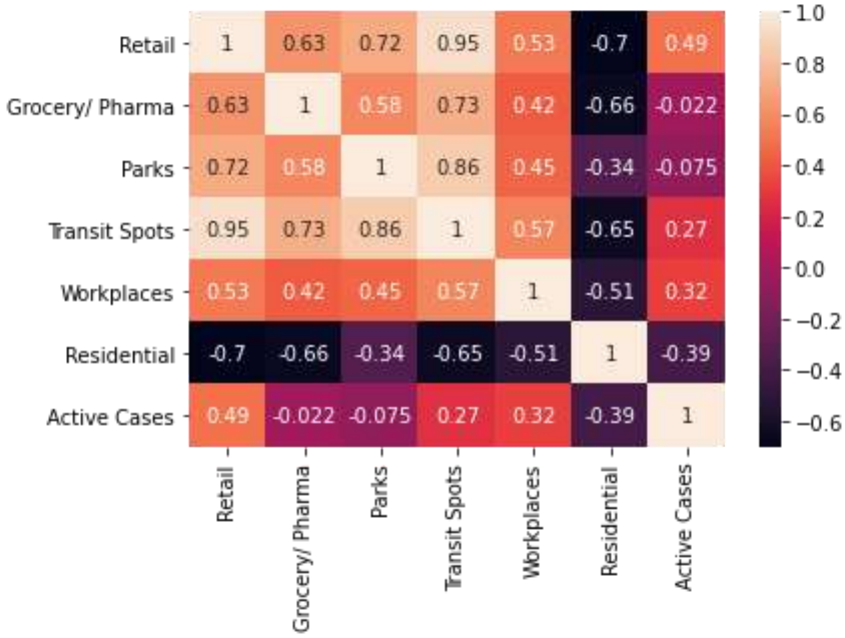


Figure 23: Heatmap for India avg. dataset

4.9 ENUMERATED DATASET WITH INDEX

Table 7: Enumerated Dataset with Index

State	Coded States	District	Coded Districts	Day	Retail	Grocery/ Pharma
Andhra Pradesh	1	Chittoor	1	1	-83	-48
Andhra Pradesh	1	East Godavari	2	1	-87	-43
Andhra Pradesh	1	Guntur	3	1	-86	-54
Andhra Pradesh	1	Krishna	4	1	-88	-58
Andhra Pradesh	1	Kurnool	5	1	-85	-47
Andhra Pradesh	1	Prakasam	6	1	-78	-34
Andhra Pradesh	1	Srikakulam	7	1	-82	-40
Andhra Pradesh	1	West Godavari	9	1	-84	-42
Bihar	3	Aurangabad	2	1	-78	-35
Bihar	3	Banka	3	1	-73	9
Bihar	3	Begusarai	4	1	-77	15
Bihar	3	Bhagalpur	5	1	-73	-27
Bihar	3	Bhojpur	6	1	-78	-1
Bihar	3	Buxar	7	1	-81	-6
Bihar	3	Gaya	9	1	-77	-26
Bihar	3	Gopalganj	10	1	-73	13
Bihar	3	Jehanabad	12	1	-75	-27
Bihar	3	Kaimur	13	1	-70	-9
Bihar	3	Lakhisarai	17	1	-76	-28
Bihar	3	Madhepura	18	1	-79	23
Bihar	3	Munger	20	1	-70	-22
Bihar	3	Nalanda	22	1	-82	-34
Bihar	3	Nawada	23	1	-79	16
Bihar	3	Patna	24	1	-88	-54
Bihar	3	Rohtas	26	1	-78	-36
Bihar	3	Saran	29	1	-77	-19
Bihar	3	Siwan	31	1	-76	-27
Bihar	3	Vaishali	33	1	-80	-8
Chhattisgarh	4	Bilaspur	5	1	-90	-75
Chhattisgarh	4	Durg	7	1	-78	-29
Chhattisgarh	4	Korba	9	1	-78	-32

This dataset was created for the I/O program that shows the trend that occurred in the user selected State and District. An index was created of all the districts and states which were coded on a number scale so that the program can filter through the dataset to show the output. Indexing was done mainly to improve user-friendliness of the program, i.e. to avoid spelling errors, case sensitivity issues during input from user and to overcome situations where strings were taking the same input of the same named districts in two different states. For example: If user wanted to find statistics of the district Aurangabad from Maharashtra, the program would include data of Aurangabad which falls in Maharashtra as well as Bihar, giving an inaccurate output. The following is the table of contents for the numbers assigned to states and its corresponding districts:

