COVID-19: Examining the case growth-rate due to Visitor vs Local Mobility using Machine Learning: A Study in the United States

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RESEARCH

COVID-19: Examining the case growth-rate due to Visitor vs Local mobility using Machine Learning: A Study in the United States

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Abstract

Background: Travel patterns of humans play a major part in the spread of infectious diseases. This was evident in the geographical spread of COVID-19 in the United States. However, the impact of this mobility and the transmission of the virus due to local travel, compared to the population traveling across state boundaries, is unknown. This study evaluates the impact of local vs. visitor mobility in understanding the growth in the number of cases for infectious disease outbreaks.

Methods: We use two different mobility metrics, namely the local risk and visitor risk extracted from trip data generated from anonymized mobile phone data across all 50 states in the United States. We analyzed the impact of just using local trips on infection spread and infection risk potential generated from visitors' trips from various other states. We used the Diebold-Mariano test to compare across three machine learning models. Finally, we compared the performance of models, including visitor mobility for all the three waves in the United States and across all 50 states.

Results: We observe that visitor mobility impacts case growth and that including visitor mobility in forecasting the number of COVID-19 cases improves prediction accuracy by 34%. We found the statistical significance with respect to the performance improvement resulting from including visitor mobility using the Diebold-Mariano test. We also observe that the significance was much higher during the first peak March to June 2020.

Conclusion: With presence of cases everywhere (i.e. local and visitor), visitor mobility (even within the country) is shown to have significant impact on growth in number of cases. While it is not possible to account for other factors such as the impact of interventions, and differences in local mobility and visitor mobility, we find that these observations can be used to plan for both reopening and limiting visitors from regions where there are high number of cases.

Keywords: Interval vs External Mobility; COVID19 Forecasting; Machine Learning

1 Introduction

COVID-19 has spread rapidly around the world, nearing 174 million confirmed cases² and more than 3.75 million deaths reported globally as of June 09, 2021 (John³ Hopkins University, 2020).

Many countries have passed the first and second peak, and aggressive vaccination⁵ efforts and containment measures have limited the spread of the pandemic. While⁶ counties are beginning to slowly reopen, the threat from the pandemic is far from⁷ over, especially as the new delta variant that has spread to multiple countries. A⁸ question remains as to the risk contribution of external visitors, as rebound travel⁹ begins as cases come down and restrictions begin to ease.

The importance of tracking human mobility as a significant indicator to un-¹¹derstand and predict the spread of COVID-19 has been an active research topic¹² [1, 2, 3, 4, 5, 6, 7]. Researchers and local governments continue to track human¹³ mobility in their communities through anonymized cell phone data made available¹⁴ through various data providers [8, 9, 10]. An earlier study by Badr et al found a¹⁵ strong linear correlation between mobility ratio and COVID-19 growth rate between¹⁶ Jan 24th, 2020, and April 17, 2020, for the top 20 US counties that had the highest¹⁷ number of cases [11]. Several studies in United States, Europe, and China report¹⁸ association between mobility and stay-at-home orders with growth in number of¹⁹ cases [12, 13, 14, 15, 16, 17, 18, 19, 20]. More recent work also studied the impact²⁰ of lockdowns on mobility [21].

The visitor mobility has also been studied in different contexts. For instance ana-²²lyzed tourist/visitor demand to various destinations to estimate potential COVID-²³19 risk exposure [22, 23, 24]. However, there are no studies to analyze the difference²⁴ between visitor and local mobility. Linka et al. used a global network mobility model²⁵ with a local epidemiology model to simulate and predict the COVID-19 outbreak²⁶ across Europe [19]. They have shown that mobility network of air travel can pre-²⁷dict the global diffusion pattern of a pandemic and unconstrained mobility could²⁸ accelerate the spread of COVID-19 in Europe, using a latent period of 2-6 days and²⁹ infectious period or 3 to 18 days. Kraemer et al, used real-time mobility data from³⁰ Wuhan and detailed travel history to elucidate the role of case transmission in cities³¹ across China [25]. They found that special distribution of COVID-19 cases in China³² and the magnitude of the early epidemic (total number of cases until 10 February³³

