Machine Learning for Predicting Traffic and Determining Road Capacity

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Abstract: This study proposes the use of machine learning techniques to predict traffic speed based on traffic flow and other road-related features, utilizing the California Freeway PeMS traffic dataset. Extensive research has been dedicated to the prediction of road speed; however, the primary challenge lies in accurately forecasting speed as a function of traffic flow. The learning methods compared include linear regression, K-nearest neighbors (KNN), decision trees, neural networks, and ensemble methods. The primary objective of this research is to develop a model capable of estimating road capacity, a crucial factor in designing an auction system for road usage. The findings reveal that the performance of each algorithm varies with the selection of features and the volume of data available. The results demonstrate that ensemble methods and KNN surpass other models in accuracy and consistency for predicting traffic speed. These models are then employed to create a flow-speed graph, which aids in determining road capacity.

1 INTRODUCTION

Transportation plays a vital role in modern society, facilitating travel, the movement of goods, and the connection of people and places. Intelligent Transport Systems (ITS) aim to enhance transportation by bringing together various elements such as vehicles, drivers, passengers, road operators, and managers in a way that interacts with the environment. The primary goals of ITS are to decrease the number of road fatalities and injuries, improve the efficiency of vehicles and traffic networks, and reduce pollution(Williams, 2008).

An important aspect of traffic assignment is estimating road capacity, defined as the maximum number of vehicles passing through a specific point within a time period, considering existing road, traffic, and control conditions (Reilly, 1997).

Traditionally, transportation capacity assessment has relied on static statistical models from a civil engineering perspective, which depend on factors such as the number of lanes, road width, the free flow speed, etc. Conversely, machine learning and deep learning models can assess road capacity based on real-time data, providing traffic management systems with a more precise understanding of network conditions, enhancing traffic control, and reducing overall travel time.

This study aims to construct machine learning and deep learning models that estimate road capacity based on current speed predictions. Our regression models account for factors that impact speed, such as traffic flow and other relevant features. Rather than projecting specific capacity thresholds, we seek to explore the interplay between flow, speed, and other variables, empowering road planners to determine optimal capacity for their desired speed. In the future these models will be combined with different optimization tools such as reinforcement learning and different search methods in order to control the traffic optimally.

The motivation for our research is to develop a comprehensive road network model that can capture the dynamics and capacity of individual roads. This model will serve as a foundation for future research, specifically focusing on the creation of an auction system for road entry. By leveraging the speed prediction models developed in this study and integrating them with the aforementioned optimization tools, the auction system will effectively assess the capacity of each road and facilitate the allocation of slots through various auction mechanisms. This integrated approach will contribute to improved road management and resource allocation in transportation systems.

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The paper begins with a literature review discussing the use of machine learning in traffic prediction and traditional capacity estimation methods. The methods chapter explains various approaches for speed prediction, followed by a results chapter discussing the obtained outcomes. Utilizing the models described, a capacity estimation model is developed and explained in the subsequent chapter. The paper concludes by highlighting potential future research directions in the field.

2 LITERATURE REVIEW

Road capacity refers to the number of vehicles that can pass a given point during a specific period under prevailing roadway, traffic and control conditions (Reilly, 1997) There are many factors that affect road capacity such as external conditions including the weather, visibility and road lighting. (Chung et al., 2006) Furthermore, road density (number of cars on the road) affects the capacity. Namely, if a road is congested, the number of cars that can enter the road without creating further congestion is much lower than the general capacity. (Chen, 2002)

The HCM (Highway Capacity Manual) (Reilly, 1997), a TRB (Transportation Research Board) publication in the US, provides guidelines and computational procedures for assessing highway facilities' capacity and quality of service. The free flow speed (FFS) is the theoretical speed of traffic when no vehicles are present, and can be calculated using HCM formulas that account for features such as lane width and ramp density (Reilly, 1997). The FFS is influenced by both intrinsic and environmental factors, such as road width and weather conditions (Kyte et al., 2000). Since the HCM propose a constant equation for calculating road capacity based on free flow speed, it fails to incorporate external and spatio-temporal factors.