Table 8: Index of Enumerated Dataset

State	Code	District	Code
Andhra Pradesh	1	Chittoor	1
		East Godavari	2
		Guntur	3
		Krishna	4
		Kurnool	5
		Prakasam	6
		Srikakulam	7
		Vizianagaram	8
		West Godavari	9
Arunachal Pradesh	2	Papum Pare	1
Bihar	3	Araria	1
		Aurangabad	2
		Banka	3
		Begusarai	4
		Bhagalpur	5
		Bhojpur	6
		Buxar	7
		Darbhanga	8
		Gaya	9
		Gopalganj	10
		Jamui	11
		Jehanabad	12
		Kaimur	13
		Katihar	14
		Khagaria	15
		Kishanganj	16
		Lakhisarai	17
		Madhepura	18
		Madhubani	19
		Munger	20
		Muzaffarpur	21
		Nalanda	22
		Nawada	23
		Patna	24
		Purnia	25
		Rohtas	26
		Saharsa	27
		Samastipur	28
		Saran	29
		Sheikhpura	30
		Siwan	31
		Supaul	32
		Vaishali	33
Chhattisgarh	4	Balod	1
		Baloda Bazar	2
		Balrampur	3
		Bastar	4
		Bilaspur	5
		Dhamtari	6
		Durg	7
		Jashpur	8
		Korba	9
		Koriya	10
		Mahasamund	11
		Mungeli	12
		Raigarh	13
		Raipur	14
		Rajnandgaon	15
		Surajpur	16
		Surguja	17
		Ahmedabad	1
		Amreli	2
		Anand	3
		Aravalli	4
		Banaskantha	5
		Bharuch	6
		Bhavnagar	7
		Botad	8
		Chhota Udaipur	9
		Dahod	10
		Gandhinagar	11
		Gir Somnath	12
		Jamnagar	13
		Junagadh	14
		Kheda	15
		Kutch	16
		Mehsana	17
		Morbi	18
		Navsari	19
		Panchmahal	20
		Patan	21
		Porbandar	22
		Rajkot	23
		Surat	24
		Surendranagar	25
		Tapi	26
		Vadodara	27

State	Code	District	Code
Haryana	6	Ambala	1
		Bhiwani	2
		Faridabad	3
		Fatehabad	4
		Hisar	5
		Jhajjar	6
		Jind	7
		Kaithal	8
		Karnal	9
		Kurukshetra	10
		Mahendragarh	11
		Palwal	12
		Panchkula	13
		Panipat	14
		Rewari	15
		Rohtak	16
		Sirsa	17
Himachal Pradesh	7	Bilaspur	1
		Chamba	2
		Hamirpur	3
		Kangra	4
		Kullu	5
		Mandi	6
		Shimla	7
		Sirmaur	8
		Solan	9
		Una	10
Jharkhand	8	Bokaro	1
		Chatra	2
		Deoghar	3
		Dhanbad	4
		Dumka	5
		East Singhbhum	6
		Giridih	7
		Godda	8
		Gumla	9
		Hazaribagh	10
		Jamtara	11
		Khunti	12
		Koderma	13
		Lohardaga	14
		Pakur	15
		Palamu	16
		Ramgarh	17
		Ranchi	18
		Sahibganj	19
		West Singhbhum	20
Karnataka	9	Belagavi	1
		Bidar	2
		Chikkamagaluru	3
		Chitradurga	4
		Dakshina Kannada	5
		Davanagere	6
		Dharwad	7
		Gadag	8
		Hassan	9
		Haveri	10
		Kodagu	11
		Kolar	12
		Koppal	13
		Mandya	14
		Mysuru	15
		Raichur	16
		Ramanagara	17
		Udupi	18
		Uttara Kannada	19
		Yadgir	20
Kerala	10	Alappuzha	1
		Ernakulam	2
		Idukki	3
		Kannur	4
		Kasaragod	5
		Kollam	6
		Kottayam	7
		Kozhikode	8
		Malappuram	9
		Palakkad	10
		Pathanamthitta	11
		Thiruvananthapuram	12
		Thrissur	13
		Wayanad	14

