Dynamic Path Planning Approaches based on Artificial Intelligence and Machine Learning

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Abstract: Prediction plays an important role where we are trying to generate probable values for an unknown variable for each record in the new data, allowing the model builder to identify what that value will most likely be and where that value will be useful. Machine learning model predictions allow businesses to make highly accurate guesses as to the likely outcomes of a question based on historical data, which can be about all kinds of things – customer churn likelihood, possible fraudulent activity, and more. In this paper we are trying to present Path prediction methods and algorithms available and compare them. In this paper we are considering the Path prediction issues and problems during taxi and cab driving. In systems today, many drivers face issues while serving client requests during the drive because of many unpredictable events that. Similarly, although a person may shop on different days or at different times, they will often vision analyse the happen daily on the roads. In this paper, we try to find out more improved methods for alternate Path prediction and switching Paths due incidents and other unexpected events based on obstacle free Path prediction also allowing the reduction of delays. This paper reviews the literature regarding various machine learning models, algorithms & approaches focusing on Path prediction.We start by analyzing road network data collection algorithms and their efficiency.In the later part of the paper, wetry to talk about metrics and parameters commonly used to evaluate prediction, in order to compare the different approaches. We list, detail and compare existing algorithms that provide Path predictions. This research leads to an understanding of advantages, disadvantages and trade-offs of the methods studied and will surely provide useful information for future development.

Keywords: Path prediction, Machine Learning, unexpected events, alternate Path, Path switching, prediction algorithms.

1. Introduction

Now days, as we seentheir is increase in population and development of smart cities has increased congestion in traffic and road closure incidents which has caused the drivers or users to find different Paths between the source and destination. A Path prediction system in this case would do the task of predicting the alternate obstacle free and cost efficientPath while driving. Such prediction system should be able to inform the driver about the upcoming road closure incidents from the particular distance. In this case decision making / recommendation can be generated based on whether the user prefers a long Path or a short Path. The Path prediction has many constraints on which the Paths are predicted, so there are many algorithms that can be used to give priority to a specific constraint. This paper gives a survey of few of the algorithms and methods used for the Path prediction. This type of navigation could help in many problem domains like the predictions can be used to provide better Path guidance without the need of input from the driver and instead relying on the prediction to infer the driver's intent. Smarter Pathregulation could be provided through the use of real time Pathestimates. The paper is structured in the following manner. In the following section we describe the basis of our survey. This survey introduces some important concepts and methods around Path prediction, providing important characteristics that should be considered when choosing or developingnew Path prediction algorithms and systems.

2. Related Work

The Path prediction and prediction algorithms have been studied and analysed by various researchers. To identify the significance of the survey that, we have studied existing methods for prediction and related domains in the field of path prediction. The recent study in the field of Path prediction focused on long-term trajectory prediction based on mined Path patterns, which performs Pattern Extraction and Future Location Prediction (FLP) in order to update existing patterns or add new ones of Paths. In the next sections of this work we have presented various findings of our research survey based on research work presented by various researchers in the field of path prediction using classical, artificial intelligence and machine learning based approaches.

(Petrou et al., 2020),ispresented a Big data framework for the prediction of streaming trajectory data by exploiting mined patterns of trajectories, allowing accurate long-term predictions with low latency. In particular, to meet this goal he followed a two-step methodology. First, efficiently identifying the hidden mobility patterns in an offline manner. Subsequently, the trajectory prediction algorithm exploits these patterns in order to prolong the temporal horizon of useful predictions. Short-term location and trajectory prediction facilitates the efficient planning, management, and control procedures while assessing traffic conditions in the road, sea and air transportation field. The latter can be extremely important in domains where safety, credibility and cost are critical and a decision should be made by considering adversarial to the environment conditions to act immediately.Two main prediction-related problems can be stated for moving objects: Future Location Prediction (FLP) and Trajectory Prediction (TP).

At first, each moving object sends its location via traditional network protocols and then a Kafka producer collects all positions and pushes them to a Kafka topic. The Pattern Extraction module identifies “typical Paths”, in an offline manner. Finally, these “typical Paths” are broadcast among all slaves and the FLP module combines them with the live incoming stream of data in order to predict the future location for each object (Fig. 1).

