Modeling the Impact of COVID-19 on Transportation at Later Stage of the Pandemic: A Case Study of Utah

Yaobang Gong[a], Tanner Isom[a], Pan Lu[b], Xianfeng (Terry) Yang[c]*, Aaron Wang[a]

[a]Department of Civil and Environmental Engineering, University of Utah, Salt Lake City, United States; [b]Upper Great Plains Transportation Institute, North Dakota State University, Fargo, United States; [c]Department of Civil and Environmental Engineering, University of Maryland, College Park, United States

Correspondence details for the corresponding author: Department of Civil and Environmental Engineering, University of Maryland, College Park, MD, U.S., 20742, Email: xtyang@umd.edu

The global COVID-19 pandemic has had a great impact on transportation across the United States. However, there is a lack of studies investigating the pandemic's impact on vehicular traffic at the later stage of the pandemic. Therefore, this paper studies the change of freeway traffic patterns in two metropolitan counties in the State of Utah at the latter stage of the pandemic. We found that with the relaxation of travel restriction and the COVID vaccine, vehicular traffic has recovered to equaling, if not exceeding, pre-pandemic levels. Truck traffic is higher than the pre-pandemic level due to the growth of online shopping and on-demand delivery. To help responsive agencies to prepare for the near-future traffic pattern, a traffic prediction model based on an innovative approach integrating machine learning with graph theory is proposed. The evaluation shows that the proposed prediction model has a desirable performance. The mean absolute percentage prediction error is between 0.38% and 1.74% for different jurisdictions. On average, the modal outperforms the traditional long short-term memory model by 31.20% in terms of root mean squared prediction error.

Keywords: COVID-19, traffic forecasting, machine learning

Introduction

Since the early March of 2020, the global COVID-19 pandemic has placed pronounced impacts on various aspects of society. In addition to the loss of life and illness, the pandemic has resulted in a great impact on the traffic across the U.S. Many studies found that at the early stage of the pandemic, traffic has been reduced significantly due to the travel restrictions imposed by the government, fear of getting sick, lower levels of economic and social activity, and the "work-from-home" style of many residents (Katrakazas et al., 2020; Kim, 2021; Zhang & Lee, 2021). Later on, with the process of re-opening local businesses, schools, etc., and the decrease in daily COVID confirmed cases, traffic demands have been gradually increased over time(Glaeser et al., 2020). It is clear to see that traffic pattern, traffic demands, and duration alter with COVID status.

As the restrictions were relaxed due to the reduced COVID-19 cases and the rollout of the vaccines, a return to a post-pandemic "normality" is on the way and will probably allow a recovery of mobility to levels comparable to the past. However, there are few studies investigating how the traffic patterns will like at the later stage of the pandemic or even post-pandemic. A policy analysis conducted by Rothengatter et al. (Rothengatter et al., 2021) discussed the impacts of COVID-1 on different travel modes. However, they ignored car traveling. Another European long-term travel demand study by Christidis et al. (Christidis et al., 2021) was conducted to investigate the post-pandemic recovery of transportation. They found that travel by car will likely return to the 2019 level around the year 2025. Unfortunately, their analysis was based on a 2018 travel survey rather than either recent traffic data or travel survey. Therefore, there is a critical research need of studying the impact of COVID-19 on traffic patterns in the later state of pandemic based upon recent data, and analyzing the relationship among traffic patterns, daily confirmed cases/deaths, government policies, economic factors, etc. Such research results will be valuable to responsive agencies such as state DOTs to better understand the long-term impacts of COVID-19 on transportation and get prepared for the near-future traffic demand pattern.

In order to fill the research gap, this study will first examine the impact of the COVID-19 and the related government policies on vehicular traffic in the later stage of the pandemic. Field traffic data will be used to quantify the traffic patterns. Then, a prediction model will be developed to forecast the traffic demand patterns in the near future (during the late stage of the pandemic). The model will be formulated with an innovative data-driven approach that integrates machine learning with graph theory.

Methodology

Study Area

The study selects the major metropolitan counties, namely Salt Lake County and Utah County, in the State of Utah as the study area. These two counties are the most populous counties in Utah and account for more than 55% population of the state (2020 estimate). The majority difference between the two counties is the political diversity. Salt Lake County is one of the more diverse politically speaking areas of Utah while Utah County is less diverse. This translates into differences in county policies towards the pandemic.

This study focuses on traffic patterns of freeways due to the data availability. Figure 1 shows the freeways in the study area. The traffic dynamics of two main freeway corridors named Interstate-15 and Interstate-80 and other smaller freeways including Interstate 80, Interstate 215, State Road 85, State Road 201, State Road 92, U.S. Route 6, and U.S. Route 189 are studied in this study. The total lane miles covered are 850 lane miles and 540 lane miles for Salt Lake County and Utah County respectively.

(Insert “Figure 1. Freeways in the Salt Lake County and Utah County in the State of Utah” here)

Data

County-wide Vehicle Miles Traveled (VMT) of all freeways are used to quantify the vehicular dynamic. The VMT data was collected from the UDOT Performance Measurement System (PeMS) (Utah Department of Transportation, 2019) from January 2019 to the first week of July 2021, which gives the traffic patterns before and during the pandemic. VMT for all vehicle types and trucks are collected and analyzed separately.

Various factors related to the pandemic and vehicular traffic are also collected as explanatory variables. Daily new COVID-19 confirmed cases and the percentage of fully vaccinated individuals over 12 years of age from the Utah Department of Health (The State of Utah, 2021a). The former one is a direct quantifier of the severity of the pandemic, which has been used by a lot of existing studies (Kim, 2021). While the latter impacts people’s risk perception in traveling.