¹2020) outside of Wuhan was very well predicted by the volume of human movement¹
²out of Wuhan alone ($R^2 = 0.89$) from a log-linear regression using cumulative cases.²
³The authors showed that although travel restrictions may have reduced the flow of³
⁴case importations from Wuhan, other local mitigation strategies aimed at halting⁴
⁵local transmission reduced the further spread of the virus.⁵

⁶
⁷
⁸ In a study evaluating the effect of mobility restriction in limiting COVID-19⁸
⁹spread, using zip code data for Atlanta, Boston, Chicago, New York (NYC), and⁹
¹⁰Philadelphia, the authors estimated that total COVID-19 cases per capita decreased¹⁰
¹¹on average by approximately 20 percent for every ten percentage points fall in mobil-¹¹
¹²ity between February and May 2020 [17]. In another study, the correlation between¹²
¹³the COVID-19 growth rate and travel distance decay rate and dwell time at home¹³
¹⁴change rate was -0.586 (95% CI: -0.742 -0.370) and 0.526 (95% CI: 0.293 0.700),¹⁴
¹⁵respectively. Increases in state-specific doubling time of total cases ranged from¹⁵
¹⁶6.86 days to 30.29 days after social distancing orders were put in place [4]. Another¹⁶
¹⁷analysis across counties in the US, showed that adoption of government-imposed¹⁷
¹⁸social distancing measures reduced the daily growth rate of confirmed COVID-19¹⁸
¹⁹cases by 5.4 percentage points after one to five days, 6.8 percentage points after six¹⁹
²⁰to ten days, 8.2 percentage points after eleven to fifteen days, and 9.1 percentage²⁰
²¹points after sixteen to twenty days [13]. In a recent European study, it was shown²¹
²²that internal mobility is more important than mobility across provinces to control²²
²³COVID-19, and the typical lagged positive effect of reduced human mobility on²³
²⁴reduced human mobility on reducing excess deaths is around 14-20 days [18].²⁴

²⁵
²⁶ A big question that policy makers at state, or country level jurisdictions face is²⁶
²⁷if the impact of visitor mobility is different than local mobility. In this study, we²⁷
²⁸examine the transmission risk propagated as a result of local mobility vs. risk prop-²⁸
²⁹agated from visitor mobility for all the states in United States. We use two different²⁹
³⁰variables to capture the infection propagation risk, namely the local transmission³⁰
³¹risk (due to local mobility) and the visitor transmission risk (due to visitor mo-³¹
³²bility), and evaluate the impact of these variables on case growth. This study was³²
³³done across all the 50 states in United States from March 2020 to December 2020.³³

Figure 1: The timeseries of the cases per capita, local transmission risk, and visitor transmission risk for various states in the United States

2 Methods

2.1 Data Collection

2.1.1 Infection Data

The confirmed cases data was retrieved from the Corona Data Scraper open-source project [26], which provides county-level data on the number of new cases per day.

We aggregated the number of cases to a state-level.

2.1.2 Mobility Data

State-level mobility dataset and metrics were provided by SafeGraph [27]. SafeGraph provides aggregated trip information at a census tract level obtained from anonymized mobile device locations. The intra-state (or local) trips represent the trips taken by individuals starting and ending within the same state (i.e., state boundary). The inter-state (or visitor) trips are those where the origin and destination are in different states (i.e., origin in one state and destination in a different

state). This data was collected for all the trips made between January 1, 2020 and¹
December 31, 2020.²

2.2 Approach⁴

In order to measure the impact of mobility (both local and visitor), we model the⁵
number of cases at a particular location based on the historical number of cases,⁶
the transmission of infection based on the mobility. Higher accuracy when a factor⁷
is included in the model shows that the particular factor is important [28]. The⁸
features used to forecast the number of cases is listed below:⁹

2.2.1 Number of Cases¹⁰

The aggregated new cases from the previous 14 days is used to forecast the number¹¹
of cases for the next 14 days; earlier studies have shown that the virus incubation¹²
period is about 14 days [29].¹³