State	Code	District	Code
Madhya Pradesh	11	Anuppur	1
		Ashoknagar	2
		Balaghat	3
		Barwani	4
		Betul	5
		Bhind	6
		Bhopal	7
		Burhanpur	8
		Chhatarpur	9
		Chhindwara	10
		Damoh	11
		Datia	12
		Dewas	13
		Dhar	14
		Guna	15
		Gwalior	16
		Harda	17
		Hoshangabad	18
		Indore	19
		Jabalpur	20
		Jhabua	21
		Katni	22
		Khandwa	23
		Khargone	24
		Mandla	25
		Mandsaur	26
		Morena	27
		Narsinghpur	28
		Neemuch	29
		Panna	30
		Raisen	31
		Rajgarh	32
		Ratlam	33
		Rewa	34
		Sagar	35
		Satna	36
		Sehore	37
		Seoni	38
		Shahdol	39
		Shajapur	40
		Shivpuri	41
		Singrauli	42
		Tikamgarh	43
		Ujjain	44
		Umaria	45
		Vidisha	46
Maharashtra	12	Ahmednagar	1
		Akola	2
		Amravati	3
		Aurangabad	4
		Beed	5
		Bhandara	6
		Buldhana	7
		Chandrapur	8
		Dhule	9
		Gadchiroli	10
		Gondia	11
		Hingoli	12
		Jalgaon	13
		Jalna	14
		Kolhapur	15
		Latur	16
		Mumbai	17
		Nagpur	18
		Nanded	19
		Nandurbar	20
		Nashik	21
		Osmanabad	22
		Palghar	23
		Parbhani	24
		Pune	25
		Raigad	26
		Ratnagiri	27
		Sangli	28
		Satara	29
		Sindhudurg	30
		Solapur	31
		Thane	32
		Wardha	33
		Washim	34
		Yavatmal	35
Meghalaya	13	East Khasi Hills	1
		West Garo Hills	2
Mizoram	14	Aizawl	1
Nagaland	15	Dimapur	1
		Kohima	2

State	Code	District	Code
Odisha	16	Angul	1
		Balangir	2
		Balasore	3
		Bargarh	4
		Bhadrak	5
		Cuttack	6
		Dhenkanal	7
		Gajapati	8
		Ganjam	9
		Jagatsinghpur	10
		Jajpur	11
		Jharsuguda	12
		Kalahandi	13
		Kandhamal	14
		Kendrapara	15
		Kendujhar	16
		Khordha	17
		Koraput	18
		Mayurbhanj	19
		Nayagarh	20
		Nuapada	21
		Puri	22
		Rayagada	23
		Sambalpur	24
		Subarnapur	25
		Sundargarh	26
Puducherry	17	Karaikal	1
Punjab	18	Amritsar	1
		Barnala	2
		Bathinda	3
		Faridkot	4
		Fatehgarh Sahib	5
		Fazilka	6
		Ferozepur	7
		Gurdaspur	8
		Hoshiarpur	9
		Jalandhar	10
		Kapurthala	11
		Ludhiana	12
		Mansa	13
		Moga	14
		Pathankot	15
		Patiala	16
		Rupnagar	17
		Sangrur	18
		Sri Muktsar Sahib	19
		Tarn Taran	20
Rajasthan	19	Ajmer	1
		Alwar	2
		Banswara	3
		Baran	4
		Barmer	5
		Bharatpur	6
		Bhilwara	7
		Bikaner	8
		Bundi	9
		Churu	10
		Dausa	11
		Dungarpur	12
		Hanumangarh	13
		Jaipur	14
		Jaisalmer	15
		Jalore	16
		Jhalawar	17
		Jhunjhunu	18
		Jodhpur	19
		Karauli	20
		Kota	21
		Nagaur	22
		Pali	23
		Pratapgarh	24
		Rajsamand	25
		Sawai Madhopur	26
		Sikar	27
		Sirohi	28
		Tonk	29
		Udaipur	30

State	Code	District	Code
Tamil Nadu	20	Ariyalur	1
		Chennai	2
		Coimbatore	3
		Cuddalore	4
		Dharmapuri	5
		Dindigul	6
		Erode	7
		Kanyakumari	8
		Karur	9
		Krishnagiri	10
		Madurai	11
		Nagapattinam	12
		Namakkal	13
		Nilgiris	14
		Perambalur	15
		Pudukkottai	16
		Ramanathapuram	17
		Salem	18
		Sivaganga	19
		Thanjavur	20
		Theni	21
		Thiruvarur	22
		Tiruchirappalli	23
		Tirunelveli	24
		Tiruppur	25
		Tiruvannamalai	26
		Vellore	27
		Virudhunagar	28
Tripura	21	Gomati	1
		North Tripura	2
		Sipahijala	3
		South Tripura	4
		West Tripura	5