Traffic is intrinsically related to the economy. Economic factors are also used as Economic factors explanatory variables to capture the unexplained heterogeneity by the pandemic-related factors. The monthly unemployment rate and daily news sentiment index are obtained from the Utah Department of Workforce Services (Utah Department of Workforce Services, 2021) and the Federal Reserve Bank of San Francisco (Shapiro et al., 2017). The unemployment rate can affect traffic as fewer people will be willing to drive due to economic hardship, especially commuting trips. The daily news sentiment index is a measure of economic sentiment based on lexical analysis of economics-related news articles from 24 major newspapers in the US. The developers of the index created a sentiment scoring model based on publicly available lexicons with a news-specific lexicon constructed by the developers. Then the scores of individual articles are aggregated into a daily time-series measure of news sentiment which are statistically adjusted to account for changes in the composition of the sample across newspapers. Then the index is constructed as a trailing weighted average of time series, with weights that decline geometrically with the length of time since article publication. The index provides information regarding economic downturns and overall sentiment in the public eye.

Weather conditions could affect the traffic operations. For example, traffic volumes could be reduced by rainstorms and from snowstorms (Maze et al., 2006). Weather related parameters such as temperature, precipitation, and snow depth were collected from the National Centers for Environmental Information (National Centres for Environmental Information (NCEI), 2020). The weather observing station at the Salt Lake International Airport was selected for weather data in Salt Lake County and another station at Spanish Fork Power House was selected for the weather data in Utah County (their locations are shown in Figure 1 as blue stars). These weather stations were selected since their locations near analyzed freeways. All aforementioned data are numeric.

Another important factor is pandemic-related policy. For instance, lock-down orders could significantly reduce the traffic volume (Kim, 2021). Important state-wide and county-level policies (The State of Utah, 2021b) are listed in Figure 2, which includes deceleration of state of emergency, mask mandate, administration of vaccines, etc. Some policies restrict traveling directly while others influence people's willingness to travel. Policy indicators are pre-processed as 0-1 dummy variables. When a certain policy is effective at a specific time, the dummy variable was set to 1; otherwise, it was set to 0.

(Insert “Figure 2. Milestones of Pandemic-Related Policies” here)

All data are aligned with VMT data and aggregate by week. In other words, economic and weather data are collected from January 2019 to the first week of July 2021, while pandemic-related data and policies are collected once they are available till the first week of July 2021.

Prediction Model: Graph Convolutional Networks-Long Short-Term Memory (GCN-LSTM)

Recently, Graphical neural networks (GNN) have been used in various traffic forecasting studies, such as traffic flow (Tang & Zeng, 2021) and speed (Zhao et al., 2020) prediction, vehicular trajectory estimation (Li et al., 2021), travel demand forecasting (Xiong et al., 2020), etc. As traffic networks are naturally graphs, GNN-based models are able to capture spatial dependency of traffic data, and thus outperform previous forecasting models such as Autoregressive Integrated Moving Average Model, Support Vector Regression, and Recurrent Neural Network(RNN)-based models such as Long Short-Term Memory (LSTM) (Jiang & Luo, 2021; J. Yuan et al., 2019; Zhao et al., 2020). In other words, the “graphs” used in almost all existing GNN-based traffic forecasting studies aim at obtaining “spatial information”. A typical “traffic graph” is defined as $G_t = (V, E, A)$, where V is the set of nodes such as roadway segment/traffic detectors for microscopic models or specific geographical areas for macroscopic models; E is the set of edges between nodes which shows the spatial connectivity; A is the adjacency matrix represent the “edge weight” such as distances (Jiang & Luo, 2021).

However, in this study, although the problem could be formulated into a time series forecasting, we are specifically interested in modeling the impacts of external factors on vehicular traffic. A preprint paper reveals that adding human knowledge as a form of “knowledge graph” to the existing GNN-based traffic forecasting model could improve the model performance (Zhu et al., 2020). Therefore, we adopted this idea and developed a knowledge graph depicting the relationships between the factors mentioned in the previous section. The directed knowledge graph $G_k = (V_k, E_k, A_k)$ is shown in Figure 3, where node set V_g consists of VMT and impact factors; edge set E_g represents the “possible” impact relations (The edge e_{ij} exists if the node i has possible impact on node j); the adjacency matrix A_g is a binary matrix showing the existence of edges only. The complex knowledge graph clearly demonstrates that these factors are highly intercorrelated, which might indicate that simple regression models may fail due to collinearity.

(Insert “Figure 3. Knowledge Graph Depicting” here)

Therefore, the forecasting problem is formulated as learning the mapping function f on the premise of knowledge graph G_k and the factor matrix X and calculate X_T in next T timestamps. In this study, a one-step forecast (one week ahead) is considered as longer-term forecasting may not be valid due to the rapid change of pandemic and policy status:

$$X_{t+1} = f\big(G_k; (X_{t-n}, \dots, X_{t-1}, X_t)\big) \tag{1}$$

where X_{t+1} is the values of all factors at the timestamp $t+1$ although we are only interested in the VMT, and n is the length of historical time series which is a tunable factor.

The model used to learn the mapping is Graph Convolutional Networks-Long Short-Term Memory (GCN-LSTM). It is a variant of the model proposed by Zhao et al (2020). The model consists of two parts (Figure4): the graph convolution network (GCN)(Defferrard et al., 2016), a popular GNN model used to obtain the relationships between factors from the knowledge graph, and the LSTM (Hochreiter et al., 1997) used to obtain the temporal dependency.

