

Real Time Taxi Prediction

Submitted in partial fulfillment of the requirements for the degree of

Bachelor of Technology **In** **Computer Science and Engineering**

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June, 2021

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We hereby declare that the thesis entitled “**TAXI DEMAND PREDICTION**” submitted by us, for the award of the degree of *Bachelor of Technology in Computer Science and Engineering* to VIT is a record of bonafide work carried out by me under the supervision of **Prof. Krishnamoorthy A.**

I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

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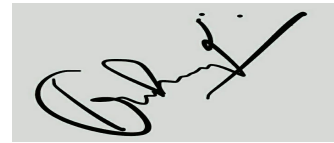
CERTIFICATE

This is to certify that the thesis entitled “**REAL TIME TAXI PREDICTION**” submitted by **SOURAV DEY (17BCE0019), ARUSHI DAS (17BCE0087) & SWETA KUMARI (17BCE2388), Vellore Institute of Technology, VIT**, for the award of the degree of *Bachelor of Technology in Computer Science and Engineering*, is a record of bonafide work carried out by him / her under my supervision during the period, 20.12.2020 to 07.06.2021, as per the VIT code of academic and research ethics.

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EXECUTIVE SUMMARY

Taxis are an important element of urban life. They are used to traveling to work, for pleasure, for solitude, and most importantly for the ease of having no pauses in between the pick-up and the end destination, as well as no other unidentified passengers to board or disembark. One of the most common questions that all taxi drivers have is where to look for a passenger. People are forced to wait for extended periods of time in risky conditions, lowering the taxi service's overall satisfaction rating, drivers are unsure of where to seek for the next fare after dropping off a passenger, and taxi drivers are hesitant to travel to a rather remote place for fear of not finding any customers and wasting time and fuel. If the demand for cabs can be foreseen, such problems can be avoided.

This knowledge may be utilized to help both new and experienced drivers meet up with the city's taxi demand more quickly. For example, taxi pick-up events near hotels may be utilized to learn about the areas that hotel guests frequently travel to in the morning. Hence, taxi demand prediction is an intelligent transportation technology to leverage digital footprint to uncover information that might aid in the improvement of public transportation. As a result, our objective is to be as certain as possible about the number of pickups in each region within a 10-minute frame. The 10-minute time frame was chosen because, in New York City, one mile may be covered in roughly 10 minutes if traffic is light.

Along with independent factors, our dataset comprises dependent or goal variables. We use independent variables to create models that predict dependent or target variables. Regression models are used to forecast the dependent variable if it is numeric. The models are evaluated using MSE as well as MAPE.

Clustering, XGBoost, Random Forest, Linear Regression, Simple Moving Average, Exponential Weighted Moving Average, and Weighted Moving Average are used in this study to compare and contrast charges and relapse models. The weighted motion average technique has the smallest loss with a MAPE of 12.957807. This method has a greater accuracy than other regression-based algorithms. Future research can include a comparison of other more modern, yet less sophisticated, algorithms.

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ABSTRACT

Urban areas are having an increase in population growth extensively and the need for transport is increasing. Number of available taxi drivers is beginning to become insufficient and we can experience this in our day to day lives. Taxis are sparsely available late at night which makes it dangerous for anyone to be around. People end up having to wait long periods of times under extreme conditions which decreases the taxi services over satisfaction rating, drivers are unaware on where to head after dropping of a passenger and look for the next fare, taxi drivers are unwilling to drive to a comparatively remote location in fears of not finding any fares there and worry about wasting time and fuel. Such cases can be solved if the demand of taxis can be predicted. Given a region, I want to be able to predict the demand so as to inform dispatch systems that can allocate taxis.

Keywords— predict taxi demand, random forest, clustering

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LIST OF ABBREVIATIONS

GPS: Global Positioning System

NN: Neural Network

TBATS: Trigonometric seasonality Box-Cox transformation ARIMA errors Trend

MAPE: Mean Absolute Percentage Error

MAE: Mean Absolute Error

MSE: Mean Squared Error

LSTM: Long Short-Term Memory

RNN: Recurrent Neural Network

MLP: Multi-Layer Protocol

NADE: Neural Autoregressive Distribution Estimation

1. INTRODUCTION

1.1. Theoretical Background:

One of the most crucial questions for all taxi drivers is where to find a passenger. The longer time a taxi driver spends seeking a new passenger, the more gasoline he uses and the fewer people he can pick up. Inexperienced taxi drivers frequently do not know where to pick up a new client because they are unfamiliar with taxi demand across time and space. The knowledge regarding upcoming taxi demand may be utilized to help both new and experienced drivers meet up with the city's taxi demand more quickly. Knowledge of taxi desire in a particular location may also be utilized to develop new enterprise prospects or new services. For example, taxi pick-up events near hotels may be utilized to learn about the areas that hotel guests frequently travel in the morning. To increase client satisfaction, the hotel might arrange a shuttle service to the route that passes that precise location. Many academics are investigating ways to leverage this digital footprint to uncover information that might aid in the improvement of the public transportation. One of these intelligent transportation technologies is taxi demand prediction. Demand patterns in areas with various functions are distinct. As a result, a single forecasting model may not be applicable to all situations.

1.2. Motivation

Taxis are an important element of urban life and are in large quantities. They are used to traveling to work, for pleasure, for solitude, and most importantly for the ease of having no pauses in between the pick-up and the end destination, as well as no other unidentified passengers to board or disembark. Many multibillion-dollar businesses have risen from the provision of such services to consumers via Internet apps, portals, or local services. An imbalance in the distribution of taxi drivers in the city is a major issue, particularly in well-established metropolitan regions where need for taxis is strong but supply is few. As a result, the following circumstances emerge: Taxi drivers are frequently unable to locate fares to serve and thus miss out on fare possibilities; taxi drivers are frequently too far away from the

fare, wasting time and fuel in the process; and clients are frequently forced to wait for long durations, either due to a lack of taxis or because the taxi is far enough away from their location. Customer satisfaction suffers as a result, and the cost of fuel and time rises. By assisting taxi drivers in determining when the next likely demand for their cab will be, the drivers will be able to proceed to the stated location, minimizing passenger wait times, lowering fuel costs, and enhancing customer satisfaction as well as assisting the driver with additional fares during the day . Taxi demand forecasting is difficult due to the numerous unconnected factors and the lack of a reliable source to collect them. Historical data may be utilized to obtain the necessary knowledge to aid in the forecasting of such requests.

1.3. Aim of the proposed Work:

The population of urban regions is rapidly growing, and the need for transportation is growing as well. The number of available taxi drivers is beginning to dwindle, and we are seeing this in our daily lives. Taxis are scarce late at night, making it risky for anybody to be around. People are forced to wait for extended periods of time in risky conditions, lowering the taxi service's overall satisfaction rating, drivers are unsure of where to seek for the next fare after dropping off a passenger, and taxi drivers are hesitant to travel to a rather remote place for fear of not finding any customers and wasting time and fuel. If the demand for cabs can be foreseen, such problems can be avoided. I'd like to be able to forecast demand in a certain region so that a dispatch system can distribute taxis.

1.4. Objectives of the proposed work

The model will be able to anticipate demand in real time. It must be deployable inside automobiles. In the following hour, drivers may choose to go to a place with higher demand. Drivers will be less inclined to switch to Uber/Lyft when their earnings increase. Taxi firms could be able to keep their leasing money for a long time. If firms keep a share of the fares, they might collaborate with drivers to devise a strategy for dispatching their taxis during the day in order to gain profit.

2. LITERATURE SURVEY

[1] The paper is divided into two sections by Kai Zhao, Denis Khryashchev, Juliana Freire, Claudio Silva, and Huy Vol. The first area is the discovery of the most extreme consistency, which is fundamentally characterized by the entropy of the taxi interest while considering both the irregularity and the worldly relationship. They have calculated maximum predictability values of Random Entropy, Shannon Entropy and Real Entropy and determined that Real Entropy has the maximum predictability value which uses the Lempel-Ziv estimator. The next step is to choose the best indication from the three options: Markov, Lempel-Ziv-Welch, and a neural organization indicator. When the Highest consistency value is low, the Neural Network indicator has much more significant exactness, but the Markov indicator is superior when the most extreme consistency esteem is high. The paper suggests that involving more factors like whether conditions will help the Neural Network perform better, but the Markov predictor is better in terms of efficiency as it does its computation at 0.003% of the NN. The maximum predictability they have reached is an average of 83%.

[2] This paper by Kiam Tian Seow, Nam Hai Dang, and Der-Horng Lee uses computerized taxicab allotment to reduce taxi demands. By relegating cabs to the quantity of mentioned administrations in a certain time period, it focuses on group customer loyalty rather than individual consumer loyalty. This means that once the dispatcher has gathered a number of taxi requests in a given time frame, it consequently dispatches all available and required taxis to those locations. The proposed architecture has two sections, first one is the taxi agent where it announces its availability, negotiates on behalf of the taxi driver once a request is open and informs the dispatcher whether it accepts or refuses the assignment. The second is the dispatcher where it updates the availability of taxis, inserts the records of various taxi requests in the queue and deletes the records of a taxi and a request if the said taxi has accepted said request. It implies that combining taxi requests based on the proximity of the taxi and its passengers before each dispatch cycle and dispatching taxicabs to locations with a high consistency of solicitations reduces client waiting time by 33.1 percent and taxi cruising time by 26.3 percent.

[3] This paper by Neema Davis, Gaurav Raina, and Krishna Jagannathan is based on a period arrangement model that assumes current and future interest have some relationship with prior interest in order to aid in anticipation. They aimed their work to Indian traffic since they realized that because it undergoes so many changes so fast, a single tied together model wouldn't suffice. They used a few models, including the Baseline model, which is primarily used to examine other time arrangement models, Linear Regression on-pattern and season to divide the data into seasons, Seasonal and Trend Decomposition utilizing Loess to achieve a fit by decaying the data into occasional and occasionally changed segments, TBATS model, which can handle a variety of irregularities, and Hole model, which can handle a variety of irregularities. They evaluated their model using the MAPE measure. In a 1 km² zone, they measured a 20% increase in outcomes and 89 percent accuracy.