State	Code	District	Code
Uttar Pradesh	22	Agra	1
		Aligarh	2
		Ambedkar Nagar	3
		Amethi	4
		Amroha	5
		Auraiya	6
		Azamgarh	7
		Bahraich	8
		Ballia	9
		Balrampur	10
		Banda	11
		Barabanki	12
		Bareilly	13
		Basti	14
		Bijnor	15
		Chandauli	16
		Chitrakoot	17
		Deoria	18
		Etah	19
		Etawah	20
		Farrukhabad	21
		Fatehpur	22
		Firozabad	23
		Ghaziabad	24
		Ghazipur	25
		Gonda	26
		Gorakhpur	27
		Hamirpur	28
		Hapur	29
		Hardoi	30
		Hathras	31
		Jalaun	32
		Jaunpur	33
		Jhansi	34
		Kannauj	35
		Kanpur Dehat	36
		Kanpur Nagar	37
		Kaushambi	38
		Kushinagar	39
		Lakhimpur Kheri	40
		Lalitpur	41
		Lucknow	42
		Maharajganj	43
		Mahoba	44
		Mainpuri	45
		Mathura	46
		Mau	47
		Meerut	48
		Mirzapur	49
		Moradabad	50
		Muzaffarnagar	51
		Pilibhit	52
		Pratapgarh	53
		Prayagraj	54
		Rae Bareli	55
		Rampur	56
		Saharanpur	57
		Sambhal	58
		Sant Kabir Nagar	59
		Shahjahanpur	60
		Shamli	61
		Shrawasti	62
		Siddharthnagar	63
		Sitapur	64
		Sonbhadra	65
		Sultanpur	66
		Unnao	67
		Varanasi	68
Uttarakhand	23	Almora	1
		Chamoli	2
		Dehradun	3
		Haridwar	4
		Nainital	5
		Pauri Garhwal	6
		Udham Singh Nagar	7
West Bengal	24	Alipurduar	1
		Bankura	2
		Birbhum	3
		Cooch Behar	4
		Dakshin Dinajpur	5
		Darjeeling	6
		Hooghly	7
		Howrah	8
		Jalpaiguri	9
		Kolkata	10
		Malda	11
		Murshidabad	12
		Nadia	13
		North 24 Parganas	14
		Purba Medinipur	15
		Purulia	16
		South 24 Parganas	17
		Uttar Dinajpur	18

4.10 PYTHON CODE TO IMPLEMENT ENUMERATED DATA SET

The jupyter notebook is intended to analyze the trends in a particular user selected district over the tenure of 269 days. It fits a polynomial regression model and calculates the R-Square values for different degrees, finally obtaining the optimal model. It also builds correlation among the parameters, thus analyzing the trends.

In [1]:

```
# pandas is a software library written for the Python programming
language for data man ipulation and analysis. To import the data into a
pandas dataframe (df) and display the first five rows using head()

import os, types import pandas as pd
```

In [2]:

```
# To import the .csv data into a pandas dataframe and display the first
five rows


df2 = pd.read_csv(body) df2.head()
```

Out[2]:

	States	Districts	Day	Retail	Grocery/ Pharma	Parks	Transit Spots	Workplaces	Residential	Lockdown
0	1	1	1	-83	-48	-57	-68	-33	23	-10
1	1	2	1	-87	-43	-74	-57	-27	22	-10
2	1	3	1	-86	-54	-70	-61	-35	25	-10
3	1	4	1	-88	-58	-68	-73	-40	24	-10
4	1	5	1	-85	-47	-72	-62	-34	27	-10

In [3]:

```
# describe() gives a outline of the dataset by providing the primary analysis

df2.describe()
```

Out[3]:

	States	Districts	Day	Retail	Grocery/ Pharma	Parks
count	111162.000000	111162.000000	111162.000000	111162.000000	111162.000000	111162.0000
mean	13.367122	16.652750	137.485544	-35.477087	16.138114	-26.6852
std	6.987798	13.920379	78.678953	23.510149	31.676661	39.7469
min	1.000000	1.000000	1.000000	-97.000000	-92.000000	-100.0000
25%	7.000000	6.000000	67.000000	-53.000000	-4.000000	-57.0000
50%	12.000000	13.000000	144.000000	-34.000000	15.000000	-31.0000
75%	20.000000	23.000000	207.000000	-18.000000	35.000000	-2.0000
max	24.000000	68.000000	269.000000	109.000000	216.000000	261.0000

In [4]:

```
# To input the user district and state for analysis

s = int(input("Enter the State Code: "))
d = int(input("Enter the District Code: "))
```