(Insert “Figure 4. GCN-LSTM Model Structure” here)

The basic concept behind the GCN model is using a filter to capture the feathers between a node and its first-order neighborhood. Then, the GCN can be built by stacking multiple convolutional neural network layers:

$$H^{(l+1)} = \sigma\left(\widetilde{D}^{-\frac{1}{2}}\tilde{A}\widetilde{D}^{-\frac{1}{2}}H^{(l)}\theta^{(l)}\right) \quad (2)$$

where $\tilde{A} = A_k + I_n$ is the adjacency matrix including self-connections of the nodes; I_n is an n-degree identity matrix representing self-connections; $\widetilde{D} = \sum_j \tilde{A}_{ij}$is the degree matrix of the graph representing the neighborhood information; $H^{(l)}$ is the output matrix the layer l and the $\theta^{(l)}$ is the associated trainable parameters; $\sigma(\cdot)$ is the sigmoid function.

(Insert “Figure 5. Illustration of a GCN Filter (Adopted from Zhao et al. (2020))” here)

Incorporating GCN with LSTM, we get:

$$h_t = o_t ReLU(c_t) \quad (3)$$

$$o_t = \sigma(W_o[f(A_k, X_t), h_{t-1}] + V_o c_t) \quad (4)$$

$$c_t = f_t c_{t-1} + i_t ReLU(W_c[f(A_k, X_t), h_{t-1}]) \quad (5)$$

$$f_t = \sigma\big(W_f[f(A_k, X_t), h_{t-1}] + V_f c_{t-1}\big) \quad (6)$$

$$i_t = \sigma(W_i[f(A_k, X_t), h_{t-1}] + V_i c_{t-1}) \quad (7)$$

where h_t is the output of LSTM unit at the timestamp t, while the forecast is the output of the final LSTM layer (as shown in Figure 4); o_t is the "output gate" that modulates the amount of memory content exposure; Ws are trainable matrixes; $f(A_k, X_t)$ is the final output of the stacked GCN layers; Vs are diagonal matrixes; c_t is the “memory” maintained by the unit at t and is updated by partially forgetting the existing memory by factor gate f_t and adding a new memory content through input gate i_t. It should be noted that normally the activation function used in LSTM is hyperbolic the tangent function (tanh). However, the tanh activation does not perform well in this forecasting problem according to extensive algorithm trainings done by the research team. Since REctified Linear Unit (ReLU) activation functions could be used in RNNs with right initialization of the weights (Le et al., 2015), the ReLU activations are adopted.

The loss function used in training is mean square errors between the predicted factors and the observed ones. Adam optimizer was selected to minimize the loss.

Forecasting models are developed for two counties separately since their demographics are very different. For example, as stated in the last section, residents of two counties have different political views and in turn, impact their risk perceptions on the virus and traveling during the pandemic. Such unobserved heterogeneity could not be modeled using the existing data. Therefore, in total, four models (2 counties × 2 VMT types) are developed.

The model is evaluated by two benchmark models, namely the persistence model and a fine-tuned LSTM. The persistence model is widely used as the benchmark for time series forecasting problems. A persistence model assumes that the future value of a time series is calculated under the assumption that nothing changes between the current time and the forecast time. It should be noted that although GCN-LSTM is able to forecast all input factors at the future timestamps, only VMT is used to quantify the model performance. Two evaluation metrics are employed, which are Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(VMT_t - \widehat{VMT_t}\right)^2} \tag{8}$$

$$MAPE = \frac{100}{n}\sqrt{\sum_{t=1}^{N}\left(\frac{VMT_t - \widehat{VMT}_t}{\widehat{VMT}_t}\right)} \tag{9}$$

Results

Impact of Pandemic on Vehicular Traffic

VMT is highly affected by the severity of the pandemic (quantified by the number of new cases), policies, and individual/societal risk perceptions of traveling during the pandemic. Figure 6 shows the VMT for all types of vehicles (Total VMT) and trucks for two counties with the progression of the pandemic. It should be noted that the Truck VMT shown in the figure is scaled up by 10 times for better illustration. The most prolonged decrease in VMT occurs during the initial phase of the pandemic. After travel restrictions regarding COVID-19 were announced (around the second week of March 2020), Total VMT dropped significantly by around 38.9% for Salt Lake County (72.9 million miles vs 44.6 million miles) and 36.7% for Utah County (37.7 million miles vs 23.8 million miles) in one month. Truck VMT also dropped by 26.2% (4.6 million miles vs 3.6 million miles) and 19.8% (3.4 million miles vs 2.7 million miles) for Salt Lake and Utah Counties respectively. Both travel restrictions issued by the state government and public concerns regarding the virus lead to this large and prolonged drop.

(Insert "Figure 6. VMT versus Number of New COVID Cases (Truck VMT is Scaled up by 10 Times for Better Illustration)" here)

However, once restrictions were relaxed, and public perception shifted even during rising case counts; starting from the last week of April 2020, VMT began to recover to pre-pandemic levels. By mid-June 2020, total VMT recovered to 89.9% (65.6 million miles) and 99.6% (37.5 million miles) of pre-pandemic level for Salt Lake and

Utah Counties respectively. Truck VMT shows a similar trend. It should be noticed that the VMT recovered faster and more for Utah County. As to this date, there is not a huge difference in pandemic-related policies between the two counties, the differences are likely to be due to the different risk perceptions of the residents living/traveling in the two counties. Interestingly, implementation mask mandates did not significantly reduce VMTs.

During the late months of 2020 and the beginning of 2021, VMT began to drop again. This decrease can partially be attributed to holidays during this time of year, especially for Truck VMT. However, the Total VMT of the first week in 2021 (52.6 million miles for Salt Lake County and 29.9 million miles for Utah County) is less than that of the first week in 2020 (57.9 million for Salt Lake County and 31.8 million miles for Utah County). The slight drop can be attributed to increased state restrictions and the highest case count totals of COVID-19. This high case counts, and restrictions remained throughout early 2021 causing the decline in VMT to stagnate as the high case counts lasted.