[4] This paper by Der-Horng Lee and Ruey Long Cheu conducts its research on the existing taxi dispatch system and its effectiveness. It Highlights that the current dispatch system assigns the taxi the request and shows the shortest time possible without considering the traffic conditions. It proposes that when a request is made the closest taxi to it is assigned. Over half of the traveler's arrival time and regular trip distance are reduced as a result of this.

[5] This study by Felix A. Gers, Douglas Eck, and Jurgen Schmid Huber provides a wealth of information on the LSTM's capabilities and requirements. LSTM is an Auto-backward model, which means it can only access contributions from the current time step, as opposed to competitors who may observe a few progressive data sources and may also have direct access to earlier events. As a competitor, it uses the Mackey-Glass Chaotic Time Series. It demonstrates that because it does not consider any previous input, it ends up addressing a Markov state, and it also demonstrates that in order to work brilliantly in the stated problem, it necessitates a round support, which is difficult for RNN to produce. It implies that the LSTM is unable to capture portions of turbulent behavior and, as a result, calibrates into basic wavering of every arrangement and is unable to properly follow the sign. It is also suggested that the LSTM be used in a cross breed method with MLP, in which the MLP prepares the loads, freezes them, and then uses the LSTM to reduce errors. The primary goal of this paper is to improve the efficiency of taxi dispatch systems by anticipating the spatial transportation of taxi passengers for a short time

frame skyline and then utilizing three different time arrangement determining procedures in particular: time changing with a weighted segment Poisson model, time-shifting Poisson model, and ARIMA model (which was initially a period differing Poisson model however had loads added to it to more readily adjust to vacillations in taxi interest at a stand). It then integrates all of these techniques in a Sliding-Windows Ensemble Framework, which produces the best model out of all of the separate techniques with the least amount of error esteem, as measured by sMAPE.

[6] The pre-planning options that are available are the focus of this work by Luis Moreira-Matias, Joo Gama, Michel Ferreira, and Joo Mendes Moreira. It emphasizes the pre-processing phases of Cleaning the data, Integration the data, Transformation of data, Data Reduction, and Data Discretion. These steps are going to be used to highlight specific keywords on a Twitter feed to best be able to do a review analysis on smartphones in the market. It will structure the tweet using a data frame and then apply these pre-processing techniques to gain vital keywords to know which features are relevant in which new phone and help the companies figure out what relevant features to add into its next model of smartphones. Although this is more complex than required in my paper, it gives great insight into the need to pre-process the data.

[7] This paper by Alexandre de Brébisson¹, Étienne Simon², and Yoshua Bengio researchers employed models, multilayer perceptron's, and bidirectional recurrent neural networks. Their purpose is to use a variable-length sequence to anticipate the length of a fixed-length output. They used a dataset that includes all 442 cabs' full trajectories over the course of a year in Porto, Portugal. A cab ride is represented by each of the 1.7 million records in the training dataset. Their neural network approach for predicting a taxi's destination is totally automated.

[8] Jun Xu, Rouhollah Rahmatizadeh, and Damla Turgut, IEEE Members, have published a work. In this paper, we used the grouping learning methodology to forecast future taxi demand in each city section, which uses late interest and other relevant data. They were given the LSTM, or Long Short-Term Method, learning approach in order to keep the important information safe for later. They utilized a taxi dataset from New York City to divide the city into several regions and

to anticipate requests in each. As seen by the results, their method outperformed alternative expectation approaches like feed-forward neural networks.

[9] Vivek Agarwal, Department of Computer Engineering, Smt. Kashibai Navale College of Engineering, 'Smash Darshan' bldg. 46/D, Aundh Road, Pune - 20 has focused on highlighting the information pre-handling steps, improving the pre-preparing steps, and expanding exactness by sifting through the less important tweets and thinking about the more fitting and certifiable tweets. The producers might be offered a portioned and specific survey of the several features related to their gadget using the concept of classified audit investigation. This allows them to examine the merits and faults of a variety of highlights in greater detail. Preparing has been done on a variety of phones, including the iPhone, OnePlus Two, and Samsung Galaxy S6.

[10] This paper by Ilya Sutskever, Oriol Vinyals and Quoc V. Le explores the drawbacks of RNN and how LSTM can be modified and used for a translation program of English to French. It compares the unoptimized LSTM network with a mature SMT model and concludes that LSTM does much better. It shows the working of the LSTM and how it deals with estimating the conditional probability and adding deep layers and multiple layers of LSTM network and splitting the work of input sequences and output sequences amongst different LSTM networks. It also found that reversing the order of words somehow increases the efficiency of the network. Although they do not know exactly how it happened, they believe that reversing the order creates several short term dependencies and makes the learning of the model network easier. It also shows that LSTM has no problem in translating long sentences despite its limited memory.

[11] This paper by Fei Miao, Shan Lin, Sirajum Munir, John A. Stankovic, Hua Huang, Desheng Zhang, Tian He, and George J. Pappas aims to reduce taxi idle time as well as the proportion of interest and supply errors. It has two sections where first it predicts and optimizes the future demand and the next design a framework for dispatching taxis. They use an RHC framework which although I am unable to fully understand, it uses information to update itself of the idle and occupied taxis for every time slot and tries to dispatch taxis based on demand. It also considers variables like any disruptive events that make the demand uncertain. It combines the

ability to predict interest based on verified data and current constant data that is updated on a regular basis. It achieves a 52% reduction in idle time distance of taxis and reduces the demand to supply ratio error by 45%

[12] Desheng Zhang, Tian He, Shan Lin, Sirajum Munir, and John A. Stankovic present an incredibly perplexing framework for reducing cab inactivity and decreasing the percentage of organic market miscalculation in this research. It sets out to create a Dmodel, and a dispatch system which can help achieve that. They infer that collecting historical demand alone isn't enough and to increase accuracy, the real time information also needs to be considered. This can be done through roving sensor technology, although its more about the cab, the sensor can operate in two phases that is one before the taxi is empty and the one after hence detecting if the taxi has a passenger or not, since passenger pick up time is a very important data. It outlines a framework that is divided into 3 sections, first is the roving sensor network, where the historical data and real time data are combines, with passenger pickup times. The next stage is the model generation which based on the collected data creates a Dmodel, which will use Markov chain to model passenger counts and will output total passenger count on a very fine level. The next is the model utilization which proposes a dispatching system. This Model achieves 83% inference accuracy in demand which it says is highly dependent on both location and time.

[13] Estimation of Neural Autoregressive Distributions Hugo Larochelle, Benigno Uria This study combines the probability item rule with a weight sharing mechanism inspired by forced Boltzmann machines to construct a controllable and generalizable assessor. They presented the deep NADE models, which may be prepared to be skeptical of the autoregressive item rule disintegration demanding information measures. They also explain how to take advantage of the topological structure of pixels in images by using a deep convolutional engineering for NADE and applying it to common images using convolutional and LSTM covered up units.

[14] This Chen, Y., Li, O., Sun, Y. and Li, F report claims that the usable information stream characterisation application demands cannot be met using customary information arrangement computation due to the increasing amount and dimension of the information. They offer a group order computation based on a characteristic decline and a sliding window in which the concept

and clamor in the information streams are managed. The way to estimate quality reductions depending on unfortunate sets is used to reduce the information dimensionality and increase the range of declining yields in the methods used for information sharing. A two-stage concept of floats discovery methodology and a three-stage sliding window control system are used to aid calculates the productivity of both commotion and concept floats. The characterisation precision is substantially enhanced by revising the baseline classifiers and their non-linear loads. Tests of actual and contrived data sets reveal that both the computational accuracy, memory consumption and time productivity of the calculation are achieved.

[15] R. K. Balan, K. X. Nguyen, and L. Jiang (June 2011). In the Proceedings of the 9th International Conference on Mobile Frameworks, Applications, and Services (pp. 99-112). The authors of this study describe the design, testing, implementation, and operational setup of a continuous excursion data platform that informs visitors on the predicted passage and duration of their taxi journey. This framework was created in collaboration with a Singapore taxi company that employs over 15,000 taxis. They look at the overall framework engineering before going into the expert calculations that were used to create the forecasts, which were based on as much as 21 months of documented data, which comprised around 250 million paid taxi journeys. The developers go on to explain the many modifications (such as district sizes, history length, and information mining approaches) and precision evaluations (such as courses and climate) they accomplished to boost both runtime productivity and accuracy rate. With a mean charge error of under 1 SGD (about 0.76 US dollars) and a mean length error of under 3 minutes, this large-scale evaluation demonstrates that their methodology is reliable. It can also handle hundreds to millions of requests per second indefinitely. Finally, they discuss the activities they learned throughout the deployment of this device into a real environment.

[16] The authors of this paper, I. Markou, F. Rodrigues, and F. C. Pereira, have recently entered the era of massive information for transportation. Most contemporary traffic flow expectation tactics mostly focus on identifying dull versatility patterns with constant/routine behavior, as well as utilizing temporary relationships with continuous perception designs. However, while attempting to enhance predicting execution, useful information that is typically accessible as unstructured data is usually overlooked. The authors of this study investigate the use of AI

processes to link time-arrangement information and text-based information in order to develop a prediction model that can continually capture predicted distressing events of the studied transportation framework. They show that using publicly available taxi data from New York, the suggested methods may dramatically reduce figure blunder. If we just consider occasion cycles, the last MAE of their estimations is reduced by about 57 percent and 19.5 percent for a three-month testing cycle, respectively.

[17] The authors of this study, J. Ma, J. Chan, J. Ristanoski, G. Rajasegarar, S. Rajasegarar, and C. Leckie, believe that present methodologies in the field of transportation trip time forecasting have two important limitations. To begin with, transportation trip times in today's metropolitan settings might be difficult to predict accurately due to more complicated continuous traffic conditions and a lack of consistent information. Second, multiple factors influence transportation duration and journey times, resulting in a variety of patterns; nevertheless, little research has been done on how to isolate travel and abiding regions and create autonomous models for each. They then developed a new section-based technique for predicting transportation trip times, which connects components of ongoing taxi and transportation datasets to organically break transportation routes into abiding and journey pieces. Two models are meant to forecast them separately by adding distinct affect traffic elements. They tested their method in June 2017 in Xi'an, China, using real-world direction data. When compared to existing methodologies, the exploratory results suggest that their technique enhances the accuracy of transportation journey time forecasting, especially under atypical traffic situations.