2.2.2 Local transmission risk¹⁵

The local transmission risk represents the transmission potential of the virus based¹⁶
on the recent number of cases per capita (which represents local case incidence)¹⁷
and the mobility both at the local level. The local transmission coefficient LT for a¹⁸
spatial region i is calculated using the formula:¹⁹

$$LT_i = M_{i,i} \times C_i$$

Where $M_{i,i}$ represents the number of trips where the origin and destination of the²⁴
trips fall within the region i . The cases per 100,000 people at the location i , which²⁵
we denote as C_i .²⁶

2.2.3 Visitor transmission risk²⁷

The visitor transmission risk represents the transmission potential of the virus based²⁸
on the recent number of cases per capita at the visitor origin. The visitor transmis-²⁹
sion VT at a location i can be calculated using:³⁰

$$VT_i = \sum_{j=0}^n M_{j,i} \times C_j \quad (1)$$

¹Where $M_{j,i}$ represents the number of trips that originate at j and end at location ¹
² i and $j \neq i$. The cases per capita at location j is represented by C_j . These three ²
³measures are illustrated in Figure 1. 3

2.3 Machine Learning Methods 5

⁶We employ various machine learning techniques to forecast number of cases based ⁶
⁷the local vs visitor mobility. The general idea is to evaluate if including visitor ⁷
⁸transmission risk improves the forecasting performance by analyzing the relation- ⁸
⁹ship between future number of cases and historical local mobility vs. future number ⁹
¹⁰of cases with visitor mobility using machine learning methods. Machine learning ¹⁰
¹¹models are more capable of capturing the non-linear relationships between various ¹¹
¹²features. The abundance of the COVID data - case data and mobility patterns, ¹²
¹³enable us to identify complex relationship patterns. In this study, three popular ¹³
¹⁴machine learning methods were used, namely, Linear regression, Random Forest ¹⁴
¹⁵Regression, and XGBoost Regression to forecast the number of cases. These models ¹⁵
¹⁶take into account the historical number of cases, local transmission risk and visitor ¹⁶
¹⁷transmission risk into account when forecasting the future number of cases. 17

2.4 Evaluation Criteria 18

¹⁹The predictive performance of the proposed approach for each of the stations is 19
²⁰compared using the following two metrics: Mean absolute percentage error (MAPE) 20
²¹measures the average percent of absolute deviation between actual and forecasted 21
²²values. 22

$$MAPE = \frac{1}{N} \sum \frac{|A - P|}{A} \times 100 \quad (2) \quad \text{24}$$

²⁵Root mean squared error (RMSE) captures the square root of average of squares of ²⁵
²⁶the difference between actual and forecasted values. 26
²⁷27

$$RMSE = \sqrt{\frac{1}{N} \sum (A - P)^2} \quad (3) \quad \text{29}$$

³⁰30
³¹Where, N is the number of test samples, A is the actual value, and P is its respective 31
³²predicted value. For each of the techniques, we evaluate the accuracy of prediction 32
³³with and without using the visitor transmission risk. 33

Model	No Mobility	Local Transmission Risk Only	Visitor Transmission Risk Only	Local and Visitor Risk
Gradient Boost	0.244	0.222	0.17	0.168
Linear Regression	0.512	0.464	0.536	0.497
Random Forest	0.335	0.327	0.309	0.306

Table 1: Comparison of MAPE to forecast the number of cases with and without visitor transmission risk for various machine learning models

Model	No Mobility	Local Transmission Risk Only	Visitor Transmission Risk Only	Local and Visitor Transmission Risk
Gradient Boost	0.084	0.075	0.055	0.055
Linear Regression	0.108	0.105	0.102	0.099
Random Forest	0.075	0.074	0.063	0.063

Table 2: Comparison of RMSE to forecast the number of cases with and without visitor transmission risk for various machine learning models

Diebold-Mariano test (DM-test) is used to evaluate the significance of the predictions of the two models [30]. The models use the forecasted number of cases generated with and without using the visitor transmission for each of the three machine learning approaches. The null hypothesis of the DM-test is that the two forecasts have similar forecast accuracy. The alternative or rejection of the null hypothesis is that the two forecasts have significantly different forecasting accuracy, i.e., the forecasts are not similar using the two models.