Enter the State Code: 12 Enter the District Code: 18 In

[5]:

```
# To segregate the district specific data

df3 = df2.loc[(df2.States == s) & (df2.Districts == d)] df3.head()
```

Out[5]:

	States	Districts	Day	Retail	Grocery/ Pharma	Parks	Transit Spots	Workplaces	Residential
148	12	18	1	-89	-47	-89	-77	-47	29
472	12	18	2	-87	-45	-88	-75	-64	36
805	12	18	3	-88	-44	-88	-74	-65	35
1138	12	18	4	-87	-41	-87	-72	-63	34
1475	12	18	5	-87	-40	-87	-73	-63	34

In [6]:

```
# Scikit-learn (formerly scikits.learn and also known as sklearn) is a free
software ma chine learning library for the Python programming language. It
features various classif ication, regression and clustering algorithms
including support vector machines, random forests, gradient boosting, k-
means and DBSCAN, and is designed to interoperate with th e Python numerical
and scientific libraries NumPy and SciPy.

from sklearn.linear_model import LinearRegression lm = LinearRegression()
import numpy as np
from sklearn.preprocessing import PolynomialFeatures
```

In [7]:

```
# To divide the dataframe into X (independent parameters) and Y (dependent
variable)

X1 = df3[['Day','Retail','Grocery/ Pharma','Parks','Transit
Spots','Workplaces','Reside ntial','Lockdown']]
Y1 = df3[['Active']]
```

In [8]:

```
from sklearn.model_selection import train_test_split
```

In [9]:

```
# To divide the dataset into training and testing dataset for enhanced
performance on u nknown data

x1_train,x1_test,y1_train,y1_test = train_test_split(X1,Y1,test_size =
0.3,random_state
= 0)
```

In [10]:

```
# To perform polynomial regression model on th training dataset and test
the model on t esting dataset to acquire the R-Square values (for degress
1-10

Rsqu_test = []
order = [1,2,3,4,5,6]
for n in order:
    pr = PolynomialFeatures(degree = n) x1_train_pr =
    pr.fit_transform(x1_train) x1_test_pr = pr.fit_transform(x1_test)
    lm.fit(x1_train_pr,y1_train)
    Rsqu_test.append(lm.score(x1_test_pr,y1_test))
```

In [11]:

```
Rsqu_test
```

Out[11]:

```
[0.49696914445925977,
 0.7062436800606247,
 -6.7383547759250115,
 -90.22388980695511,
 -73.85085342844842,
 -102.08701361530281]
```

In [12]:

```
# Maximum Value of R-Square value to select the optimum model

i = Rsqu_test.index(max(Rsqu_test)) Rsqu_test[i]
```

Out[12]:

```
0.7062436800606247
```

In [13]:

```
# To get the model with highest R-Square Value

pr = PolynomialFeatures(degree = i+1) x_train_pr =
pr.fit_transform(x1_train) x_test_pr = pr.fit_transform(x1_test)
lm.fit(x_train_pr,y1_train)
```

Out[13]:

```
LinearRegression()
```

In [14]:

```
# To get the coefficients and intercept value of the model

print("Coefficients: \n", lm.coef_, "\n\n","Intercept:", lm.intercept_)
```

```
Coefficients: 
    [[ 1.94558242e+12  3.01360418e+03 -1.35344423e+03  2.12195272e+03
  -5.87595856e+03 -4.43815217e+02 -1.21405673e+03  3.20873305e+03
  -1.27995789e+03 -4.60378416e+00  2.76322123e+00 -4.76483522e+00
   2.65538020e+01 -6.80750594e+00  2.35782487e+00 -8.51807802e+00
   3.58980167e+00 -1.19272595e+01  1.36862341e+01  6.37641864e+01
  -6.46028716e+01 -2.26723272e+01  2.95994251e+01  3.08887855e+00
  -6.99060068e+00 -3.73947622e+00  1.87313956e+01  7.32008694e+00
  -9.97067601e-01  3.90219954e-01 -4.78886337e+01  2.98364777e+00
   8.61262278e+00  2.35303926e+01 -1.93153983e+01  1.80742698e+01
  -7.11251858e+00 -6.02016883e+01  7.13250338e+00 -5.54911608e+00
  -2.08909036e+01  1.26044882e+00 -5.04989432e+01  5.29117582e+00
   0.00000000e+00]]

 Intercept: [-1.94558289e+12]
```

In [15]:

```
# Seaborn is a Python data visualization library based on matplotlib. It
provides a hig h-level interface for drawing attractive and informative
statistical graphics.

import seaborn as sns
```