In our research we used the California Freeway Performance Management System, a system that collects real-time data from all the highways in California. The data is collected by over 40,000 sensors spanning over 20,000 road segments. This database includes data such as the average speed, flow rate and occupancy for every 30 seconds on all the highways, and has calculated values such as the average delay on each of the roads (Chen, 2002). Many of the recent works conducted on traffic prediction have been done with data obtained from the PeMS (Tedjopurnomo et al., 2020).

Traditional time series techniques have been used for traffic speed and flow prediction. This include the ARIMA (Billings and Yang, 2006) (Lee and Fambro, 1999) and it's variants (SARIMA, ARIMAX, etc.) (Ghosh et al., 2007) and Kalman filtering(Kumar, 2017). Moreover, Machine Learning and Deep Learning have been used in many different transportation problems studies(Haghighat et al., 2020). Regression techniques such as linear regression and logistic regression were used for traffic flow prediction(Lonare and Ravi, 2020). Multi-variate regression has also been used for congestion prediction (Liu et al., 2020). Other models such as SVM have been used for traffic volume prediction (Mingheng et al., 2013) and decision trees have also been used for congestion prediction (Tamir et al., 2020).

With the recent developments in deep learning, there has been a lot of traffic flow and traffic speed prediction done using deep learning (Tamir et al., 2020). On top of the regular data used as input of a neural network, there are specific models that utilize the spatial and temporal dimensions of the data. Spatial models use deep learning frameworks such as CNN(Song et al., 2017) that use the geographical data in order to build the model. Temporal models employ deep learning frameworks such as RNN and LSTM(Tian et al., 2018) that make use of historic data in order to improve the prediction. There are hybrid models that combine both spatial and temporal data such as the CNN-LSTM hybrid model(Cao et al., 2020).

Graph Neural Networks (GNNs) are deep learning methods designed to perform inference on data described by graphs. GNNs are neural networks that can be directly applied to graphs, and provide an easy way to implement node-level, edge-level, and graph-level prediction tasks. GNNs do not only have the ability to learn using each of the segments features, but can also catch the connections between the different road segments using spatial data.

Extensive research has focused on predicting road speed, however the difference between most research and our research is that we are attempting to accurately forecast speed as a function of traffic flow, and utilizing this model for simulated data that we create for the capacity model.

The definition of road capacity is the maximum number of vehicles or amount of traffic flow that a roadway can accommodate effectively and efficiently within a given time period. In the review of the research conducted in this field, we found only one study (Huo et al., 2022) on capacity estimation using deep learning. The error function for the network was calculated by using the travel time as a function of the road capacity and the error value is the difference between the predicted travel time and the real travel time. The present study is different from the work conducted by Huo et al. (Huo et al., 2022) in that a precise quantification of the road capacity is not provided. Instead, we seek to understand the traffic flow in relation to velocity and leverages the advantages of spatio-temporal data, rendering it more dynamic in nature, which will allow more flexibility for the auction system.

3 MACHINE LEARNING METHODS FOR SPEED PREDICTION

The goal of the model is to accurately predict the speed of the leftmost lane for each road segment as a function of the different input features chosen. To accomplish this, we employed various machine learning algorithms, namely decision trees, random forest, k-Nearest Neighbors (k-NN) regressor, neural networks , and linear regression. By applying these algorithms, we aimed to capture the underlying patterns and relationships within the data and leverage them for accurate speed prediction.

Our research employs two distinct methodologies for the analysis. The first methodology involves constructing machine learning models that utilize data from all segments collectively. In contrast, the second methodology focuses on developing individual machine learning models for each segment. By exploring these two approaches, we aim to investigate the comparative effectiveness and performance of both centralized and decentralized modeling strategies in capturing the complexities of the data.