During the later stage of the pandemic, the vaccine plays an important role in the recovery of traffic. Figure 7 shows the changes of VMT with the percentage of fully vaccinated individuals over 12 years of age. COVID vaccines began to be administered in the State of Utah in December 2020 during the peak of the pandemic. In the ensuing months as vaccines became more available, the new confirmed cases began to decrease significantly. A Pearson correlation study reveals that Total VMT is positively correlated to the percentage of fully vaccinated individuals with coefficients of 0.837 and 0.937 for Salt Lake and Utah counties respectively (Figure 7). At the end of the study period, VMT has gradually recovered to if not exceed pre-pandemic levels. In late June of 2021, the Total VMT is 75.8 million miles for Salt Lake County and 32.5

million miles for Utah County, which yield a 2.2% and 6.8% of increase compared with Total VMT of late February of 2020 respectively. Again, VMT increased faster and more for Utah County due to similar reasons. As for the truck VMT, it increased by more than 10% (4.6 million miles vs 5.2 million miles) for Salt Lake County. A possible reason is the significant growth of online shopping and on-demand during the pandemic(AASHTO, 2020; Christidis et al., 2021; Shamshiripour et al., 2020). Online shopping and on-demand delivery are increased during the crisis as a response to limitations in retailing, risk aversion, and social distancing. The growth of online shopping requires more trips of delivery trucks then in turn significantly increases the truck VMT.

(Insert "Figure 7. VMT versus Percentage of Fully Vaccinated People (Truck VMT is Scaled up by 10 Times for Better Illustration)" here)

In summary, the pandemic significantly impacts the traffic in Salt Lake County and Utah County in the State of Utah. At the earlier stage, traffic drops significantly due to the direct travel restrictions. Once the restrictions have been reduced, traffic has been gradually recovered while the recovering process may be impacted by the pandemic if it is severe. As the vaccinated population continuously growing, traffic of both counties has been fully recovered to the pre-pandemic level. The recovery is much faster than the forecast by Christidis et al.(2021), which states that vehicular traffic will return to the pre-pandemic level around the year 2025. The truck traffic even increased as a result of the growing online shopping activities.

Forecasting Model

Table 1 shows the specifications and hypermeters used in the GCN-LSTM model and the benchmarking LSTM. As stated earlier, due to the rapid change of pandemic and policy status, only the data of the later stage of the pandemic, i.e., after the rollout of vaccines, was selected to develop the forecasting model. Twenty weeks of data are used for training and four last weeks of data are used for testing. During the training, an early stopping technique was employed to prevent overfitting. It also should be noted that for GCN-LSTM, the data of the past two weeks were used to construct the direct input according to the model tuning. The turning process shows that adding data of previous timestamps into the knowledge graph improve the model performance, possibly due to some independent variables may have delayed impacts on the others. Therefore, $X_{t+1,g}$ is calculated as follows:

$$X_{t+1,g} = f_g\left(G_k; (X_{t-1}, X_t)\right) \tag{10}$$

However, for LSTM, the turning process indicates that adding data of previous timestamps may distort the memory since it does not have a structure that allows the interactions between independent variables. Thus, the $VMT_{t+1,l}$ is as follows:

$$VMT_{t+1,l} = f_l(X_{t-1}) \tag{11}$$

(Insert "Table 1. Model Configuration" here)

The GCN-LTSM is developed using Python programming language with the support of machine learning packages StellarGraph (Data61, 2018), Keras (Chollet, 2015), and TensorFlow (Abadi et al., 2016).

Table 2 shows the performance of GCN-LSTM and other benchmark models for different scenarios (2 counties × 2 vehicle types). It can be seen that GCN-LSTM obtains the best forecast performance for all four scenarios in terms of both evaluation metrics. On average, GCN-LSTM reduced RSME by 31.20% and MAPE by 31.48% compared with traditional LSTM models. Thus, incorporating knowledge regarding the interrelationships between explanatory factors significantly improves the model's prediction ability, which is also confirmed by previous studies (Y. Yuan et al., 2021; Zhu et al., 2020).

(Insert "Table 2. Model Performance" here)

To better understand the GCN-LSTM model, the prediction results of the model and the benchmarks on testing data are visualized (Figure 8). The results show that:

(1) Persistence models fail to forecast future VMTs due to the rapid change of the pandemic status. Take the Total VMT of Salt Lake County as an example. The Total VMT of the fourth week (74.5 million miles) increased by 5.4% (70.7 million miles) in three weeks. This also implies that long-term forecasting during the pandemic might not be valid.

(2) Both LSTM and GCN-LSTM are able to capture the general increasing trend of VMT. GCN-LSTM has smaller prediction errors for almost all prediction points. This re-confirms that human knowledge helps to improving model performance.

(3) However, there exists a sudden drop of VMT from the third week to the fourth. Both LSTM and GCN-LSTM models have poor capability in predicting this drop. LSTM failed to predict drops for all scenarios while GCN-LSTM only captured the drop when predicting the Truck VMT of Utah County. We speculate that the main cause is uncaptured randomness. Prediction models tend to make smoother predictions.

(Insert "Figure 8. Prediction Results of the Models (Up Left: Total VMT for Salt Lake County; Up Right: Total VMT for Utah County; Down Left: Truck VMT for Salt Lake County; Down Right: Truck VMT for Utah County)" here)

Conclusions and Discussion

The global COVID-19 pandemic has placed a great impact on the traffic across the U.S.