[18] The authors of this paper, S. Ishiguro, S. Kawasaki, and Y. Fukazawa, suggest a future taxi request anticipation estimate based on steady populace information derived from cell organizations. The influence of continuous population information on the exactness of taxi request expectation was tested using stacked denoising autoencoders. According to the results of an unconnected investigation done thus, the root mean squared expectation blunder of the proposed computation was 1.370 when continuing populace information was included, compared to 1.513 when populace information was not used. Furthermore, they conducted a field test. They promote the world's first online true test, a continuing forecast approach based on continuous population data. In the preliminary round, 26 drivers put their interest-determination strategy to

the test. Overall, compared to drivers who did not use the framework, there was a 3.9 percent increase in transactions.

[19] The authors of this study, L. Moreira-Matias, J. Gama, M. Ferreira, J. Mendes-Moreira, L. Damas, L. Moreira-Matias, J. Gama, J. Ferreira, M. Ferreira, M. Ferreira, M. Ferreira, M. Ferreira, M. Ferreira, M. Ferreira, M. Ferreira, M. Ferreira, M. Ferreira, M. Ferreira, Creators have been investigating the information provided by each car in order to provide dynamic with continuous data. In this research, we offer an approach for using a learning model based on recorded GPS data in a continuous situation. They must foresee the spatiotemporal appropriation of taxi-traveler traffic in a short time frame skyline. They accomplished it by adding learning requirements to the perceptron, a popular online calculator. The finds were promising: we had the opportunity of putting together a good show for the next conjecture in a short amount of time.

3. OVERVIEW OF THE PROPOSED SYSTEM

3.1. Proposed System

Objectives:

- We'll most likely estimate the number of pickups for each region in a 10-minute interval as precisely as possible. The entire city of New York will be divided into regions. The 10-minute time frame was chosen because, in New York City, one mile may be covered in roughly 10 minutes if traffic is light.

Constraints:

- **Latency:** In view of the present place and time of a cabbie, each one herself wants to be remarkably quick in its domain and neighboring countries. A medium postponement is necessary thereafter.
- **Interpretability:** The cab driver is unconcerned about the interpretability of the result as long as it yields a reasonable figure. The person is unconcerned about why he or she is getting this result. As a result, there is no need to worry about interpretability.
- **Relative Errors:** The Mean Absolute Percentage Error is the overall blunder we'll look into. If the extended pickups for a particular site are 100 and the actual pickups are 102, the rate blunder is 2% and the ultimate blunder is 2. More than the extreme incorrectness, the rate error will pique the taxi driver's curiosity. If we assume that prolonged pickups in a certain zone cost \$250 and that the cab driver is aware that the average error rate is 10%, the predicted result will be in the range of 225 to 275, which is crucial.

3.1.1. Features:

Below is a list of feature templates we use to extract features from each data point:

Field Name	Description
VendorID	A code that identifies the TPEP provider who created the record. 1. CM Technologies 2. VeriFone Inc.
tpep_pickup_datetime	The date & time when the meter was turned on.
tpep_dropoff_datetime	The date & time when the meter was turned off.
Passenger_count	The number of passengers; value entered by the driver.
Trip_distance	Total trip distance in miles reported by the taximeter.
Pickup_longitude	Longitude where meter was started.

Table 1. Features of templates of data sets

Pickup_latitude	Latitude where meter was started.
RateCodeID	The final rate code in effect: 1. Standard rate 2. JFK 3. Newark 4. Nassau or Westchester 5. Negotiated fare 6. Group ride
Store_and_fwd_flag	This flag indicates whether the trip record was held in vehicle memory before sending it to the vendor, aka "store and forward," because the vehicle did not have a connection to the server. Y= store and forward trip N= not a store and forward trip
Dropoff_longitude	Longitude where the meter was stopped.
Dropoff_latitude	Latitude where the meter was stopped.
Payment_type	A numeric code signifying how the passenger paid for the trip. 1. Credit card 2. Cash 3. No charge 4. Dispute 5. Unknown 6. Voided trip
Fare_amount	The time-and-distance fare calculated by the meter.
Extra	Miscellaneous extras and surcharges. Currently, this only includes the \$0.50 and \$1 rush hour and overnight charges.
MTA_tax	0.50 MTA tax that is automatically triggered based on the metered rate in use.
Improvement_surcharge	0.30 improvement surcharge assessed trips at the flag drop. The improvement surcharge began being levied in 2015.
Tip_amount	This field is automatically populated for credit card tips. Cash tips are not included.
Tolls_amount	Total amount of all tolls paid on the trip.
Total_amount	The total amount charged to passengers. Does not include cash tips.

3.1.2. Evaluation:

To examine the exhibition of our model, we separated the data into a preparation set (80% of the informative index) and a testing set (20% of the informative collection). To evaluate the presentation of our concept, the preparatory models are totally placed sequentially before the testing models. This arrangement resembles the problem of predicting future taxi pickup numbers based on reliable data. We used MSE to test our hypothesis since it encourages consistency and penalizes numbers that differ significantly from the actual number of pickups. Any crucial error in gauging taxi interest for a certain tpep provider might be expensive from the perspective of a taxi dispatcher. Consider deploying 600 taxicabs to a tpep pickup region when only 400 people are needed. This misallocation results in a large number of unutilized taxis crammed into a small area, therefore it should be rejected more severely than dispatching 6 taxicabs to a zone that only requires 4, or, in any case, dispatching 6 taxicabs to 100 different zones, each requiring just 4 taxicabs. Critical misallocations are punished the greatest by MSE, which best reflects the correctness of our models' predictions.

When comparing the outcomes of our various models, we use the MAPE esteem (coefficient of assurance) to determine how effectively the models react to changes in the informative index.

	Model	MAPE(%)	MSE
0	Simple Moving Average Ratios	19.582447	1177.280010
1	Simple Moving Average Predictions	13.426683	311.275954
2	Weighted Moving Average Ratios	19.162557	1072.040084
3	Weighted Moving Average Predictions	13.163834	293.489068
4	Exponential Weighted Moving Average Ratios	21.776898	1817.878181
5	Exponential Weighted Moving Average Predictions	16.235122	436.496180

Table 2: Models provide a comparison analysis of the informational index's change.

3.2. System Architecture Design

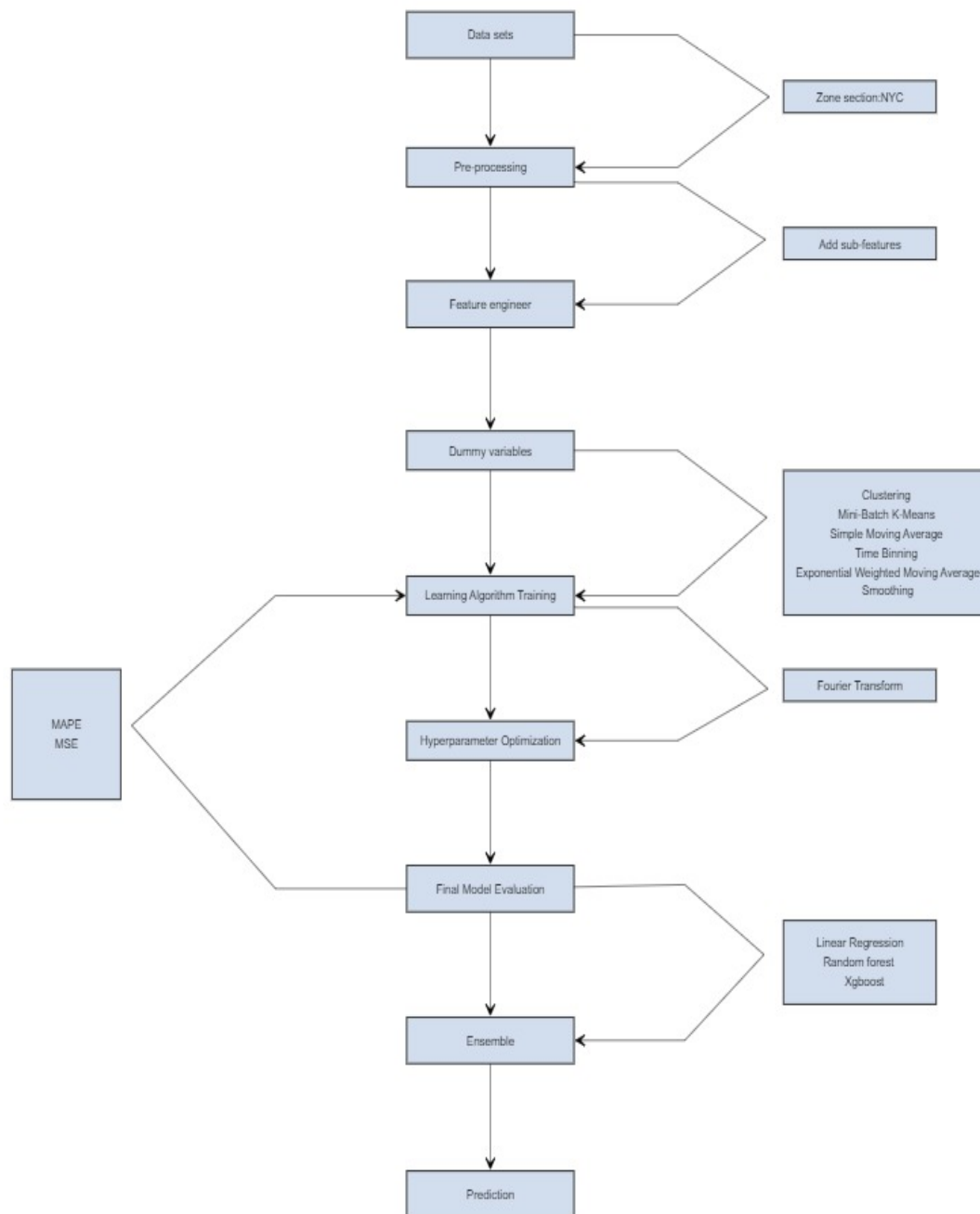


Fig 1: System architecture

3.3. Proposed System Models

3.3.1. Clustering

Bunching, or group exploration, is a problem with solo learning. It is frequently used as a data analysis process for locating interesting examples in data, such as client gatherings according on their behaviour. There are numerous grouping calculations to consider, and there is no single ideal bunching computation that applies to all situations. When all else is equal, it's a good idea.