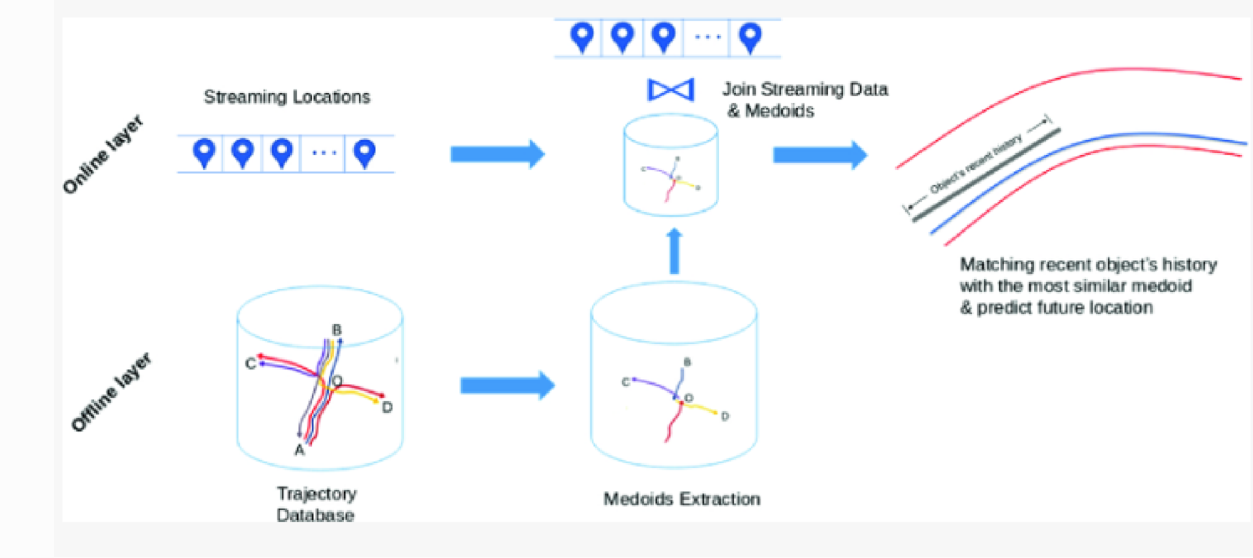

Fig.1. Trajectory projections based on Mined Path patterns

The FLP module takes advantage of an individual's typical movement (medoids from now on), based on the observation that moving objects often follow the same Path patterns. The Future Location Prediction (FLP) module aims to make an accurate estimation of the next movement of a moving object within a specific look-ahead time frame.
In this work, a novel approach was introduced for the long-term FLP problem (FLP-L). The approach is based on purely data-driven extraction of mobility patterns, i.e. sub-trajectory cluster medoids. It is important to emphasize that the proposed framework relies end-to-end in big data technologies This framework is directly applicable and valid in the aviation domain, especially since the medoids discovery is based upon some form of clustering to discover groups and common motion patterns, either with or without considering flight plans as input in the predictive models. The accuracy as well as the performance results, prove that it is a very efficient and scalable Big data solution for real-world applications, easily adaptable to various other domains.

(Tu et al., 2021),conveyed the Electric vehicles (EVs) challenges in promotion, i.e., short driving ranges, long charging times, and few charging stations are considered, thereby limiting their acceptability to taxi drivers. Leveraging massive-scale taxi GPS trajectory data, the work present a novel real-time Path recommendation system for electric taxi (ET) drivers. Taxi travel knowledge, including the probability of picking up passengers and the distribution of destinations, is learned from the raw GPS trajectories. Considering the cascading effect of Path decision making, consecutive ET actions are modelled with an action tree. The corresponding expected net revenue is estimated based on the learned knowledge. A prototype online system is developed for providing Path recommendations, e.g., when to go to a charging station or cruise on certain roads. An experiment in Shenzhen demonstrates that the average daily net revenue of ET drivers is better than that of 76.2% of gasoline taxi drivers. The presented approach not only increases the revenue of ET drivers in the short term but also improves the viability of EVs in the long run.