3 Results

Tables 1 and 2 show the comparison of the machine learning forecasts with and without the inclusion of visitor mobility and local mobility. We compare the performance of the three machine learning models (Gradient Boost, Linear Regression, and Random Forest) using the MAPE and RMSE. In addition a DM test was performed to evaluate the significance of forecasts when visitor mobility is included in the model.

Table 1 shows the MAPE of machine learning models for the complete duration (i.e. March 2020 to December 2020). We observe that the MAPE of the best performing model (i.e. Gradient Boost) has a MAPE of 16.8% when using visitor mobility compared to 22% when just the local transmission risk is taken into account. Linear regression model shows better performance when using local transmission risk than combined local and visitor transmission risk. However, Table 2 shows that

Model	No Mobility	Local Transmission Risk Only	Visitor Transmission Risk Only	Local and Visitor Transmission Risk
First Wave (March - June)				
Gradient Boost	0.376	0.308	0.169	0.174
Linear Regression	1.064	1.029	1.094	0.938
Random Forest	0.422	0.409	0.329	0.327
Second Wave (July - September)				
Gradient Boost	1.038	0.999	0.885	0.834
Linear Regression	1.411	1.35	1.251	1.208
Random Forest	1.023	1.007	0.887	0.875
Third Wave (October - December)				
Gradient Boost	0.469	0.492	0.352	0.341
Linear Regression	1.401	1.369	1.174	1.142
Random Forest	0.498	0.508	0.369	0.359

Table 3: Comparison of forecasting performance using MAPE with and without local and visitor transmission risk for three waves using various machine learning models

the RMSE is lower when using the combination of local and visitor transmission risk than local transmission risk. In addition, the RMSE is lower when local and visitor mobility is used for all the three models.

The significance of the results is evaluated using the Diebold-Mariano score that evaluates the null hypothesis that both the forecasts are the same, the p-value shows that the null hypothesis is rejected and the difference in forecasts are statistically significant. The DM scores for the gradient boost, linear regression, and random forest are 8.7(p=0.2), 2.66(p=0.04), and 8.26(p=0.04) respectively. The MAPE and RMSE on the state level data in Table 5 shows that the inclusion of external mobility leads to better forecasts for all 50 states in the United States.

We make similar observations when the data is separated into three waves (Tables 3 and 4). The MAPE and RMSE for all the three approaches report lower MAPE and RMSE when visitor transmission risk is included in the model generation compared to when local mobility is used. The inclusion of the visitor transmission risk improves the MAPE of the forecast by about 57.19% on average across all states for the three waves. During the first phase, the external mobility results in a decrease in MAPE by 110% with the percentage error at $17.14 \pm 0.28\%$ and $30.81 \pm 0.48\%$ with external and only local transmission coefficient respectively. Similarly, the improvement for MAPE for the phase 2 and 3 are 34.23% and 26.17% respectively.

Figure 2: Distribution of the number of cases, Local Transmission Risk and Visitor Transmission Risk to various states across all phases (March - December), phase 1 (March - June), phase 2 (July - August), and phase 3 (October - December). Certain states that have high number of cases have high local transmission risk, where as others have high visitor transmission risk, where risk is imported from outside the state boundaries.

14 Discussion of Results

Figure 2 shows the cumulative number of cases per capita, local transmission risk, and the visitor transmission risk for each of the states in the United States for the entire pandemic and the three phases of the pandemic. We observe that certain states have a lower local transmission risk and a higher visitor transmission risk. For example, during the second phase of the pandemic, states like Illinois and Georgia, the local transmission risk is much lower than the transmission risk posed by travelers from other states to Illinois. Similarly, for states like New York in phase 1, the local transmission risk is higher than the visitor transmission risk. There are also variations between the interplay of local and visitor transmission risks for different phases of the pandemic. The first phase is primarily driven by local mobility, and the other two phases are a combination of local and visitor mobility.