Mini-Batch K-Means: On a small scale Batch K-Means is a modified version of k-means that updates group centroids using small clusters of tests rather than the entire dataset, which can make it faster for large datasets and maybe more resistant to factual turmoil.

3.3.2. Ratios and Previous Time Bins for Baseline Models

We've already segmented our regions into clusters and split our cameras into ten-minute barrels since then. We've focused on two aspects: measurements & past barrels. We can create two simple models: one that uses ratios and the other that uses previous drums to forecast future drums. We used data from 2015 and 2016 to make a comparison and we only used 2016 data in the previous version of the drums.

Assessments: Now, assume bundle 1. The 2016 download's "Rt" situation was taken in 2015 at "t." Also, if we have costs Rt+1 and Pickup_t+1_2015 from our 2015 planning data, we can discover

$$\begin{aligned}R_t &= \text{Pickup}_t_{2016} / \text{Pickup}_t_{2015} \\ R_{t+1} &= \text{Pickup}_{t+1}_{2016} / \text{Pickup}_{t+1}_{2015} \\ \text{Pickup}_{t+1}_{2016} &= R_{t+1} * \text{Pickup}_{t+1}_{2015}\end{aligned}$$

Past Barrels: Now in veritable creation, time game plan data, we can go through our data to time to make time 't' assumptions. Since cabbies in New York City approach 4G web, they can rapidly send in the nuances. Starting now and into the foreseeable future, we can make the limit 'f', which will enable us to make time conjectures "t".

$$\text{Pickup}_t = f(\text{Pickup}_{t-1}, \text{Pickup}_{t-2}, \text{Pickup}_{t-3} \dots)$$

3.3.3. Simple Moving Average

Ratings: As we analyzed, we will figure

$$Pickup_{t+1_2016} \text{ as } Pickup_{t+1_2016} = R_{t+1} * Pickup_{t+1_2015}$$

Past Barrels: Now, we can make an endeavor like

$$Pickup_{t+1} = (Pickup_t + Pickup_{t-1} + Pickup_{t-2} + Pickup_{t-n})/N$$

3.3.4. Time Binning

To make brief drums, we took the time in standard configuration, changed it over to a Unix timestamp, and isolated it by 600. For information from January 2015, each barrel addresses a 10-minute duration equivalent to the first run through - in short order - from 12 PM January 2015, split by 600 (to make it into a 10minute barrel). Subsequently, there will be brief drums altogether, with 10 for the period of January 2015.

We got bunch ID/local ID drums and 10 min time drums. Presently, for any territorial ID and brief minutes. The quantity of blunders should be anticipated. We'll presently change the entirety of the information for January 2015 and January 2016 into a bunch ID and a 10-minute time container.

We just subtract the take-off time from offline on January 1, 2015 at 12:00 A.M., and after that we split that with 600 to make a 10-min barrel, that's all. For the month of January 2016, the details we are simply deleting its recording time corresponding to UNIX time of 12:00 AM on January 1st, 2016.

3.3.5. Exponential Weighted Moving Average

We've figured out how to distribute higher loads to the most recent qualities and lower loads to the following ones using weighted midpoints, but we're not sure which weighting scheme is best because we're not distributed in an expanding request and the hyperparameter window size can be adjusted in an infinite number of different ways. We utilize Exponential Moving Averages to simplify weights, while still utilizing the best window size, to make this process easier. Only a single (α) hyperparameter, which has a value between 0 and 1, is included in exponential motion averages. The sizes of weights and windows are defined by an alpha. Here we will use the previous predicted result along with the previous actual value to make predictions for the next value.

$$R'_t = \alpha * R_{t-1} + (1-\alpha) * R'_{t-1}$$

R'_t is the current anticipated proportion

R'_{t-1} is the past anticipated proportion

R_{t-1} is the real past proportion

Presently, when $\alpha = 0.7$, at that point it implies we are giving 70% weightage to the past anticipated proportion and 30% weightage to the past genuine proportion.

$$R'_0 = 0$$

$$R'_1 = 0.7 * R'_0 + 0.3 * R_0$$

$$R'_2 = 0.7 * R'_1 + 0.3 * R_1$$

$$R'_3 = 0.7 * R'_2 + 0.3 * R_2$$

Let's take R'_3

$$R'_3 = 0.3 * R_2 + 0.7 * R'_2$$

$$R'_3 = 0.3 * R_2 + 0.7 * (0.7 * R'_1 + 0.3 * R_1)$$

$$R'_3 = 0.3 * R_2 + 0.7 * (0.3 * R_1 + 0.7 * (0.7 * R'_0 + 0.3 * R_0))$$

$$R'_3 = 0.3 * R_3 + 0.7 * 0.3 * R_1 + 0.7 * 0.7 * 0.3 * R_0 + 0.7 * 0.7 * 0.7 * R'_0$$

$$R'_3 = 0.3 * R_3 + 0.7 * 0.3 * R_1 + 0.7 * 0.7 * 0.3 * R_0 + 0$$

Alpha is a hyper-parameter which needs to be tuned manually. It is found that alpha = 0.5 gives lowest MAPE value.

$$P'_t = \alpha * P_{t-1} + (1-\alpha) * P'_{t-1}$$

S.No.	Model	MAPE(%)	MSE
1	Simple Moving Average Ratios	19.123931	967.209543
2	Simple Moving Average Predictions	13.220558	297.449031
3	Weighted Moving Average Ratios	18.739608	849.303196
4	Weighted Moving Average Predictions	12.957807	279.576867
5	Exponential Weighted Moving Average Ratios	21.245534	1250.643802
6	Exponential Weighted Moving Average Predictions	16.007452	424.459020

Table 3: Model Error Percentage

According to the preceding error table, the optimal forecasting model for our prediction would be(Weighted Moving Averages Prediction for January 2016 Values):

$$P_t = (N * P_{t-1} + (N-1) * P_{t-2} + (N-2) * P_{t-3} \dots 1 * P_{t-n}) / (N * (N+1) / 2)$$

3.3.6. Smoothing

- Smoothing is a technique for removing fine-grained variation between time steps from measurements.
- Smoothing is completed with the goal of removing turbulence and revealing the sign of the underlying causal cycles. In factual examination and proclamations, moving midpoints are a simple and widely used smoothing procedure.
- Making a substitution ar is part of computing a moving normal.

3.3.7. Regression Model

Linear regression, XGBoost Regression and, Random Forest Regression, are the three regression models we used. Only data from January 2016 was used. However, we must first organize the features before we can feed the data to the models. A sum of 19 highlights have been set up in the accompanying request:

- The past time canisters are very exact in anticipating the pickup for the following time container in a similar group, as indicated by the standard models. Thus, we've selected to factor in the past 5 time-container pickups inside a similar bunch while anticipating the following time canister pickup inside a similar group.
- Cluster center's latitude and longitude will be the 6th and 7th features.
- The day of the week that pickup will take place will be the 8th feature.
- We choose the 9th function because the “Weighted Moving Average Predictions” prediction results are the easiest of all the baseline models to anticipate future pickup.
- The Fourier transform features will make up the remaining ten features.

As features, add the top five frequencies and amplitudes of the Fourier transform.

When we have a repetitive plan for a wave, such as here when we have a recurring example of pickups in 24 hours of your timeframe, the Fourier Change indicates that this repeating wave decays into numerous other sine waves. Each wave will have a recurrence and adequacy With frequencies on the x-hub and abundancy on the y-hub, we'll convert our underlying wave from time-area to recurrence space portrayal. Singular sine wave frequencies will be addressed on the x-hub, and their abundancy esteems in the recurrence space will be addressed on the y-pivot. The Fourier decayed frequencies and their plentifulness are commonly presented as highlights in our information on the off chance that we have a rehashing design in time-arrangement information. When there is an intermittent pattern in time-arrangement discoveries, these properties are amazingly advantageous.

On the surface, the amplitude is a relative measure of how important one frequency is in comparison to other frequencies. A sine-wave with a higher amplitude will reflect more time-series data. Thus, we can essentially sort the frequencies with the biggest amplitudes to track down the key frequencies and amplitudes. At last, we'll incorporate them as information include.

Our information has an aggregate of 30 bunches. The pickup design (which is rehashing) will be the basic in every individual bunch. It's significant that pickup designs in various bunches can differ. Thus, in the event that we plot FFT for one bunch of 'n' focuses, and take the best three frequencies and their connected plentifulness esteems as a capacity, these three frequencies and amplitudes will continue as before for these n focuses. It will simply move for focuses in an alternate bunch.