(Malik and Kim, 2019), described Keeping in mind the ease of travel, the optimalPath identification & recommendation was proposed for the tourist vehicle. This paper describes the methods for generating recommendations for the prediction of next tourist attraction and finds an optimal path recommendation to reach the point. They have used artificial neural networks (ANN) for performing prediction and then used particle swarm optimization (PSO) for generating optimal Path. For the Optimization, the parameters considered are distance, road congestion, Path popularity, weather conditions and user Pathpreference. The system performance was done based on comparison of the test data result over varying Path sizes. For the Path optimization, the results are compared with a similar implemented genetic algorithm. The work considers two main factors of travel identified as Path selection and sightseeing. The two modules important in the research are next tourist attraction prediction module and Path optimization module. To generate the recommendations, past tourists data is generated and the data is processed to identify the most likely site to be visited for the tourist. Majorly, the optimization keeps the objective to minimize the distance and certain parameters that would save time on Paths that will allow tourist to stay more at the destination

(Simmons, Browning, Yilu Zhang and Sadekar, 2006),presented predicting drivers intent from the everyday driving pattern. They have proposed to predict drivers intended Path and destination based on the Hidden Markov Model (HMM). The GPS sensor data and Map database is used to survey the Paths and destinations used by the driver.The Corpus driving data is used to make the survey. The performance of the model is measured taking into account traffic density, better trip duration, etc. The accuracy of the system developed is due to the fact that the predictions are forced. For places where choices are available, the use of additional factors (time-of-day, speed, day-of-week) often advances prediction accuracy immeasurably.

Laha A. and PutatundaA. , 2018 [5], have taken up the destination problem taking into consideration efficiency of the GPS enabled taxi service. They have proposed solution for streaming data-setup. In the paper they have examined four incremental learning methods using a Damped window model namely, Multivariate multiple regression(MMR), Spherical-spherical regression, Randomized spherical K-NN regression and an Ensemble of these methods for their effectiveness in solving the destination prediction problem. The Multivariate multiple regression method and the Ensemble of the three methods were found to be the efficient during the analysis. They noticed that the prediction of final destination of a vehicle while in service considering the location of the pickup place can improve the efficiency of the system. They also tried to predict the drop-off location co-ordinates taking the pickup location co-ordinates. The proposed work is developing the dynamic model which uses most relevant information and performs prediction of dynamic drop and next pickup.From the methods that the researcher implemented, the MMR and the Ensemble method performs better than others. The MMR method is more recommended in this paper when the training dataset is large and prediction accuracy is required.In this paper, they have examined the destination / next pickup location prediction problem and have proposed four new incremental learning methods out of which the MMR method is more better even if compared with the ANN method.

(Sudhanva, Kishore and Dixit, 2017),has concentrated over the dynamic Path prediction taking population growth as the factor for increase in the congestion on the Paths. Personalized Path prediction system considers user requirements for selecting the Paths. The user may prefer a long Path with less congestion over a short Path with more congestion. Path prediction here considered many constraints. This paper surveys few of the algorithms and methods used for such constraints involved predictions.In this survey, the authors tried to find out ways to reduce the drivers travel time avoiding congestion. This will help the driver to reduce fuel consumption providing a more efficient way of travelling. An extensive survey on Path prediction methods done in this paper is given below. Different algorithms that are existing with it's pros and cons has been tabulated which can be used to achieve prediction more efficiently through Machine learning.

(Wu et al., 2017), considered the average taxi travel speed mined from historical taxi GPS trajectory data and the allocation of cruising Paths to more than one taxi driver in a small-scale region to neighbouring pick-up locations. They have presented a spatio-temporal trajectory model with load balancing allocations to explore pick-up/drop-off information. This can help taxi drivers in cruising Paths to the recommended pick-up locations. In simulation experiments, their study shows that taxi drivers using cruising Paths recommended by our spatio-temporal trajectory model significantly reduces the average waiting time and travel less distance in order to find next passengers immediately, and the load balancing strategy significantly alleviates road loads. These objective measures can help us better understand spatio-temporal traffic patterns and guide taxi navigation.An STT model has been developed to explore spatio-temporal traffic patterns and guide taxinavigation. This model has considered large volume of historical taxi GPS trajectories for spatial and temporal analysis, and the pick-up location clusters, average taxi travel speed and cruising Paths are considered in the STT model. Specifically, average taxi travel speeds are estimated as traffic resistance, and the load balancing method has been utilized for cruising Path allocation.