However, there are few studies investigating the pandemic's impact on vehicular traffic at the later stage of the pandemic. Therefore, this paper studies the change of freeways traffic patterns in two metropolitan counties, Salt Lake County and Utah County, in the State of Utah, during the pandemic. We conclude that:

(1) Vehicular traffic is decreased during the early stage of the pandemic due to the government restrictions and individuals' risk perception in traveling.
(2) With the relaxation of travel restriction and COVID vaccine, vehicular traffic has been recovered to if not exceed pre-pandemic levels.
(3) Truck traffic at the later stage of the pandemic is higher than the pre-pandemic level due to the growth of online shopping and on-demand delivery.

The summarized traffic patterns at the later stage of the pandemic could help transportation agencies better understand the impacts of COVID-19 on traffic mobility. These can also potentially support the long-term urban planning strategic goals during the post-pandemic periods. For example, relevant agencies need to prepare adequate facilities such as truck parking and rest facilities in response to increasing truck traffic.

A prediction model based on innovative GCN-LSTM is then developed to forecast traffic patterns in the near future. GCN-LSTM is able to capture the interrelations between the explanatory variables. The evaluation results show that the proposed prediction model has a highly desirable performance. The highest MAPE of the model among all four scenarios (2 counties × 2 vehicle types) is only 1.74% while the lowest is 0.38%. The model outperforms the benchmarking persistence models and LSTM models by -68.91% and -31.20% in terms of RSME. This reassures that incorporating human knowledge helps to improve model performance. The developed prediction model could be used by responsive agencies such as state DOTs to get prepared for the near-future traffic demand pattern.

Although discussing how the new “traffic normality” likes is not the main objective of this study, according to our conclusions, the vehicular traffic likely remains on the pre-pandemic level for a considerably long period. Firstly, governments are highly unlikely to place travel restrictions due to the high vaccination rate (As of July 21, 2021, 56.9% of the U.S. population received at least one dose of COVID-19 vaccine (Mathieu et al., 2021)) and huge damage to the economy (U.S. economy drops 32.9% during the “lock-down”(Horsley, 2020)). As the government restriction is the major reason leads to the drastic decrease of vehicular traffic, a “huge” drop is not expected in the near future. Secondly, other pandemic-related policies such as mask mandate did not significantly reduce the traffic. Although the U.S. Centers for Disease Control and Prevention changes mask guidance to recommend fully vaccinated people in certain areas of the country wearing masks indoors in public areas on July 27, 2021 (Centers for Disease Control and Prevention (CDC), 2021), such guidance and possible state/local policies on mask mandate will unlikely negatively impact the traffic. Thirdly, although data is not sufficient enough, we did see the traffic was continuously increasing in June 2021 despite the newly confirmed COVID-19 cases was also increasing (see Figure 6). This may imply that people’s risk perception on traveling during the pandemic has been changed. Therefore, unless the decrease changed conspicuously, people’s willingness to travel by car would highly unlikely be changed. In the future, we will continue monitoring the status of the pandemic and its impact on vehicular traffic. Additional jurisdictions and types of roadway facilities (such as local roads) may be added when data are available.

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Table 1. Model Configuration.

Model	GCN-LSTM	LSTM
Layer Configuration	GCN: (16,10)	N/A
	LSTM: (20, 20, 40, 40, 40, 40, 20, 20)	20
Learning Rate	0.001	0.01
Optimizer	Adam	Adam
Past Data Used	Two weeks	One week

Table 2. Model Performance.

County	Vehicle Type	Persistence		LSTM		GCN-LSTM	
		RSME (10^6 Miles)	MAPE	RSME (10^6 Miles)	MAPE	RSME (10^6 Miles)	MAPE
Salt Lake	Total	2.3979	2.98%	0.9440 (-60.63%)	1.25% (-58.08%)	**0.6374** (-73.42%)	**0.72%** (-75.90%)
	Truck	0.2480	4.53%	0.1449 (-41.56%)	2.19% (-51.57%)	**0.1006** (-59.45%)	**1.74%** (-61.67%)
Utah	Total	1.8757	3.09%	0.9327 (-50.28%)	1.76% (-42.91%)	**0.5943** (-68.32%)	**1.39%** (-55.01%)
	Truck	0.0689	1.93%	0.0236 (-65.76%)	0.64% (-66.62%)	**0.0176** (-74.46%)	**0.38%** (-80.43%)
Average Performance Improvement		Persistence / LSTM		Persistence / GCN-LSTM		LSTM / GCN-LSTM	
		RSME	MAPE	RSME	MAPE	RSME	MAPE
		-54.56%	-54.80%	-68.91%	-68.25%	**-31.20%**	**-31.48%**

Figure 1. Freeways and Weather Stations in the Salt Lake County and Utah County in the State of Utah