In [16]:

```
# Select a dataframe of all parameters (dependent and independent)

D = df3[['Retail','Grocery/ Pharma','Parks','Transit
Spots','Workplaces','Residential', 'Active']]
```

In [17]:

```
# To find pearson correlation among the parameters

corr = D.corr()
```

In [18]:

```
# To visualize the correlation in form of a heatmap

sns.heatmap(corr,annot = True)
```

Out[18]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7effa5434b10>
```

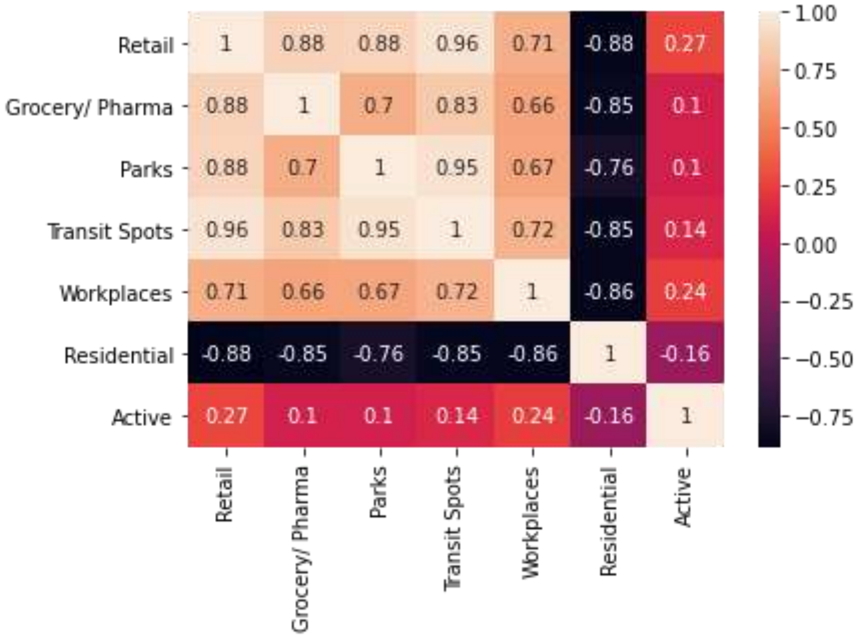
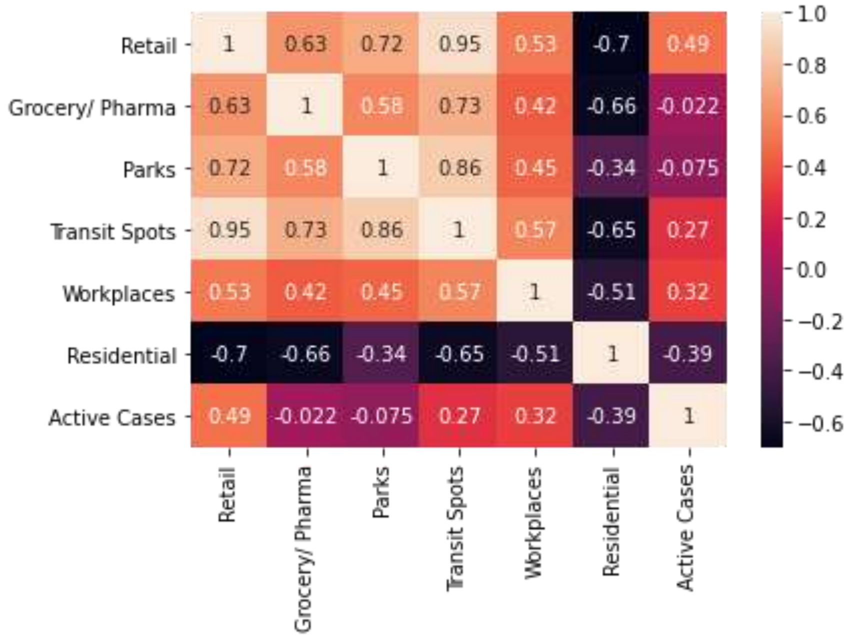


Figure 24: Correlation Heatmap for Enumerated dataset with Index

4.11 CORRELATION HEATMAP & CAUSAL LOOP DIAGRAM

Correlation heat map is relationship between different variables and relationship is visualized based on magnitude of colour. The values in the correlation heatmap ranges from -1 to +1. Positive values represent positive relationships (i.e. the values of both the variables increase or decrease simultaneously).

Figure 25: Heatmap of India avg. dataset



Negative values represent negative relationships (i.e if one variable increases other decreases and vice versa). The values closer to -1 or +1 have stronger relationships. The values closer to 0 have a weaker relationship. The 0 value means no relationship between variables. The values of diagonal are +1 which means they have a stronger positive relationship as it is a relationship with itself. Generally, as mobility towards residential increases mobility of retail, parks, transit spots increases which is clearly visible in heat map correlation between residential and all other variables are negative. From the heat map we can conclude that increase in covid active cases is mainly due to retail, transit spots, workplaces as they have positive relationship active cases. Active cases have smaller negative values (approximately 0) correlation values with grocery and parks which says active cases don't have any relation with grocery and

parks. Practically this means people going to grocery and parks are maintaining social norms and sanitization. Active cases decrease as people move towards the residential areas as it has a negative relationship with active cases.
Workplaces don’t have stronger correlation with all others which means we can say that as people move towards workplaces their mobility of remaining places cannot be predicted. Retail, grocery, parks, transit spots have slightly stronger correlation with respect to others which means we can predict the mobility of remaining when one of the retail, grocery, parks, transit spots mobility is known.

A causal loop diagram (CLD) is a causal diagram that aids in visualizing how different variables in a system are interrelated. The diagram consists of a set of nodes and edges. Nodes represent the variables and edges are the links that represent a connection or a relation between the two variables. A link marked positive indicates a positive relation and a link marked negative indicates a negative relation. A positive causal link means the two nodes change in the same direction i.e., if the node in which the link starts decreases, the other