In the first methodology, we gathered traffic data from multiple segments and used data from all the segments to help with the prediction (the segment id was not part of the input for the model). This holistic approach allowed us to capture the collective traffic dynamics and identify broader trends across the road network. Utilizing the aforementioned algorithms, we trained models on this dataset to predict the speed on the roads.

In the second methodology, we focused on the individual segment level, where we isolated the data from each segment to predict the speed specific to that segment. This approach provided insights into the localized factors influencing road speed, allowing for more targeted predictions. Similar to the previous methodology, we employed the decision trees, random forest, k-NN regressor, SVR, and linear regression algorithms to build segment-specific models.

To capture the temporal aspect, we introduced lag features that integrate time-series information. Specifically, these lag features were constructed by considering the flow and speed values from the previous three time slots, encompassing both the entire road segment and specifically the first lane. Furthermore, we incorporated the hour of travel as an additional feature, which was represented as an integer between 0 and 23.

In order to investigate the influence of different input features on our predictive model, we conducted a series of experiments utilizing various combinations of inputs. Our objective was to systematically vary the input variables and evaluate whether specific attributes resulted in improved outcomes, meaning better MSE and R2 and also models that generalize well to unseen data. We employed three distinct sets of input variables for this purpose.

The first set focused on road-specific information, encompassing factors such as the number of lanes, road type obtained from the Pems database, and flow data. The flow data consisted of the current flow, as well as lag features representing flow from the previous three time slots.

For the second set, we expanded the feature space by including the lag features for road speed from the previous three time slots. This addition allowed us to capture temporal dependencies in the speed data.

In the third set, we introduced the free flow speed to the first input set. This augmentation enhanced the speed-related information without the need to incorporate the most recent history of speed. There was no reason to use this input set for the second methodology since the free flow speed would be equal for all of the data because the learning is on each segment individually.

We had a specific motivation for conducting an experiment using an input set solely comprised of flow lag features, excluding the speed features. The rationale behind this decision was to evaluate whether our model could achieve satisfactory performance by solely relying on flow values. By doing so, we aimed to develop a capacity model that could accurately predict optimal capacity without relying on knowledge of recent speed variations on the road. This approach would allow us to create a model based on the flow data and other constant features, providing us with the capability to estimate optimal capacity independently of recent speed information. Utilizing speed methods can be useful for a live system with real data, and the values for the MSE and R2 can also set a benchmark for the accuracy that can be acheived.

3.1 Learning Methods

Linear Regression. A statistical method for modeling the relationship between a dependent variable and one or more independent variables. It assumes a linear relationship between the variables and aims to find the best-fit line that represents the data.

K-nearest Neighbors (KNN). A non-parametric machine learning algorithm used for classification or regression. It works by finding the K nearest data points to a given query point and using their labels/values to make a prediction.

Neural Network. A type of machine learning algorithm modeled after the structure and function of the human brain. It consists of layers of interconnected nodes (neurons) that process information and learn from data through a process called backpropagation.

Decision Trees. A machine learning algorithm that uses a tree-like structure to model decisions and their possible consequences. Each node in the tree represents a decision based on a feature, and each branch represents the possible outcomes based on the decision.

Random Forest. A type of ensemble machine learning algorithm that combines multiple decision trees to improve prediction accuracy and reduce overfitting. It works by building multiple decision trees on random subsets of the data and aggregating their predictions.

3.2 The Data

The research was carried out using data from the California Freeway PeMS (Performance Management System), a system that collects real-time data from all the highways in California. Over 40,000 sensors spanning over 20,000 road segments collect the data which include the average speed, the flow rate and the occupancy for every 30 seconds on each of the road segments, as well as calculated values such as average delays (Chen, 2002). The data used in our basic model was obtained from District 3 in California and spanned the whole of the month of September 2022, and the segments in the district can be seen in Figure 1. Our dataset comprises 12 million observations, and we used a 75:25 train-test split after eliminating some of the data as part of the pre-processing stage.