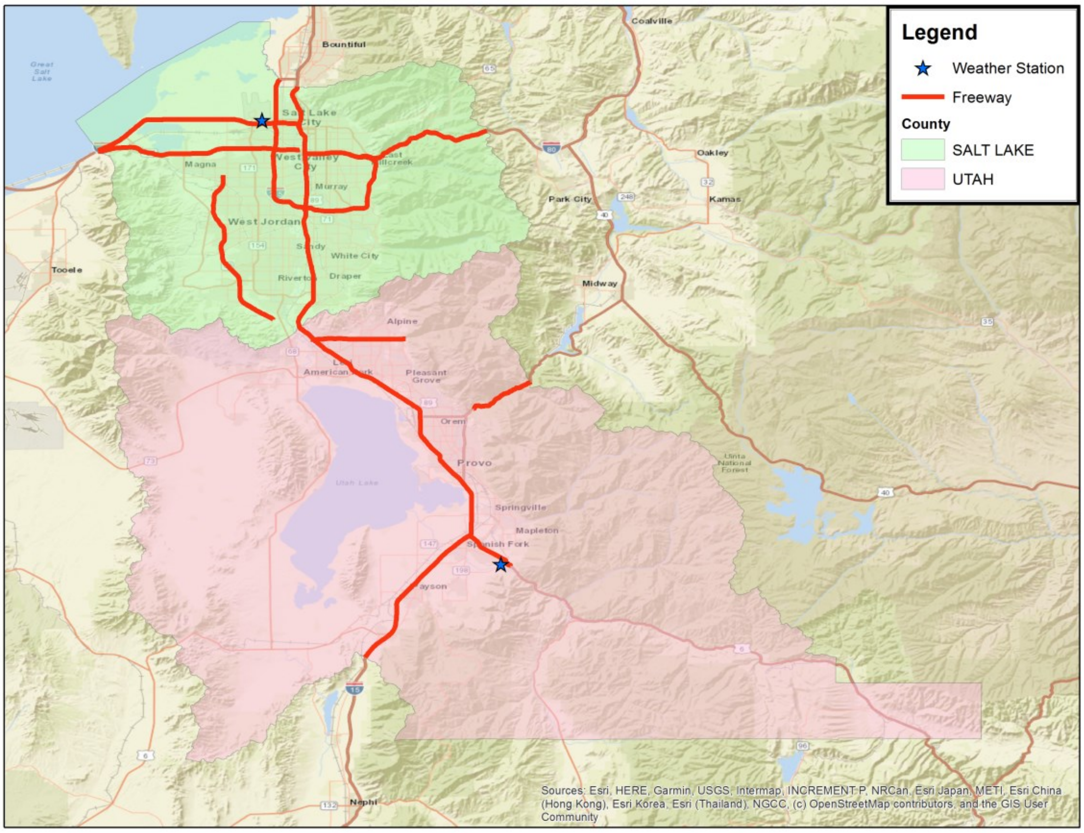

Figure 2. Milestones of Pandemic-Related Policies

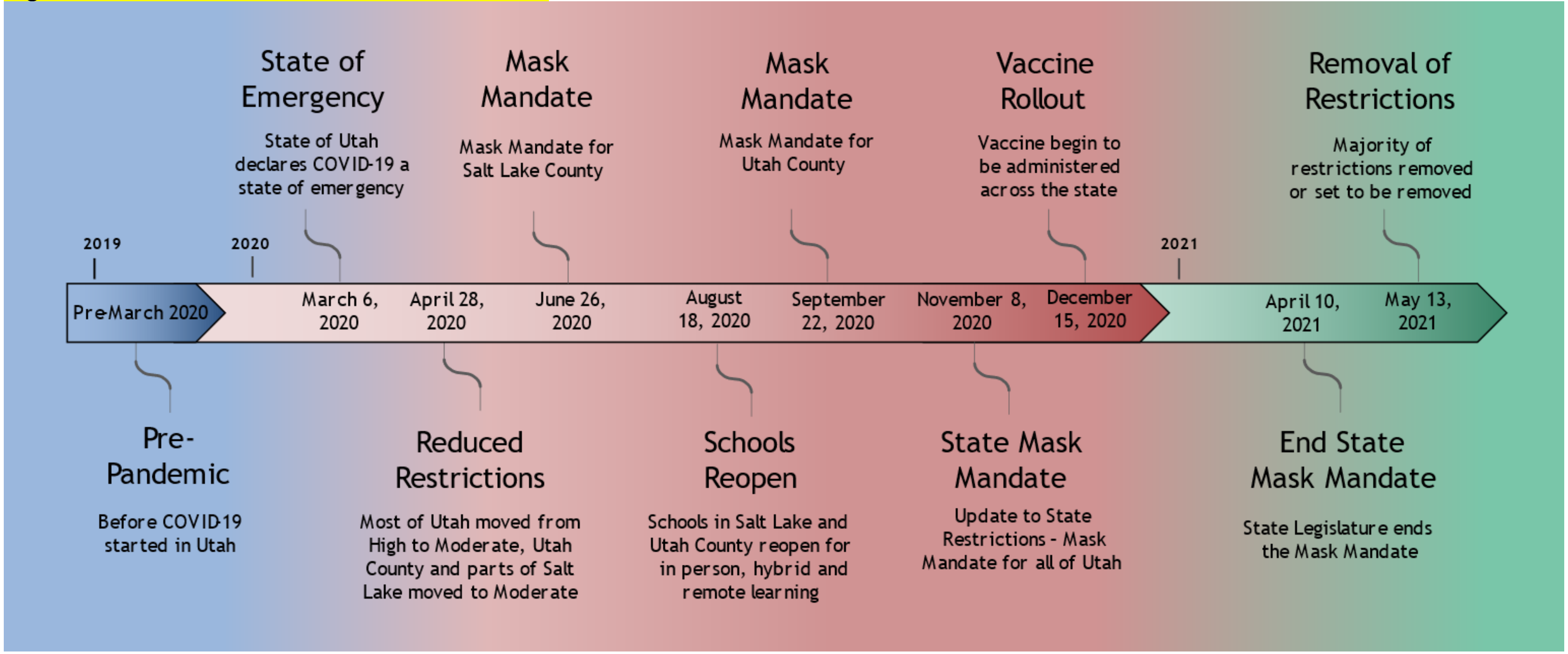

Figure 3. Knowledge Graph Depicting