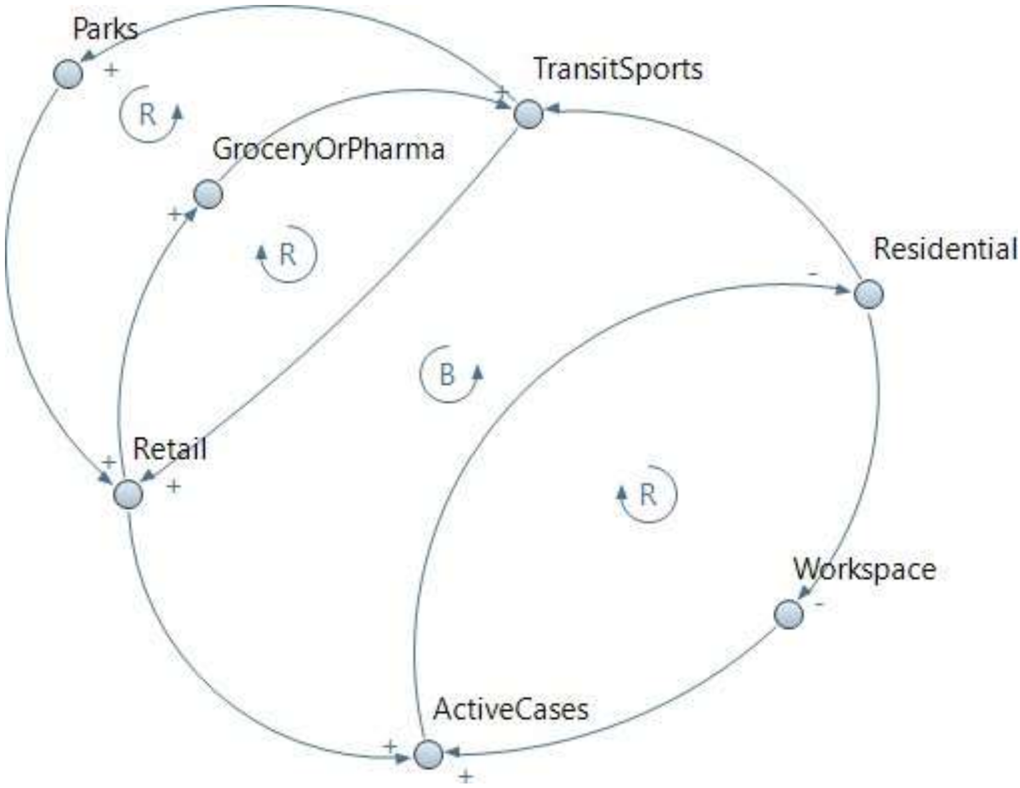


Figure 26: Causal loop diagram to relate mobility parameters with active cases

node also decreases.

A causal loop is reinforcing or balancing, one can start with an assumption, e.g. "Node 1 increases" and follow the loop around. The loop is:

- reinforcing if, after going around the loop, one ends up with the same result as the initial assumption.
- balancing if the result contradicts the initial assumption.

Or to put it in other words:

- reinforcing loops have an even number of negative links (zero also is even, see example below)
- balancing loops have an odd number of negative links.

In our case there are three reinforcing loops and one balancing loop. The diagram is basically a visual translation of the correlation heatmap.

The correlation values are filtered out on the basis of strong positive and negative correlation values. The selected values are used to build the causal loop diagram.

Even mobility out of residential needs transit spots to reach other destinations. Transit spots has positive correlation with retail groceries and parks creating a reinforcing loop.

It is evident from the diagram that people's movement out of the residential areas increases mobility in other zones such as transit spots, parks, groceries and retails leading to rise in cases. Even the increased mobility in workplaces leads to increase in cases. Residential areas have negative correlation with all others areas creating a need for people to stay at home to decrease the spread of disease.

CHAPTER 5:
RESULTS

5. RESULTS

Tasks accomplished:

- Understanding the scenario of COVID-19 in the country
- Collection of data (Community Mobility, Number of Cases, Lockdown phases)
- Dissemination of data to acquire insights into the state of Maharashtra, Andhra Pradesh & Uttar Pradesh and India
- Study of data analysis and associated software
- Visualizing and analyzing region wise data for Maharashtra

In relation with the aspects of analysis of our projects, following conclusions can be made:

5.1 Economic Aspect

- The economic aspect in India can be observed with mobility at Groceries/ Pharma, Workplaces, and Retail stores. The fall in percentage of people visiting a business point directly impact the sales.
- As time progressed, the imposed restrictions were being phased off and businesses were allowed to function, which meant they were conducting business as usual, but the economy had not yet been restored as mobility trends are not back to pre-lockdown scenarios.
- States of Maharashtra & Andhra Pradesh show sudden change in mobility trends to Groceries and Pharmacies indicating unstable economic conditions
- States of Uttar Pradesh, Rajasthan & Punjab show the most positive trends to Groceries and Pharmacies indicating a normal cash flow in their economies.

5.2 Psychological Aspect

- Due to lack in conveying the phases of unlock, a havoc among the people resulted in ill-managed movement among the districts based on the density maps.