4 RESULTS

In this section, we want to discuss the results of the different models built and how we can use them for capacity models. We measured the results of the models using the value of the mean squared error (MSE) and the R2 score.

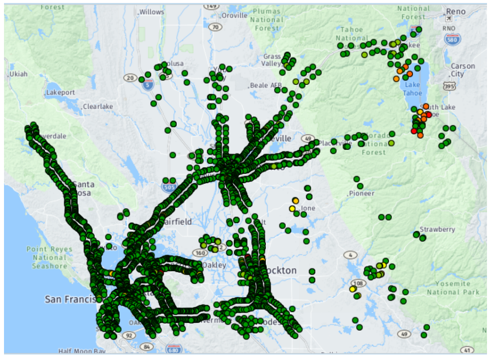

Figure 1: PeMS District 3 segments.

The first three tables are the tables that utilized the first methodology, where the models learn from all the segment's data together. The results for the first input set, the input set that includes the speed lag features can be seen in table 1, the results for the second input set - the input set with flow features and without any speed related features can be seen in table 2 and the results for the third set, the set that includes the ffs as the speed related feature can be seen in table 3.

Table 1: First methodology, first input set (speed lag features).

Regression Scores - first input set		
Model	MSE	R2
Decision Tree	3.59	0.937
Random Forest	2.98	0.948
Nearest Neighbors	3.43	0.940
Neural Network	3.20	0.944

Table 2: First methodology, second input set (no speed related features).

Regression Scores - second input set		
Model	MSE	R2
Decision Trees	39.38	0.315
Random Forest	36.71	0.362
Nearest Neighbors	35.19	0.352
Neural Network	42.64	0.275

Table 3: First methodology, third input set.

Regression Scores - third input set (ffs feature)		
Model	MSE	R2
Decision Tree	24.98	0.56
Random Forest	19.94	0.65
Nearest Neighbors	20.47	0.64
Neural Network	27.54	0.52

The results for the second methodology for speed prediction, predicting the speed using only data from each individual segment, are presented in the following tables. Table 4 shows the results for the first input set, the input set with speed related features and table 5 shows the results for the second input set, the input set without any speed related features.

Table 4: Second methodology, first input set.

Regression Scores -speed lag features				
Model	Mean MSE	Median MSE	Mean R2	Median R2
Linear Regression	3.71	2.31	0.71	0.80
Decision Trees	4.17	2.50	0.61	0.79
Random Forest	3.35	2.00	0.70	0.83
Nearest Neighbors	3.66	2.23	0.75	0.83
Neural Network	4.92	3.04	0.6	0.78

Table 5: Second methodology, second input set.

Regression Scores - no speed related features				
Model	Mean MSE	Median MSE	Mean R2	Median R2
Linear Regression	21.81	10.4	0.28	0.26
Decision Trees	16.23	7.98	0.34	0.38
Random Forest	13.19	6.52	0.46	0.48
Nearest Neighbors	13.29	6.76	0.45	0.47
Neural Network	4.92	3.04	0.6	0.78

The findings obtained indicate that in the context of individual segment-based predictions, basic machine learning techniques like linear regression exhibit comparable performance to more sophisticated algorithms such as random forest and neural network. This observation suggests that the data pertaining to each individual segment is not characterized by substantial complexity.

We experimented with different values for the amount of neighbors from which to learn in the KNN algorithm, here too there wasn't much difference between the results for different parameters. We experimented with different values for the depth of the tree, where the optimal value changed for each of the different feature input sets. Additionally, we experimented both with the maximum depth and number of estimators for the random forest algorithm. The MSE value for the different depths were pretty similar and varied for each of the different input sets.