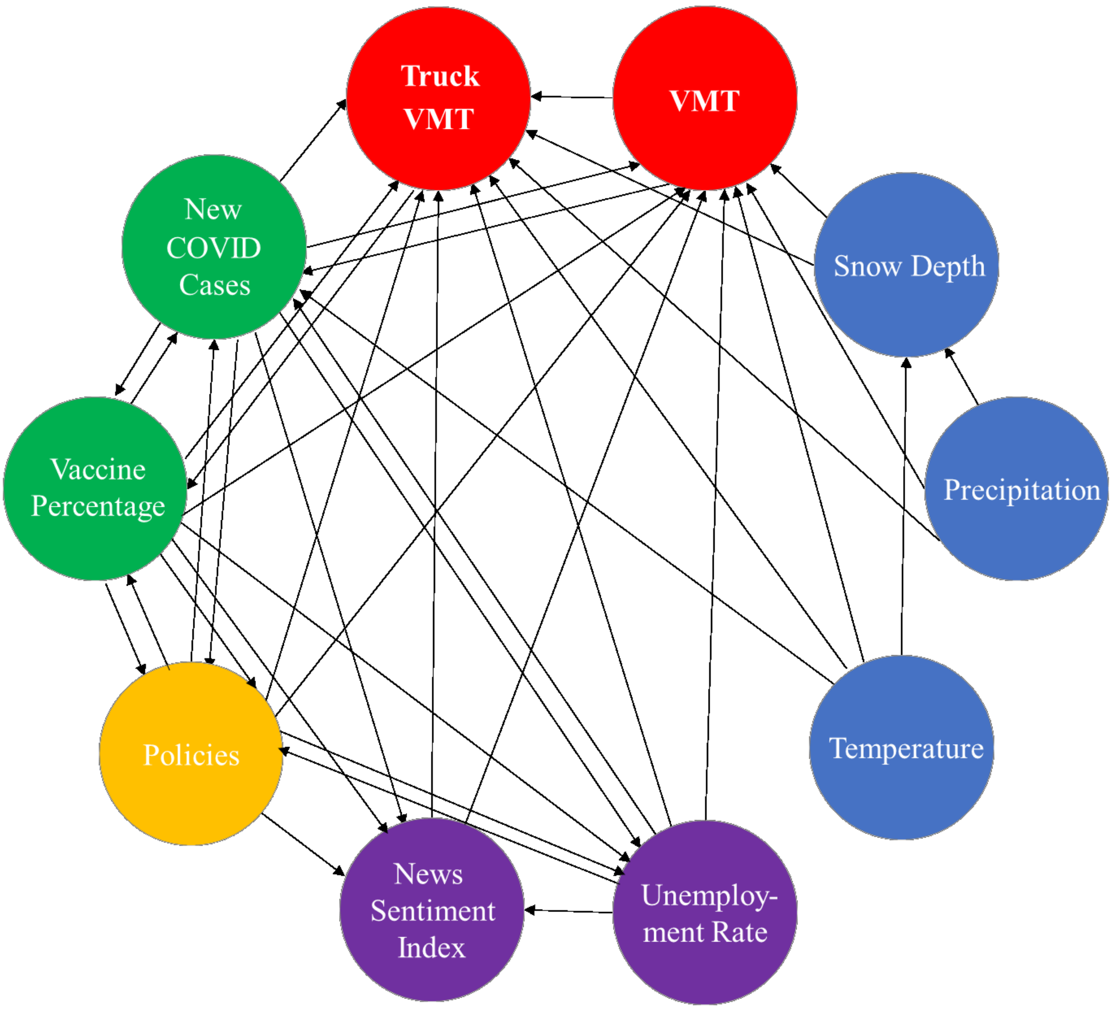

Figure 4. GCN-LSTM Model Structure

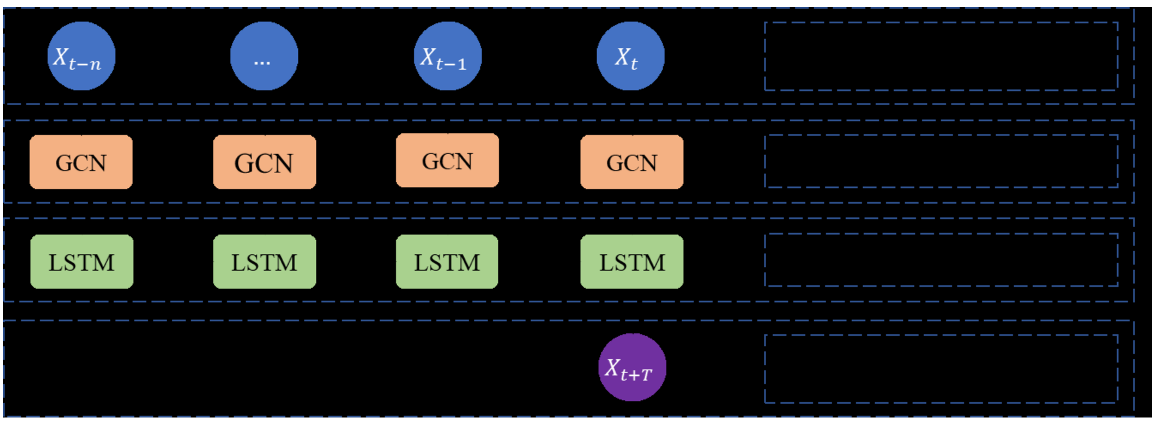

Figure 5. Illustration of a GCN Filter (Adopted from Zhao et al. (2020))