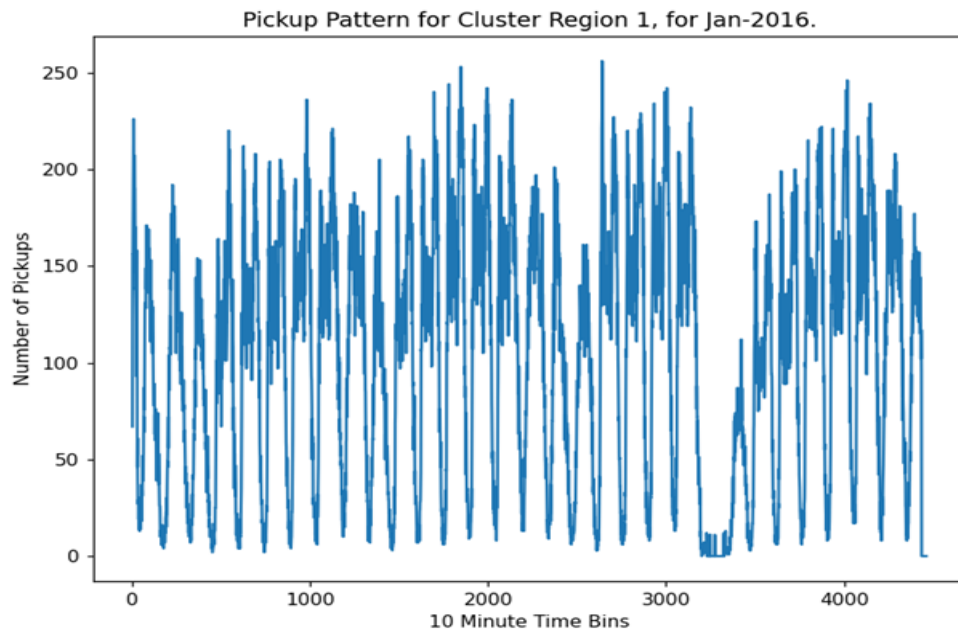


Fig. 2: pickup pattern for cluster region 1

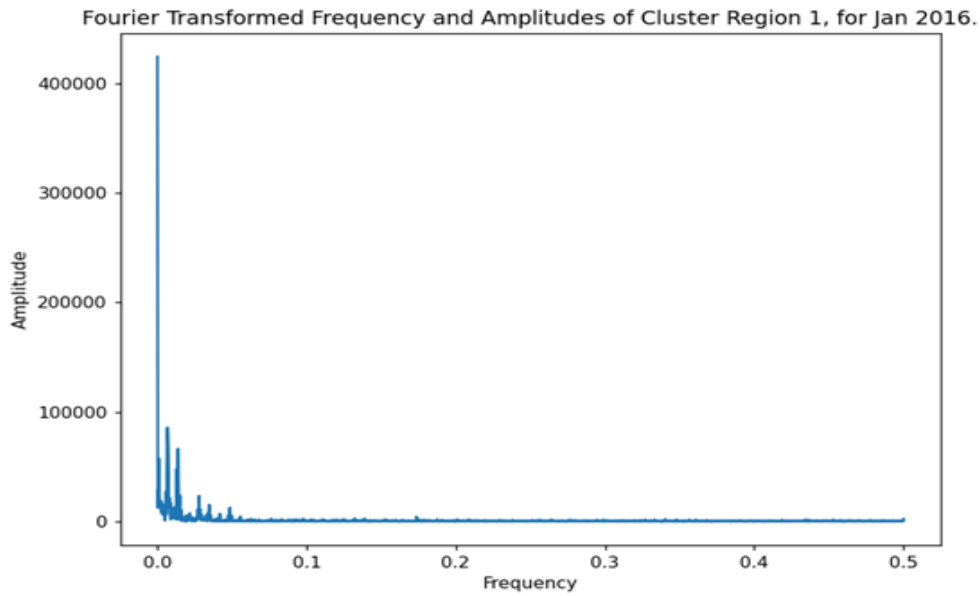


Fig. 3: Fourier Transformed frequency and amplitudes of cluster region 1

There is one peak at $1/144$ of a second, which is comparable to 24 hours. This peak is catching complete 24-hour pickups, and since pickups are high during rush hours, the wave's peak is also high at $1/144$. Another peak can be found at $1/72$ of a second, which is equivalent to 12-hours. Now, aside from the DC section, which we aren't considering, and so on, since this peak collect information from the quietest hours, it is the best. If we continue in this manner, the recurrence of $1/36$ will be like 6 hours, the recurrence of $1/18$ to 3 hours, etc. A wave's recurrence is the quantity of motions it finishes in a single second.

As demonstrated in the above plot, the essential pinnacle could be a DC variable that records the adequacy of the wave that happens before the wave showed in the plot. We will not consider the abundancy and recurrence of the wave we've Fourier changed over in light of the fact that it very well may be an intermittent wave.

From the second peak onwards, we'll start recording frequency and amplitudes. We agreed that the top five highest amplitudes, as well as their five corresponding frequencies, should be included in our results.

We've completed all of our features. Finally, we've identified 19 characteristics in our results:

1. **f_t_1:** Number of pickups occurred previously in t-1st 10min interval
2. **f_t_2:** Number of pickups occurred previously in t-2nd 10min interval
3. **f_t_3:** Number of pickups that occurred previously in t-3rd 10min interval
4. **f_t_4:** Number of pickups that occurred previously in t-4th 10min interval
5. **f_t_5:** Number of pickups that occurred previously in t-5th 10min interval
6. **Freq1:** Fourier Frequency corresponding to 1st highest amplitude
7. **Freq2:** Fourier Frequency corresponding to 2nd highest amplitude
8. **Freq3:** Fourier Frequency corresponding to 3rd highest amplitude
9. **Freq4:** Fourier Frequency corresponding to 4th highest amplitude
10. **Freq5:** Fourier Frequency corresponding to 5th highest amplitude
11. **Amp1:** Amplitude corresponding to 1st highest Fourier transformed wave.
12. **Amp2:** Amplitude corresponding to 2nd highest Fourier transformed wave.
13. **Amp3:** Amplitude corresponding to 3rd highest Fourier transformed wave.
14. **Amp4:** Amplitude corresponding to 4th highest Fourier transformed wave.
15. **Amp5:** Amplitude corresponding to 5th highest Fourier transformed wave.
16. **Latitude:** Latitude of Cluster center.
17. **Longitude:** Longitude of Cluster Center.
18. **WeekDay:** Day of week of pickup.
19. **WeightedAvg:** Weighted Moving Average Prediction values.

In this situation, a following pickup would be our genuine class label. On the surface, regression models seem to forecast future pickups in a comparable package that occurred at a time "t."

- **Train-Test split and Highlights:** At now there are a total of 30 groups. There are 4464-time bins in each cluster zone. As a result, there will be $4464 \times 30 = 133920$ pickups for all 30 clusters. However, since we're using a mix of 5 consecutive pickups as training info, we'll end up with $4464 - 5 = 4459$ pickups in each cluster. As a result, the clusters would have a total of $4459 \times 30 = 133770$ pickups.

Before we start predicting with tree-based regression models, break the data so that 80 percent of it is in training and 20 percent is in testing for each field, ordered date-wise. Since this is frequently a time-series issue, we've divided our train and test data according to your time. We have designed the complete data set depending on your time. The first 80% of our lines have been used as train information at this point and the last 20% as test information.

3.3.7.1. Random Forest

A random forest is a collection method which uses a number of choice trees as well as the cycle known as Bootstrap Accumulation, sometimes referred to as sacking. You might be wondering what bagging is all about. Bagging is a step in the Random Forest process that involves training each decision tree on a unique data sample and replacing it with new data. The basic concept is to use a combination of decision trees to determine the final production rather than relying solely on individual decision trees.

The random forest is a monitored algorithm of learning. It produces a "forest" from a group of decision tanks generally taught by the process of "bagging." The fundamental aim of the bagging procedure is to improve the overall result by combining outstanding learning models. In other words, irregular forests are trees of choice that combine several trees to create a stronger and more precise expectation.

One huge advantage of arbitrary forests is that most of the present AI frameworks are routinely used for all characteristics and relapse problems. The irregular timberland should be examined in grouping since characterisation is usually taken as the square of AI structures.

As a decision tree or a texture classification, the arbitrary woodlands have almost identical hyperparameters. Fortunately, there was no opportunity to mix a decision tree with a

classification of a texture because you would only have the choice to use an irregular timberland class class. You may also make ruthless relapse orders with irregular backwoods by abusing the regressor of the computation.

Although trees are developed, arbitrary forests add extra haphazards to the picture. Maybe it searches for the least difficult piece in an array of possibilities rather than the key component while clamoring a hub. This comes in a vast range which normally turns into a more energetic model.

Thus, the requirement for dissonanting a hub is only taken into account in an arbitrary forest by an uneven arrangement of options. You may try to mount trees more irregular by abusing arbitrary bounds for each element rather of finding the least complicated feasible edges (like a standard call tree does)

Feature Importance

Another appealing feature of the haphazard woods decision is how simple it is to see the overall relevance of each component on the forecast. Sklearn provides a fantastic tool for this that measures an element's importance by looking at how much the tree hubs that use that element reduce degeneration across all trees in the woods. When educating, it processes this score accurately for each part and scales the results such that the overall add is satisfactory. By noticing the component significance, you'll be able to deduce that some options are likely to disappear because they don't add enough (or nothing at all) to the forecast approach. This is frequently necessary since an overarching AI principle is that the more options you have, the more likely your model will suffer from the negative impacts of overfitting, and vice versa.

3.3.7.2. XGBoost for Regression

Continuous or real values are the outcomes of regression issues. Linear Regression and Decision Trees are two of the most commonly used algorithms. In retrospect, several metrics are involved, such as mean-squared error (MSE). These are some of the most significant members of the XGBoost models, each with a distinct role to play

- **MAPE:** MAPE is an average of absolute percentage inaccuracy minus current values divided for every time period by real values.
- XGBoost is a robust way to build backup models. The validity of the model can be attributed to the knowledge of its (XGBoost) work with students.

Purpose work consists of job loss and time to get used to. It handles the comparison between genuine and expected qualities, such as how close model outcomes are to true qualities. Reg: direct is the typical unfortunate work in XGBoost for deferral difficulties, and reg: coordinations is the parallel split.

Group learning is combining multiple models (known as base students) to generate a single forecast, and XGBoost is one of the most well-known outfit learning methods. XGBoost aspires to have the lowest number of pupils who are consistently dangerous at the rest of the time, so that expectations are consolidated on the whole. Perilous forecasts fade away, and a far higher one emerges to set the final astute expectations.

The misfortune perform isn't in charge of dissecting the model's nature, and if the model becomes too intense, there's a need to penalise it, which should be avoided at all costs. The process of regularisation. To prevent overfitting, it punishes more intensive models by each LASSO (L1) and Ridge (L2) regularisation. The ultimate goal is to display plain and correct models.