Upon analyzing the outcomes of the second input set, the input set with no speed related features, it becomes evident that relying solely on the flow lag features does not suffice to generate a robust model. This limitation could be attributed to the insufficient availability of comprehensive data pertaining to each road's characteristics, necessitating the inclusion of speed lag features. The models may lack adequate temporal context when considering only the three most recent flow values. Incorporating additional time series features and utilizing specialized temporal models such as CNN and RNN could potentially enhance the model's performance by capturing more intricate temporal patterns.

Notably, the results obtained from the third input set demonstrate a substantial improvement in performance upon incorporating speed data, even though it does not encompass the most recent historical speed information. This finding underscores the significance of incorporating speed-related information, as it yields significant enhancements in model accuracy, despite not relying on the immediate speed history.

The first methodology that learns from all the segments collectively proves to perform as well as the second which just learns from each segment separately, this shows us that models can generalize pretty well over a road network given enough data and features, and the models generalize well for the whole of the road network.

5 THE CHALLENGE OF CAPACITY PREDICTION

According to the Highway Capacity Manual (HCM), the definition of road capacity is the maximum number of vehicles or amount of traffic flow that a roadway can accommodate effectively and efficiently within a given time period, taking into account factors such as lane width, number of lanes, geometric design, signal timings, and other operational characteristics (Reilly, 1997).

The capacity is calculated using the following formula:

Capacity = MSFE * PHF * N * fhv * fp (Reilly, 1997)

Where: PHF = peak-hour factor which represents the variation in traffic flow within an hour fHV = an adjustment factor for the presence of “heavy” vehicles fp = an adjustment factor to account for the fact that all drivers of the facility may not be commuters or regular users N = number of lanes in the given direction of flow MSFe = maximum possible flow rate we can have to still be at level of service e

The first four variables are variables that can't be changed by the road planner, and the last the MSFE is the maximum service flow rate that is required to

EXHIBIT 23-2. LOS CRITERIA FOR BASIC FREEWAY SEGMENTS

Criteria	LOS				
	A	B	C	D	E
FFS = 120 km/h					
Maximum density (pc/km/ln)	7	11	16	22	28
Minimum speed (km/h)	120.0	120.0	114.6	99.6	85.7
Maximum v/c	0.35	0.55	0.77	0.92	1.00
Maximum service flow rate (pc/h/ln)	840	1320	1840	2200	2400
FFS = 110 km/h					
Maximum density (pc/km/ln)	7	11	16	22	28
Minimum speed (km/h)	110.0	110.0	108.5	97.2	83.9
Maximum v/c	0.33	0.51	0.74	0.91	1.00
Maximum service flow rate (pc/h/ln)	770	1210	1740	2135	2350
FFS = 100 km/h					
Maximum density (pc/km/ln)	7	11	16	22	28
Minimum speed (km/h)	100.0	100.0	100.0	93.8	82.1
Maximum v/c	0.30	0.48	0.70	0.90	1.00
Maximum service flow rate (pc/h/ln)	700	1100	1600	2065	2300
FFS = 90 km/h					
Maximum density (pc/km/ln)	7	11	16	22	28
Minimum speed (km/h)	90.0	90.0	90.0	89.1	80.4
Maximum v/c	0.28	0.44	0.64	0.87	1.00
Maximum service flow rate (pc/h/ln)	630	990	1440	1955	2250

Figure 2: HCM capacity table (Reilly, 1997).

maintain a certain speed. The values for these can be found in the HCM table in figure 2:

With these guidelines the capacity doesn't depend on the amount of cars in the road or the previous speeds and flows observed on the road. Using machine learning algorithms can provide us with much more accurate values for this and allows a system to be dynamic and change the capacity according to the exact current road conditions. On top of this, the machine learning algorithm allows us to find optimize the capacity for each of the roads, and find the values of the speed and flow that allow for maximizing the distance traveled on the road which we defined as our utility function, but this could be expanded to other utility functions too.