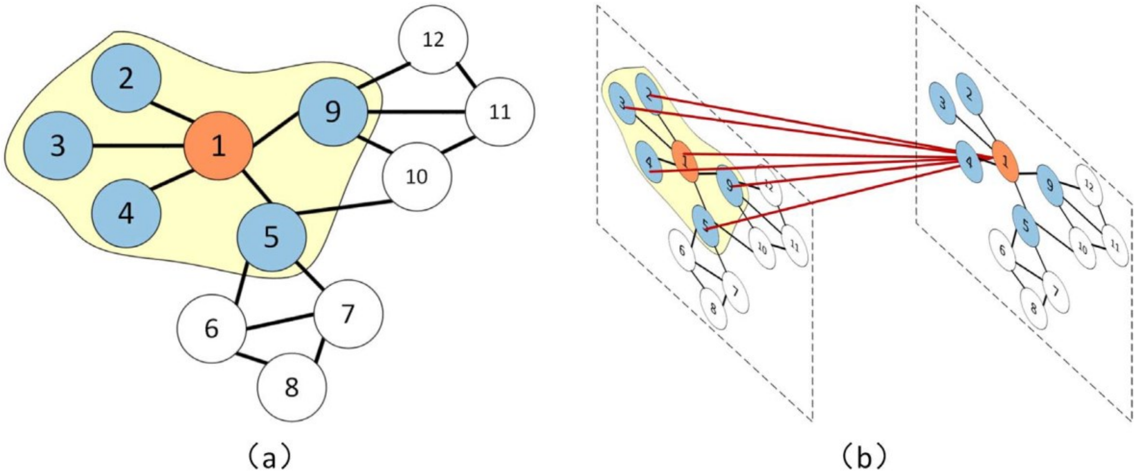

Figure 6. VMT versus Number of New COVID Cases (Truck VMT is scaled up by 10 Times for Better Illustration)

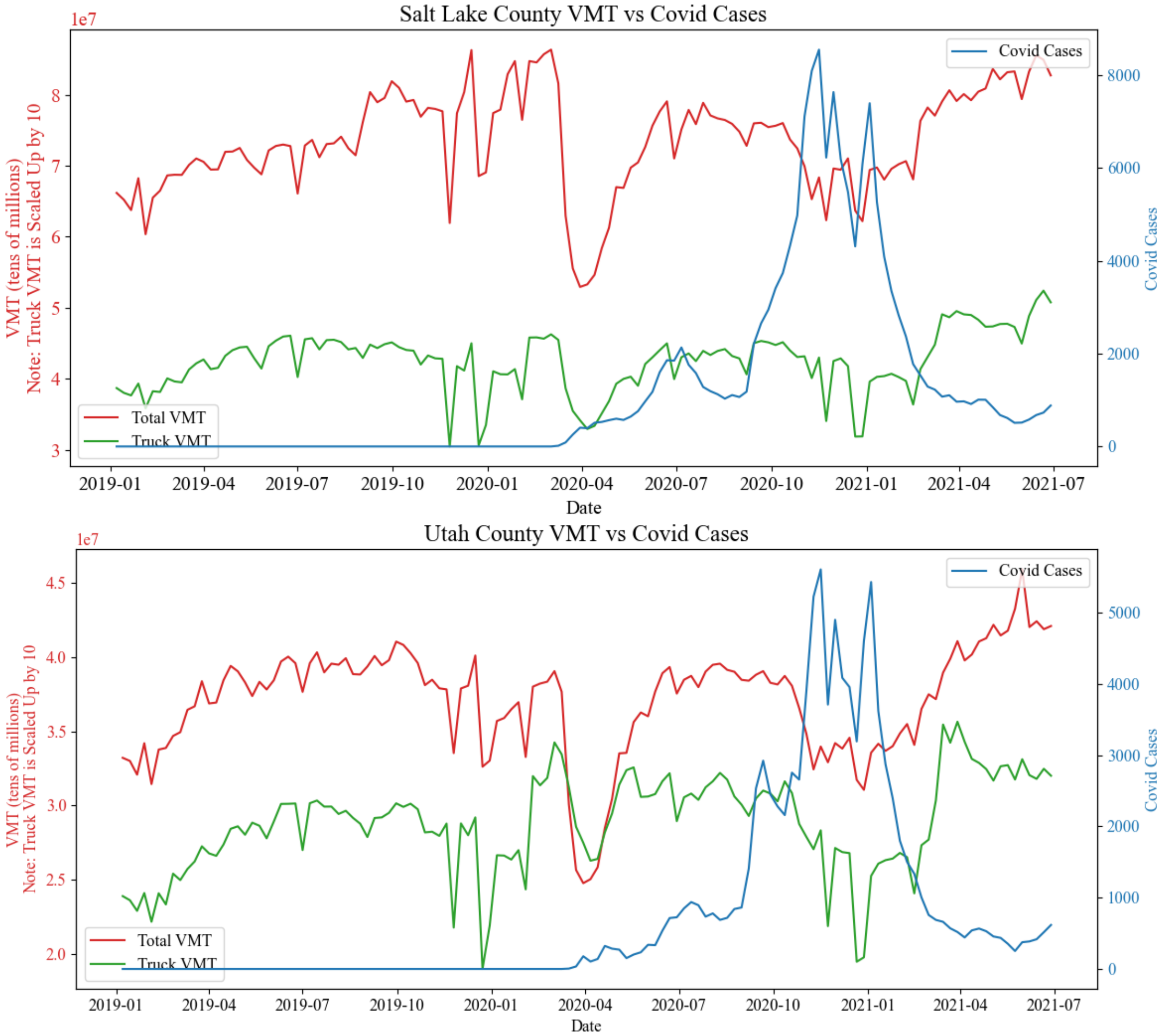

Figure 7. VMT versus Percentage of Fully Vaccinated People (Truck VMT is scaled up by 10 Times for Better Illustration)

Figure 8. Prediction Results of the Models (Up Left: Total VMT for Salt Lake County; Up Right: Total VMT for Utah County; Down Left: Truck VMT for Salt Lake County; Down Right: Truck VMT for Utah County)