Figure 3: Visitor transmission risk and mobility patterns to the state of Louisiana from other states in the United States

Figure 4: Visitor transmission risk and mobility patterns to the state of New York from other states in the United States

While it is apparent that the majority of the visitor transmission risk is due to travelers crossing state boundaries from neighboring cities, there is also consider-

Figure 5: Visitor transmission risk and mobility patterns to the state of North Dakota from other states in the United States

able transmission risk due to long-distance travel. For example, for Louisiana, the majority of the risk for its second peak is contributed by Mississippi, Texas, and Florida, which is higher than the Arkansas that borders the state in the north. The states of Mississippi and Florida contributed more to the second peak, whereas travelers from Texas contributed to the second and third phases of the pandemic. For the states like North Dakota, most of the visitor transmission risk is attributed to their neighboring states. New York, on the other hand, has a huge increase in visitor transmission risk from Florida during the late winter when the state of Florida opened up to travelers compared to the rest of the country. These trends are presented in Figures 3, 4 and 5

5 Limitations and Future Work

This study presents a novel approach to examine the association between the effect of local and visitor mobility on the number of cases for various states in the United States. There are several areas where this study can be potentially improved. First, this study focuses on the association between the internal and external mobility and their effect on the increases in the number of cases. This study does not consider the many other factors like usage of masks, social distancing, the impact of regulations, and the varying compliance from the public that could have had an effect on the number of cases. Second, the associations are computed at a daily granularity. The majority of the states have issues related to non-uniform cases where a higher number of cases are reported over Mondays and Tuesdays. In comparison, the number of cases reported over the weekend is lower. We solved this problem by smoothening

the data over seven days. Third, the case data might be prone to errors due to both reporting issues and the outliers in testing when states update their case numbers post-hoc. Fourth, the mobility data considers the number of individuals traveling from one state to another, but does not capture the distance traveled by individuals during the trip. Incorporating the distance traveled might help enhance the relationship between the number of cases and the mobility of individuals. Finally, we consider the state as a single unit to measure the mobility and the number of cases. We do not consider the population density at origin and destination and the number of people traveling to a particular city in a state. For example, the first wave (March – June) was dominated by cases from metropolitan areas, whereas the cases during the third wave were primarily in the rural areas of the state. In the future, we would like to extend this model for various metropolitan areas in the county for analysis at a more refined level of granularity.

6 Conclusions

In this paper, we evaluated the impact of the disease transmission risk due to visitor and local mobility on the number of cases at a state level for all 50 states in the United States. We observed that visitor mobility is an important factor to explain case growth. The prediction accuracy improved by 29% for the whole duration of the pandemic in 2020 (March – December) when visitor mobility was used in the forecasting model. The impact of transmission risk due to external mobility is observed across all three phases of the pandemic in the United States. We observe the influence of mobility is much stronger in the first phase of the pandemic compared to the second or third phase. These observations are consistent with some of the earlier studies [4, 11] where mobility was observed to be an important predictor for case growth in the first phase of the pandemic.

Appendix

Ethics approval and consent to participate

Not Applicable

Consent for publication

Not applicable

Competing interests

The authors declare that they have no competing interests.