3.3.7.3. Linear Regression

Linear Regression is arguably one of the most well-known and well-understood numerical and AI approaches. AI, particularly in the field of predictive analytics, is mostly responsible for reducing model error or generating the most precise projections possible, hence facilitating comprehension. To achieve these AI goals, we can obtain, reuse, and use computations from a wide range of domains, including science. Despite the fact that linear inversion was created in the field of mathematics and is primarily used to illustrate the relationship between value instability, consideration and deduction, it has been acquired by AI. A numerical calculation is the same as an AI calculation.

Model	TrainMAPE(%)	TrainMSE	TestMAPE(%)	TestMSE
Linear Regression	13.108002	298.046658	18.381391	342.346335
Random Forest Regression	4.873230	46.862610	13.642314	251.198503
XGBoost Regressor	12.375957	237.939413	13.232612	226.042825

Table 4: MAPE & MSE of Training & Testing Data

4. PROPOSED SYSTEM ANALYSIS AND DESIGN

4.1. Requirement Analysis

4.1.1. Functional Requirements

It should feature a routing system that can analyse the client's present circumstances and offer the best location. Due to the fact that the idea is primarily based on the information area, it might very well be any place that has precise longitude and scope information, and thus, customers will be able to not only find the next pickup place based on their present location, but also find the ideal place by physically entering it.

Apart from the distance and travel time, the main purpose of the application is to provide the expected number of accessible clients at each point in time when the driver should arrive at the location, as well as the quantity of expected clients as a proportion of the total number of clients and available cabs. To give the recommended pickup focuses grouped by distance, a distance limit is required so that the application can course all of the focuses in the circular region and produce estimates for this point.

4.1.2. Non-Functional Requirements

4.1.2.1. Product Requirements

4.1.2.1.1. Efficiency (in terms of Time and Space):

With the authentic features of this program, which operates by analyzing large amounts of verifiable data, the most important test is intensity. To reduce execution time, time complexity and house complexity should be fully assessed. There are several angles that can significantly increase the product's power: the code's norm - The equation's understanding, which is a well-practiced methodology - large amounts of data and data preparation software - data style - network capability - server capacity

4.1.2.1.2. Reliability:

This is one of the most important features that might represent the decision moment quality for any item, particularly in this practical forecasting application. In reality, in order to establish a reputation, the machine must be trustworthy from the start. The following are some examples of endowments that might be recorded:

- Adaptability (simple to grow with no outcome on the current worker) - portability (ensured to constantly be accessible)
- Safety is paramount (ready to stay away from network assault)
- Repairs and assistance (The defects in the equipment will be discarded by the organization)
- Instrument for quick failover (if the worker is down, it will rapidly be communicated to an alternate host)
- Monetary assessment (numerous proposals for clients from most help providers, especially inside the improvement interaction)

4.1.2.1.3. Usability:

A human-made object's usability refers to however straightforward it's to use and learn. however, as a result of it's going to be outlined by the organization, it's AN abstract notion. Clients may make a few cash mentioned aims with viability, effectiveness, and fulfillment in an extremely declared setting of use in terms of a product package, for example.

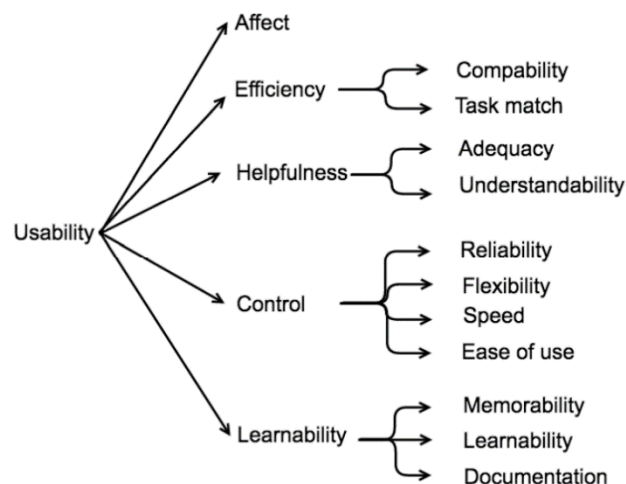


Fig 4: Usability

4.1.2.1.4. Dependability:

Informally, dependableness refers to what quantity users will have confidence in the system's qualities. dependableness, on the opposite hand, contains qualities like dependableness, safety, security, and handiness. the subsequent diagram depicts the fundamental qualities of dependability:

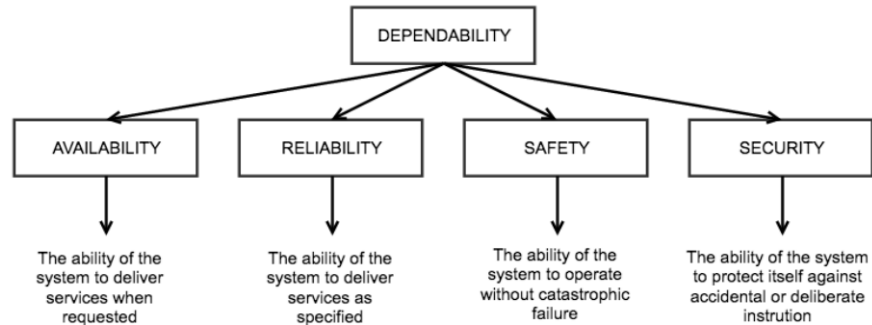


Fig 5: Dependability

Rather than being autonomous, the traits of dependableness area unit mutualist. as an example, safe system operation necessitates the system's handiness and actual operation. reliableness, handiness, safety, and security area unit non-functional criteria zthat have got to be outlined.

4.1.3. System Requirements

4.2.3.1. Hardware Requirements

- Laptop with sufficient computational power i.e. CORE i7
- Laptop with enough memory i.e. at least 16GB RAM
- Windows Operating System

4.2.3.2. Software Requirements

- **Python 3.7.5:** Python is a programming language that supports both structured and article-based programming. Python 3.0 was released in 2008 as a successor for Python 2.0 which was discontinued in 2020. Python 3.0 isn't backward compatible.
- **Anaconda3 1.7.0:** It is an open-source distributor for R and Python Programming languages. It is used for scientific computing like Machine Learning, Data Science, Predictive Analysis, etc. It helps in simplifying packet deployment and management.
- **Jupyter Notebook:** The Jupyter Notebook is an open-source online program that allows you to create and share live code, conditions, perceptions, and text archives. It's used in logical processing such as Machine Learning, Data Science, and Predictive Analysis, among other things.

5. RESULTS AND DISCUSSION

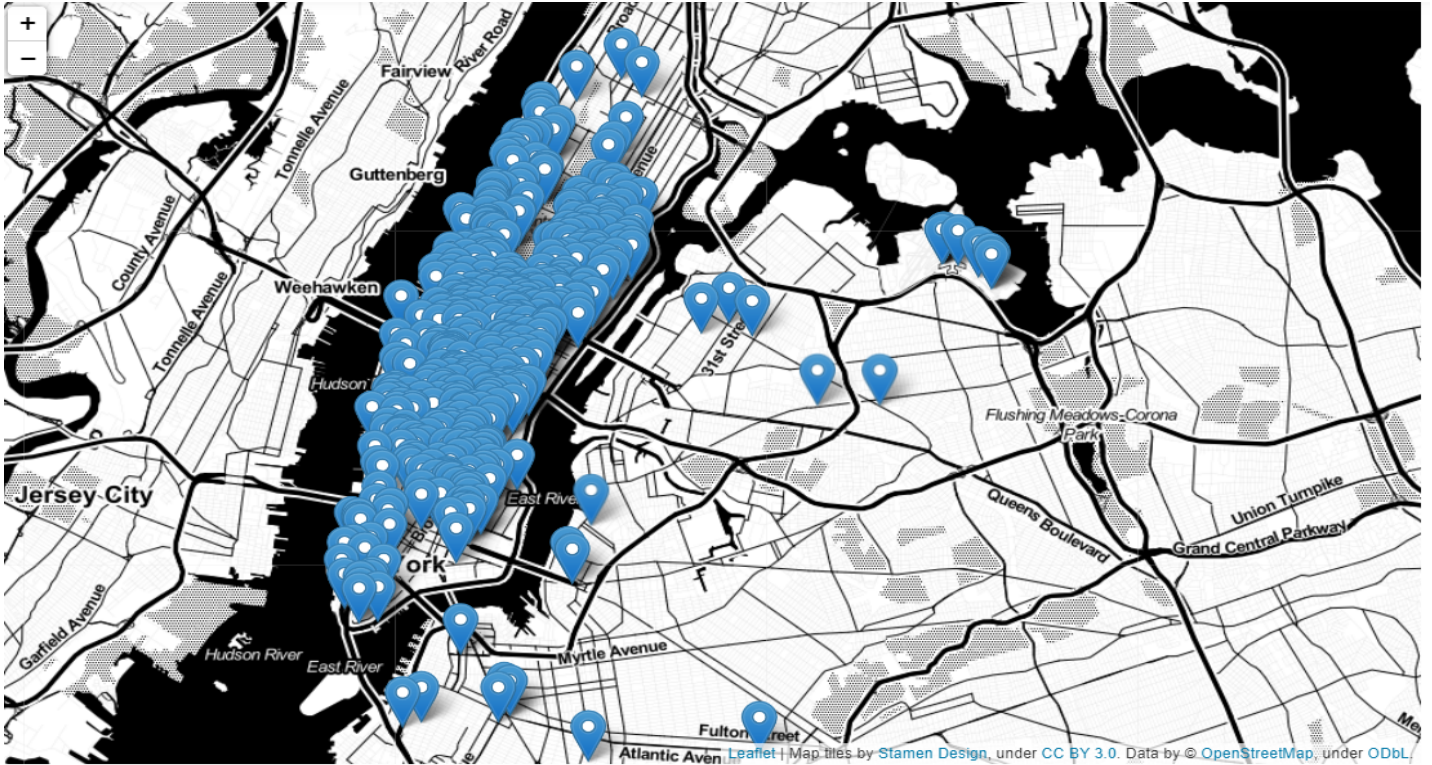


Fig 6: Pickup Locations in New York

Now, the Manhattan area of NYC has large number of pick up, so cluster size in Manhattan area will be small as compared to outskirts areas of NYC.