For the sake of this research, we are going to define the road's capacity as the flow that produces the highest utility, where the utility function is the amount of kilometres covered on the road, which is the multiplication of the speed and flow. To estimate road capacity, we developed a procedure based on the top performing machine learning models built in the previous stage and used them to predict the speed under different conditions. We built these models based on both input sets - the first including road metadata and flow features and the second that includes speed features too, we did this with both methodologies used in the previous section - i.e using all segments data for prediction and prediction using only the individual segment.

To determine the optimal flow for each road, we adopted a two-stage approach. In the first stage, we created a list of optional flows and speeds for each road (depending on the input set), considering a maximum flow of the road as the maximum flow observed in the dataset for that road. Subsequently, we utilized the trained random forest model to predict the corresponding speeds for each of these flows. A minimum optional speed threshold was defined, and the flow that maximized the utility function, which is the product of flow and speed i.e the total distance traveled on the road, was selected as the optimal flow.

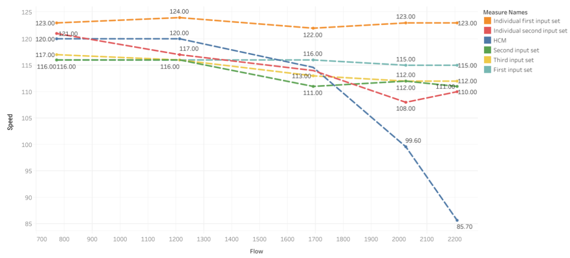

Figure 3: Flow to speed graph for road 313114, prediction using random forest with 5 different input sets and HCM.

We found the corresponding speeds for the different values for the maximum flow service rate that's shown in the HCM table in figure 2 using the different machine learning algorithms used in the previous chapters. Using the first input set - the set that includes the previous speeds proved to overfit to the speed features and these algorithms didn't generalize well to the hypothetical situations. Because of this, we tried to improve the second input set with other features that don't include the previous speed values. We added the free flow speed for each of the segments that was calculated by taking the mean speed between 00:00 and 01:00 every day. This improved the MSE to 25 and the R2 to 0.56, and in future work we want to improve this even further, so that we can produce a model that learns just from the flow and constant variables that define the road and make sure that we don't use the speed features.

In the following table we can see an example of a comparison between the capacity used by applying the HCM capacity equation and the random forest and KNN models using the 5 different models - 2 input sets for the individual based models and 3 for the generalized based models explained in the previous section. We have assumed the PHF is 0.92 (Tarko and Perez-Cartagena, 2005) and that no modifications need to be made for heavy vehicles and that all drivers are regular commuters. This has been done on a road with a FFS of 74mph and we used the HCM guidelines for 120 kmh which is almost exactly equivalent. The road we picked is road with the ID 313114. The results for the random forest models are presented in figure3 and the results for the KNN models are presented in figure 4.

Based on the observed outcomes, it is evident that the utilization of speed features in the models leads to overfitting to the particular road data, thereby hindering their ability to generalize effectively. Moreover, the graph depicts a consistent trend where all models fail to adequately capture traffic dynamics, particularly where the value of the flow is high. This inade-

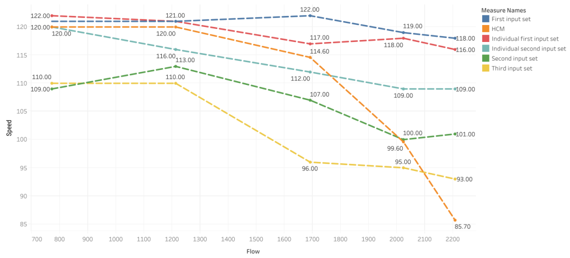

Figure 4: Flow to speed graph for road 313114, prediction using KNN with 5 different input sets and HCM.

quacy may arise from the limited availability of relevant data, high traffic data isn't as common as normal traffic data. To elucidate this phenomenon, we can invoke the well-known concept that correlation does not necessarily imply causation. In this context, the models that incorporate speed features excel in capturing correlation patterns but fall short in capturing the underlying causal relationships.