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The analysis code for this paper is available on GitHub at	
⁹ https://github.com/raviteja-bhupatiraju/Covid19-Phasewise-Mobility-Association	9
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¹²References	12
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FIPS	All Waves				First Wave				Second Wave				Third Wave			
	MAPE		RMSE		MAPE		RMSE		MAPE		RMSE		MAPE		RMSE	
	Visitor + Local	Local	Visitor + Local	Local	Visitor + Local	Local	Visitor + Local	Local	Visitor + Local	Local	Visitor + Local	Local	Visitor + Local	Local	Visitor + Local	Local
1	0.39	0.43	0.13	0.14	0.31	0.53	0.14	0.18	1.78	2.79	0.23	0.36	0.84	0.51	0.12	0.12
2	0.5	0.68	0.09	0.12	0.73	1.48	0.15	0.22	0.33	0.84	0.1	0.16	1.22	0.62	0.13	0.13
4	0.79	1.04	0.15	0.23	0.33	0.5	0.11	0.17	1.54	2.33	0.17	0.28	1.06	1.21	0.09	0.11
5	0.23	0.29	0.09	0.13	0.3	0.47	0.11	0.12	0.56	0.71	0.12	0.14	1.92	2.01	0.25	0.32
6	0.45	0.74	0.14	0.2	0.22	0.21	0.13	0.12	3.72	4.09	0.26	0.33	1.05	3.15	0.09	0.21
8	0.49	1.31	0.11	0.26	0.14	0.26	0.08	0.11	0.75	2.06	0.15	0.27	0.32	0.3	0.11	0.12
9	0.73	1.61	0.12	0.23	0.61	0.92	0.24	0.26	0.63	0.98	0.24	0.19	0.32	0.14	0.06	0.06
10	0.35	0.47	0.14	0.18	0.25	0.69	0.16	0.17	0.55	0.7	0.14	0.15	0.91	1.15	0.11	0.27
12	0.52	0.69	0.16	0.24	0.44	0.69	0.13	0.22	1.46	1.18	0.21	0.22	0.5	2.08	0.1	0.32
13	0.38	0.59	0.14	0.19	0.31	0.35	0.14	0.17	2	1.98	0.18	0.25	2.29	3.24	0.19	0.27
15	1.04	1.34	0.09	0.15	1.68	2.73	0.2	0.3	0.33	1	0.07	0.19	0.81	2.18	0.09	0.23
16	0.49	0.63	0.09	0.11	0.48	0.89	0.17	0.19	0.54	1.47	0.12	0.18	0.31	0.25	0.08	0.08
17	0.46	0.74	0.12	0.22	0.24	0.43	0.12	0.16	0.44	0.37	0.14	0.16	0.17	0.13	0.05	0.04
18	0.62	0.77	0.15	0.19	0.1	0.29	0.05	0.07	0.94	0.99	0.18	0.18	0.18	0.14	0.05	0.04
19	0.45	0.49	0.13	0.14	0.1	0.33	0.05	0.07	0.45	0.44	0.15	0.16	0.35	0.27	0.09	0.09
20	0.3	0.35	0.09	0.08	0.25	0.36	0.11	0.16	0.76	0.84	0.15	0.17	1.08	0.89	0.22	0.22
21	0.34	0.35	0.07	0.08	0.11	0.23	0.04	0.07	0.45	0.51	0.1	0.11	0.52	0.34	0.1	0.14
22	0.45	0.56	0.2	0.23	0.13	0.27	0.08	0.1	2.09	2.42	0.31	0.32	2.96	2.74	0.25	0.26
23	0.5	0.6	0.09	0.12	0.17	0.8	0.09	0.16	0.95	0.87	0.18	0.21	0.76	1.21	0.08	0.09
24	0.45	0.5	0.18	0.21	0.12	0.27	0.07	0.08	0.63	0.69	0.19	0.2	0.5	0.45	0.06	0.07
25	1.14	1.19	0.2	0.22	0.53	0.83	0.22	0.22	0.42	0.46	0.19	0.22	0.44	0.58	0.05	0.06
26	0.64	1.06	0.17	0.25	0.21	0.74	0.07	0.16	0.88	0.96	0.17	0.21	0.31	0.14	0.06	0.06