Observation: Most of the pickups are concentrated in and around the Manhattan district of New York.

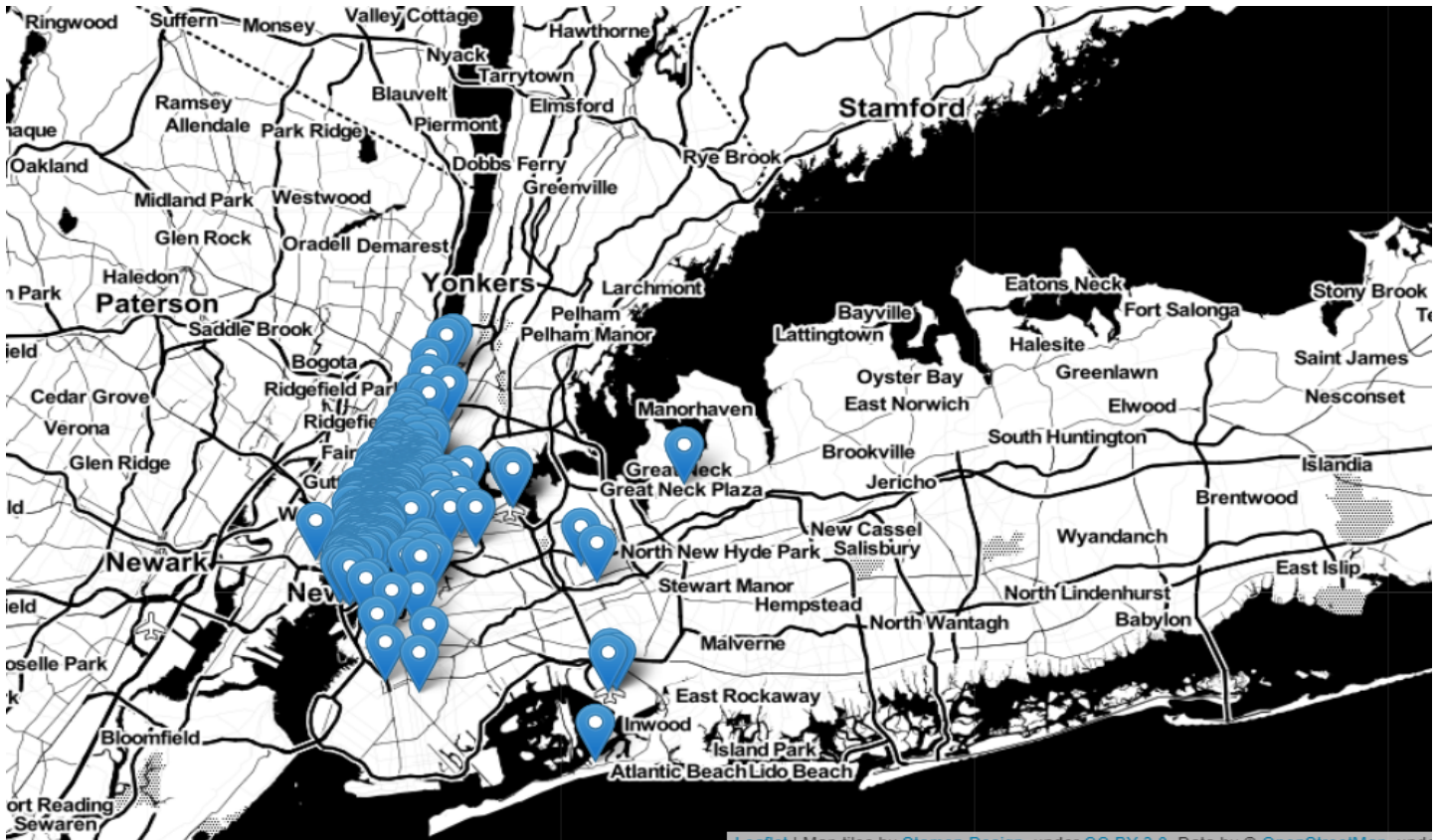


Fig 7: Drop off Locations in New York

Now, the Manhattan area of NYC has large number of drop off, so cluster size in Manhattan area will be small as compared to outskirts areas of NYC.

Observation: Most of the drop-offs are concentrated in and around the Manhattan district of New York.



Fig 8: Plotting cluster centers

Different cluster regions in New York City-based on latitude and longitude with unique cluster-ID. Using folium to plot the cluster centers using Mini Batch KMeans.

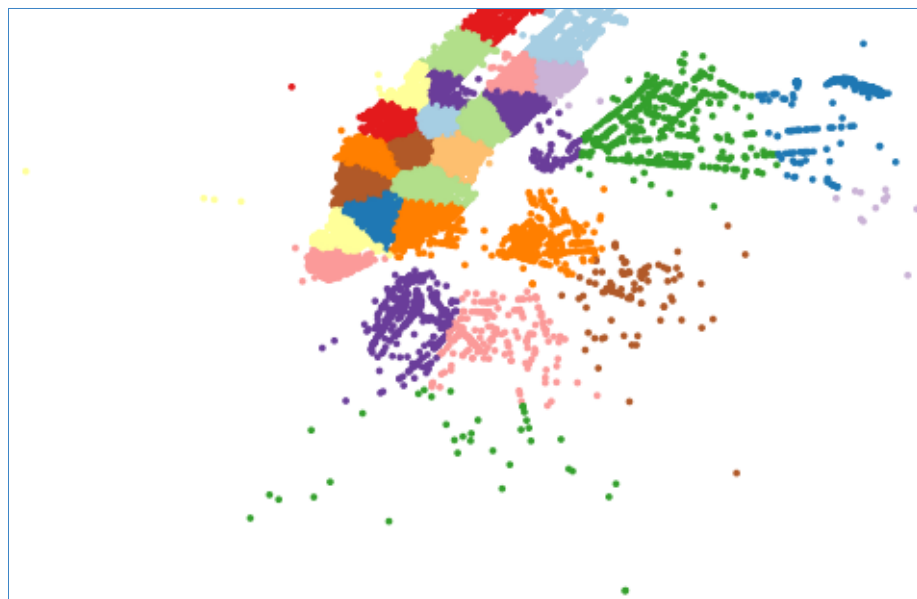


Fig 9: Plotting regions in NYC

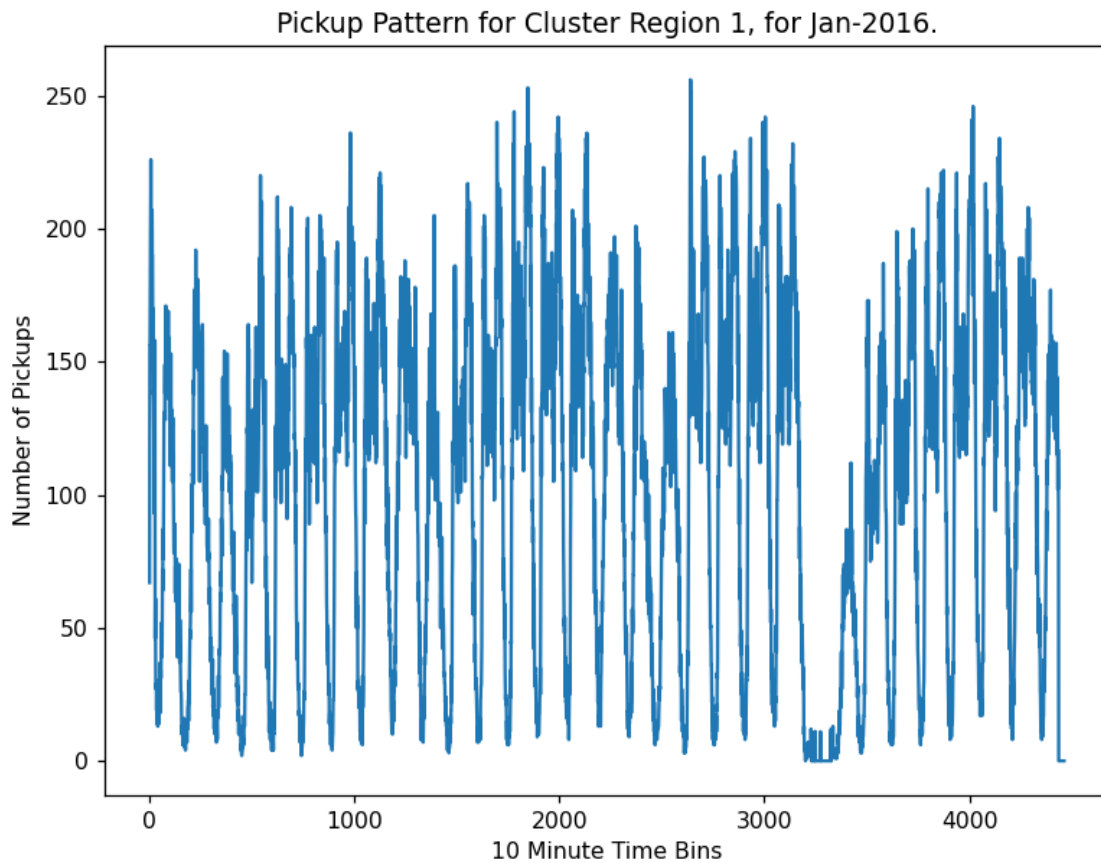


Fig 10: Pick Up Pattern for cluster region 1

The Fourier Transform states that at any point where we have a rehashing design in a wave-like format, such as here where we have a rehashing example of pickups over a 24-hour period, this rehashing wave can be disintegrated into a number of different sine waves. Every sine wave will have a certain amount of recurrence and abundance. We may now handle our unique wave by moving from time to recurrence space, with recurrence introduced on the x-pivot and abundance introduced on the y-hub. The x-hub frequencies of distinct sine waves will be discrete frequencies in the recurrence region, and the y-pivot amplitudes will be their corresponding abundance estimates. When it comes to time-arrangement data, the Fourier disintegrating frequencies and their abundance might be included as an element in our information at any point when we have a repeating design. These highlights are particularly useful when there is a repeating design in the time-arrangement data. Naturally, adequacy measures the size of one occurrence in relation to other occurrences. The more adequacy there is, the more time-arrangement the sine-wave can handle. Along these lines, we may effectively find the

frequencies with the largest amplitudes by arranging them to obtain the significant frequencies and their relative amplitudes. Along these lines, we may effectively find the frequencies with the largest amplitudes by arranging them to obtain the significant frequencies and their relative amplitudes. There are now 30 bunches of information in our database. The pickup design (which is repetitive) will continue in each unique group. It's worth noting that each group's pickup design will be different. As a result, if we plot FFT for one group, and let's suppose that one group has 'n' focuses, and we use the first three frequencies and their corresponding sufficient esteems as a component, these three frequencies and their comparative amplitudes will remain the same for those 'n' focuses. It will only alter for the focuses in a different group.