- The fall in mobility around December shows that people were accepting of

the new strain being fatal and were taking the necessary steps before being intimated by the governing bodies

5.3 Impact Analysis

- People were following restrictions imposed at the early stages of the pandemic, but as relaxation in these laws was brought, a pattern of carelessness and negligence could be observed as cases started to rise.
- States of Maharashtra and Tamil Nadu can be said to be the most impacted in terms of number of Covid cases.
- Trends suggest that while lockdown seemed to fail in aforementioned states, it seemed to curb the spread in every other state.

Mobility trends suggest that while lockdown restrictions were being removed to support the economy, it led to an increase in cases again in most parts of the country. This indicates that a proper trade-off was tough to come about where economy could not be impacted as much and the spread of the virus could be controlled.

5.4 Theoretical Model

So a theoretical model is proposed with well being of the society being the primary concern. The following are the points mentioned in the proposed model:

- For containment zones within districts where spread of virus could not be controlled or people were not following the cited precautions sincerely, policies LD26-CI & LD40-CI are recommended to follow as per the severity of disease in the locality and the population density present.
- LD26-PE- CI is recommended for states where the virus did not spread to or the authorities were able to contain the spread.
- LD26-PE- SCCI is recommended for states where facilities require a buffer period to prepare to handle the outbreak, if population density is as compared to that of states in the earlier scenario, and if compliance of people is a concern which is contributing to spread of the virus.
- LD26- PEOE-CI is recommended for states which are densely populated, spread of the virus is proving difficult to be managed, public is non complacent or trends of cases don't seem to lower or be affected by the previous scenarios.

5.5 Mathematical Model

All the aspects of analysis helped to understand, visualize and study the data which assisted in formulation of the proposed theoretical model. The model was determined by selecting the highest R square value. To support it, a mathematical model was also formulated –

$$Y = \sum_{i=1}^{n} a_{ii} X_i^2 + \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} a_{ij} X_i X_j + c$$

where Y = Active Cases

X_i / X_j = Mobility parameter (Input parameters)

a_{ii} / a_{ij} = Constants of equations from code In [12]

c = intercept of line from code In [12]

n = 8 (Input parameters)

Taking the India average value dataset, it can be concluded that Community Mobility and No. of Active Cases can be related by a 2nd degree relation.

The same equation was also formulated from the Enumerated dataset with index for the user selected case of Nagpur.

CHAPTER 6:
REFERENCES

6. REFERENCES

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