27	0.2	0.64	0.04	0.16	0.14	0.24	0.09	0.08	0.67	1.05	0.22	0.22	0.22	0.16	0.06	0.05
28	0.33	0.47	0.12	0.19	0.16	0.3	0.1	0.11	1.98	2.12	0.26	0.3	0.99	1.22	0.11	0.12
29	0.55	0.59	0.1	0.11	0.16	0.38	0.08	0.11	0.78	0.86	0.1	0.12	0.98	1.06	0.23	0.22
30	0.44	0.49	0.07	0.09	1.12	1.65	0.11	0.15	0.26	0.35	0.09	0.11	0.49	0.74	0.12	0.2
31	0.31	0.34	0.07	0.08	0.2	0.39	0.09	0.12	1.3	2.24	0.22	0.25	0.35	0.37	0.08	0.09
32	0.86	0.9	0.19	0.21	0.23	0.38	0.12	0.15	1.07	1.62	0.19	0.31	0.68	0.58	0.1	0.08
33	1.48	1.38	0.21	0.22	0.14	0.67	0.07	0.13	0.63	0.84	0.15	0.16	0.74	0.85	0.11	0.14
34	0.73	1.03	0.18	0.23	0.54	0.58	0.23	0.25	0.5	0.71	0.16	0.21	0.5	0.39	0.05	0.05
35	0.43	0.51	0.09	0.11	0.1	0.41	0.06	0.08	1.39	1.97	0.22	0.29	0.36	0.34	0.05	0.05
36	0.82	1.3	0.18	0.26	0.21	1.13	0.06	0.32	0.38	0.36	0.14	0.14	0.29	0.27	0.03	0.03
37	0.23	0.3	0.08	0.09	0.27	0.44	0.14	0.15	1.17	1.41	0.19	0.21	1.44	1.13	0.2	0.2
38	0.41	0.56	0.08	0.12	0.17	0.54	0.09	0.11	0.41	0.4	0.07	0.07	0.71	1.6	0.16	0.26
39	0.67	0.95	0.15	0.2	0.12	0.34	0.06	0.06	1.53	1.41	0.18	0.18	1.39	1.64	0.13	0.17
40	0.24	0.58	0.06	0.08	0.15	0.31	0.07	0.09	0.57	0.88	0.18	0.28	0.38	0.28	0.11	0.11
41	0.45	0.52	0.1	0.12	0.33	0.46	0.13	0.18	1.05	1.59	0.21	0.24	0.92	0.91	0.08	0.09
42	0.28	1.19	0.06	0.25	0.24	0.47	0.15	0.14	1.26	1.62	0.15	0.18	0.32	0.27	0.05	0.04
44	1.06	1.2	0.18	0.22	0.27	0.97	0.1	0.18	0.24	0.29	0.1	0.15	0.45	0.31	0.09	0.1
45	0.51	0.57	0.14	0.19	0.75	0.71	0.25	0.26	0.91	1.34	0.2	0.24	1.72	2.66	0.19	0.32
46	0.33	0.43	0.06	0.06	0.14	1.75	0.07	0.22	0.8	2.37	0.13	0.19	0.59	1.09	0.1	0.12
47	0.18	0.17	0.06	0.05	0.16	0.4	0.06	0.11	0.57	0.62	0.09	0.11	0.54	0.46	0.13	0.11
48	0.41	0.5	0.14	0.16	0.3	0.37	0.11	0.21	0.9	0.53	0.15	0.15	0.93	0.92	0.19	0.19
49	0.42	0.63	0.1	0.16	0.27	0.52	0.13	0.19	0.44	0.89	0.08	0.12	0.78	0.73	0.17	0.17
50	0.97	1.91	0.14	0.25	0.32	1.4	0.07	0.28	1.18	1.24	0.24	0.2	0.49	1.26	0.11	0.11
51	0.35	0.45	0.15	0.2	0.12	0.15	0.07	0.07	1.24	1.22	0.21	0.2	2.29	4.77	0.16	0.3
53	0.44	0.88	0.13	0.22	0.13	0.19	0.08	0.12	0.71	2.34	0.14	0.36	0.49	0.49	0.07	0.09
54	0.34	0.42	0.07	0.08	0.21	0.78	0.08	0.13	0.36	0.52	0.07	0.09	1.27	1.16	0.1	0.11
55	0.32	0.44	0.07	0.08	0.15	0.39	0.07	0.1	1.8	2.36	0.28	0.36	0.31	0.3	0.07	0.08
56	0.74	0.68	0.08	0.08	0.21	0.98	0.1	0.17	1.43	2.1	0.25	0.28	0.33	0.51	0.1	0.1

Table 4: The accuracy for each state for case forecasting using only visitor and local mobility, for the three machine learning models.