	Model	MAPE(%)	MSE
0	Simple Moving Average Ratios	20.049454	5215.312918
1	Simple Moving Average Predictions	13.355991	304.223775
2	Weighted Moving Average Ratios	19.498482	3312.809685
3	Weighted Moving Average Predictions	13.092488	286.828614
4	Exponential Weighted Moving Average Ratios	22.633691	13307.207183
5	Exponential Weighted Moving Average Predictions	16.188570	425.485425

Table 5: Error table for baseline models

The data set contains dependent or target variables along with independent variables. We build models using independent variables and predict dependent or target variables. If the dependent variable is numeric, regression models are used to predict it. MSE is used to evaluate the models.

We also calculated the Mean Absolute per Error (MAPE), the sum of the individual absolute errors divided by the demand (each period separately). It is the average of the percentage errors, despite being a poor-accuracy indicator. As you can see in the formula, MAPE divides each error individually by the demand, so it is skewed: high errors during low-demand periods will significantly impact MAPE. Due to this, optimizing MAPE will result in a strange forecast that will most likely undershoot the demand.

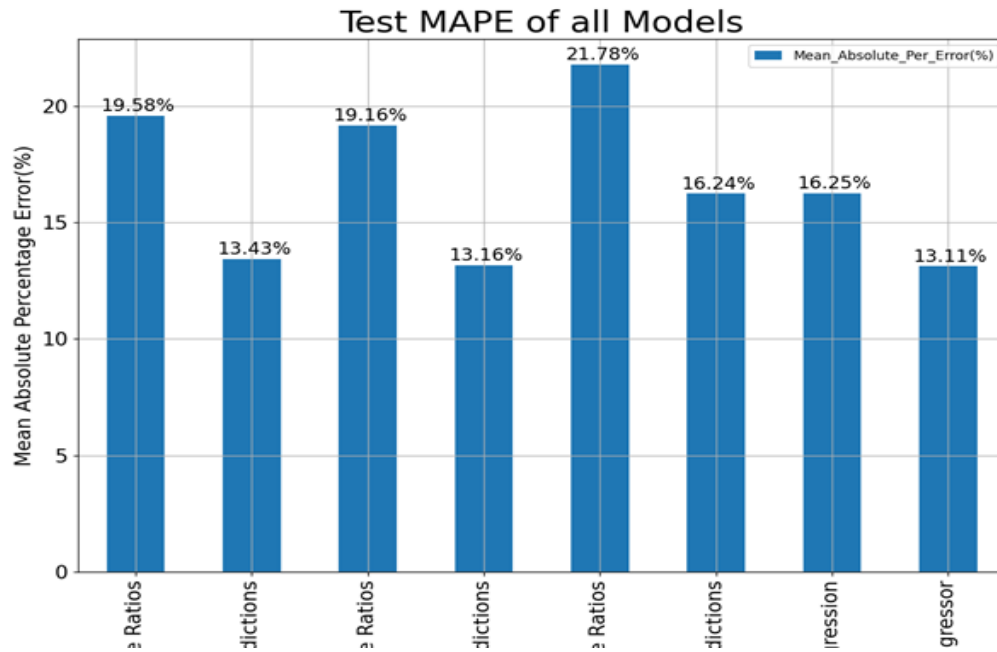


Fig 12: Test MAPE of all models

	Model	Mean_Absolute_Per_Error(%)
0	Simple Moving Average Ratios	20.049454
1	Simple Moving Average Predictions	13.355991
2	Weighted Moving Average Ratios	19.498482
3	Weighted Moving Average Predictions	13.092488
4	Exponential Weighted Moving Average Ratios	22.633691
5	Exponential Weighted Moving Average Predictions	16.188570
6	Linear Regression	16.664007
7	XGBoost Regressor	13.170606

Table 6: Test MAPE list of all models

Increasing the number of neurons had less than significant change in the results. Hence, Weighted Moving Average Predictions with the least MAPE of 13.092% is our obvious choice.

Deployment weblink: <https://taxi-demand.herokuapp.com/>

Taxi Demand Prediction

Taxi Demand Prediction

Linear Regression

n_5

147.0

n_4

166.0

n_3

166.0

n_2

193.0

n_1

208.0

freq1

0.013916

freq2

0.006836

freq3

0.00708

freq4

0.012939

freq5

0.007812

Amp1

95578.903097

Amp2

94781.54766

Amp3

87580.311633

Amp4

45088.918373

Amp5

44501.696661

Latitude

40.749414

Longitude

-73.992649

WeekDay

1

WeightedAvg

203

Predict

[84278.1255335]

6. REFERENCES

Weblinks:

- [1] <https://machinelearningmastery.com>
- [2] <https://towardsdatascience.com>
- [3] http://www.nyc.gov/html/tlc/html/about/trip_record_data.shtml
- [4] <https://stackoverflow.com/questions/31572487/fitting-data-vs-transforming-data-in-scikit-learn>
- [5] <https://colah.github.io/posts/2015-08-Understanding-LSTMs/>
- [6] <https://www.flickr.com/places/info/2459115>

Journals:

- [1] Zhao, K., Khryashchev, D., Freire, J., Silva, C., & Vo, H. (2016, December). Predicting taxi demand at high spatial resolution: Approaching the limit of predictability. In 2016 IEEE International Conference on Big Data (Big Data) (pp. 833-842). IEEE.
- [2] Seow, K. T., Dang, N. H., & Lee, D. H. (2009). A collaborative multiagent taxi-dispatch system. IEEE Transactions on Automation Science and Engineering, 7(3), 607-616.
- [3] Davis, N., Raina, G., & Jagannathan, K. (2016, November). A multi-level clustering approach for forecasting taxi travel demand. In 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC) (pp. 223-228). IEEE.
- [4] Lee, D. H., Wang, H., Cheu, R. L., & Teo, S. H. (2004). Taxi dispatch system based on current demands and real-time traffic conditions. Transportation Research Record, 1882(1), 193-200.
- [5] Gers, F. A., Eck, D., & Schmidhuber, J. (2002). Applying LSTM to time series predictable through time-window approaches. In Neural Nets WIRN Vietri-01 (pp. 193-200). Springer, London.
- [6] Moreira-Matias, L., Gama, J., Ferreira, M., Mendes-Moreira, J., & Damas, L. (2013). Predicting taxi-passenger demand using streaming data. IEEE Transactions on Intelligent Transportation Systems, 14(3), 1393-1402.
- [7] De Brébisson, A., Simon, É., Auvolet, A., Vincent, P., & Bengio, Y. (2015). Artificial neural networks applied to taxi destination prediction. arXiv preprint arXiv:1508.00021.
- [8] Xu, J., Rahmatizadeh, R., Bölöni, L., & Turgut, D. (2017). Real-time prediction of taxi demand using recurrent neural networks. IEEE Transactions on Intelligent Transportation Systems, 19(8), 2572-2581.
- [9] Agarwal, V. (2015). Research on data preprocessing and categorization technique for smartphone review analysis. International Journal of Computer Applications, 975, 8887.

- [10] Sutskever, I., Vinyals, O., & Le, Q. V. (2014). Sequence to sequence learning with neural networks. arXiv preprint arXiv:1409.3215.
- [11] Miao, F., Han, S., Lin, S., Stankovic, J. A., Zhang, D., Munir, S., ... & Pappas, G. J. (2016). Taxi dispatch with real-time sensing data in metropolitan areas: A receding horizon control approach. *IEEE Transactions on Automation Science and Engineering*, 13(2), 463-478.
- [12] Zhang, D., He, T., Lin, S., Munir, S., & Stankovic, J. A. (2016). Taxi-passenger-demand modeling based on big data from a roving sensor network. *IEEE Transactions on Big Data*, 3(3), 362-374.
- [13] Larochelle, H., & Murray, I. (2011, June). The neural autoregressive distribution estimator. In *Proceedings of the Fourteenth International Conference on Artificial Intelligence and Statistics* (pp. 29-37). *JMLR Workshop and Conference Proceedings*.
- [14] Chen, Y., Li, O., Sun, Y., & Li, F. (2018). Ensemble classification of data streams based on attribute reduction and a sliding window. *Applied Sciences*, 8(4), 620.
- [15] Balan, R. K., Nguyen, K. X., & Jiang, L. (2011, June). Real-time trip information service for a large taxi fleet. In *Proceedings of the 9th international conference on Mobile systems, applications, and services* (pp. 99-112).
- [16] Markou, I., Rodrigues, F., & Pereira, F. C. (2018, November). Real-Time Taxi Demand Prediction using data from the web. In *2018 21st International Conference on Intelligent Transportation Systems (ITSC)* (pp. 1664-1671). IEEE.
- [17] Ma, J., Chan, J., Ristanoski, G., Rajasegarar, S., & Leckie, C. (2019). Bus travel time prediction with real-time traffic information. *Transportation Research Part C: Emerging Technologies*, 105, 536-549.
- [18] Ishiguro, S., Kawasaki, S., & Fukazawa, Y. (2018, October). Taxi demand forecast using real-time population generated from cellular networks. In *Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers* (pp. 1024-1032).
- [19] Moreira-Matias, L., Gama, J., Ferreira, M., Mendes-Moreira, J., & Damas, L. (2013, September). On predicting the taxi-passenger demand: A real-time approach. In *Portuguese Conference on Artificial Intelligence* (pp. 54-65). Springer, Berlin, Heidelberg.