We can further discern that the K-nearest neighbors (KNN) model outperforms the random forest model in the right region of the graph. This superiority can be attributed to the KNN model's ability to learn from very similar examples, allowing it to effectively learn from rarer data instances, in contrast to the random forest model, which learns from the entirety of the data. In light of this, it becomes evident that the KNN model's performance advantage stems from its specific learning characteristics and its ability to leverage similar and rare data patterns. The advantage of the KNN is that it succeeds in learning well even when the value of the flow is high and it the model doesn't underfit. However, the compute time for the test set is very high and also we can observe that for the first methodology the model doesn't learn the base speed well enough.

6 CONCLUSIONS

In this study, we aimed to estimate road capacity using machine learning and deep learning models based on real-time data and speed predictions. Our regression models accounted for factors such as traffic flow and other relevant features that impact speed. Rather than projecting specific capacity thresholds, our models explored the interplay between flow, speed, and other variables, empowering road planners to determine optimal capacity for their desired speed. By leveraging these models in combination with optimization tools, we aimed to improve road management and resource allocation in transportation systems. Our research introduces specifically a speed prediction model using the flow data.

To construct our models, we employed various machine learning algorithms, including decision trees, random forest, k-Nearest Neighbors (k-NN) regressor, and linear regression. Through two distinct methodologies, we investigated the effectiveness of centralized and decentralized modeling strategies in capturing the complexities of traffic dynamics. Temporal dependencies were considered by incorporating lag features that integrated time-series information. We systematically varied the input variables to evaluate their influence on the predictive models, focusing on road-specific information, speed lag features, and the addition of free flow speed. The evaluation of our models was based on metrics such as Mean Squared Error (MSE) and R2 score.

Based on our findings, we concluded that machine learning and deep learning models, in conjunction with optimization tools, hold promise in accurately estimating road capacity. By considering the dynamics of individual roads and incorporating real-time data, our models provide insights into localized factors influencing road speed. This research contributes to the field of transportation systems by providing a comprehensive road network model and showcasing the potential of using machine learning for determining road capacity.

Future research endeavors are expected to significantly augment the existing model's predictive capabilities by integrating a more comprehensive range of external conditions. The inclusion of supplementary data sets, such as weather and spatio-temporal data, holds tremendous promise for further enhancing the model's performance. Combining ensemble methods using decision trees together with neural networks has showed improvements even with tabular data (Shwartz-Ziv and Armon, 2021) so building ensemble models could improve results even without adding anymore data. Moreover, incorporating the structural layout of the road network and the interdependence among roads by using spatial data and graph neural network (GNN) architecture can potentially elucidate the intricate connections between nodes in the graph.

Furthermore, to comprehend the underlying temporal structure, time series features will be integrated into the model's architecture. To capture the intricacies inherent in the data and enable the model to make precise predictions, the proposed research endeavors will utilize deep learning architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM). These architectures have demonstrated impressive capabilities in analyzing time series data, thereby enabling the model to extract relevant features and make accurate forecasts. By integrating these cutting-edge techniques into our model, we aim to enhance its predictive capabilities and offer valuable insights into transportation planning and management. Conversely, instead of using neural networks for the temporal structure, as shown in our current findings the random forest model performs well on time series, and this can be combined together with the GNN for the spatial structure as demonstrated in the following research (Ivanov and Prokhorenkova, 2021).

Future research will incorporate spatial-temporal models, aiming to encompass the entire network. Additionally, advanced optimization algorithms, such as genetic algorithms and simulated annealing, will be employed to determine the optimal capacity for the entire network dynamically at any given time. We plan on using advanced optimization techniques such as genetic algorithms and simulated annealing. After incorporating these advanced optimization algorithms, our future plan involves developing a simulator that accurately replicates real traffic data. This simulator will serve as a platform to evaluate and compare the performance of different optimization algorithms.

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