(Katrakazas, Quddus, Chen and Deka, 2015),concentrated on planning algorithms that are responsible for mission-critical decision. It is known that the motion planning methods/ approaches use searching for a path to follow, avoiding obstacles, and then generate the best Path that ensure safety and provides efficiency. In this paper, a range of different planning approaches have been proposed.The authors have reviewed the existing approaches and then compared different methods employed for the motion planning of autonomous on-road driving that consists of (1) finding a path, (2) searching for the safest manoeuvre and (3) determining the most feasible trajectory. Based on a critical review of existing methods, research challenges to address current limitations are identified and future research directions are suggested so as to enhance the performance of planning algorithms at all three levels. This critical review on planning techniques have been presented in this paper, along with the associated discussions on their constraints and limitations, seek to assist researchers in accelerating development in the emerging field of autonomous vehicle research.Focus was given to incremental and local path search, as well as behaviour and trajectory planning, since global routing between an O–D pair has been discussed in the literature. The work identified that incremental path planning relies on searching data structures such as trees or lattices, while local usually takes place in a continuous space with sampling from the final states. Since decision making and the handling of dynamic obstacles were found to be the main areas of concern, the implementation of agent-based mathematical formulations and the incorporation of transport engineering aspects have been proposed. In addition, a recommendation was made for the use of alternative ways of sensing, such as vehicular communications, which would enhance the field of view of vehicles and improve both their estimating capabilities and localisation performance. Finally, directions for the incorporation of dynamic models into planning were made to improve the real-world performance of current approaches.

(Ye et al., 2015),presented a driving Path prediction method that is based on HiddenMarkovModel (HMM). They showed that this method can accurately predict a vehicle's entire Path as early in a trip's lifetime as possible without inputting origins and destinations beforehand. Firstly, theyproposed the Path recommendation system architecture, where Path predictions play with important role in the system. Secondly, we define a road network model, normalize each of driving Paths in the rectangular coordinate system, and build the HMM to make preparation for Path predictions using a method of training set extension based on K-means++ and the add-one (Laplace) smoothing technique. Thirdly, we present the Path prediction algorithm. Finally, the experimental results of the effectiveness of the Path predictions that is based on HMM are shown. This work firstly presented a driving Path recommendation system, where the prediction module is the core of recommendation system. The method will accurately predict a drivers entire Pathbeforehand. Then, a road network model was defined and normalized each of driving Paths in the rectangular coordinate system.

(Wang, H. et al, 2015),attempted to develop a real-time Path recommendation system, called R3 in order to provide users with the real-time Pathrecommendations . R3 recommends diverse Paths for different users to alleviate the traffic pressure. R3 utilizes historical taxi driving dataand real-time traffic data and integrates them together to provide users with real-time Path recommendation.The system here have considered real time traffic conditions between source and destination. They have compared their system R3 with Google Maps and Baidu Map. The results show that the recommended Paths are much better than those of Google and Baidu.

(Dong et al., 2014),stressed on poor performance of the driver and driving if the taxi drivers cruise according to their own experience. Therefore, it is valuable to recommend a profitable cruising Path for the taxi drivers in order to increase their income and reduce waste in fuel. In this paper, they proposeto use a system of linear equations to calculate the score of each road segment based on a large-scale real-world GPS data set. The score of each road segment consists of 1) the total income of the road segment and 2) the attractiveness of the drop-off location with respect to the next pick-up. Then, we get the profitable cruising Path based on the score of each road segment using skyline computation. In this work, they tried to construct a system for the taxi driver to find a profitable passenger using historical data set. They used a system of linear equations to calculate the score of each road segment. The locations of currently waiting passengers is known in advance. When there are several waiting passengers called through the taxi booking apps, recommending a taxi driver to pick up a passenger can be done based on the distance to that passenger and the drop off location of the deal. However, it is more practical to recommend a waiting point for the taxi drivers when there are no passengers called through the taxi booking apps.

(Ji-hua, Ze and Jun, 2013),discussed that Effective path planning is an important requirement for Path navigation in Intelligent Transportation Systems (ITS). However, the paths computed by the conventional path planning algorithms are usually not optimal. They identified that the Paths chosen by taxi drivers are believed to be more representative. This can be used in the Path planning. In this work, they present a hierarchical path planning method based on the experiential Paths of taxis. The algorithm consists of three steps. Firstly, extracting the Paths from original taxi trajectories. Secondly, categorizing the roads according to the track data and then the road network is classified into two grades using travel frequency for road segments. Thirdly, a hierarchical path planning method which searches paths by traversing the hierarchy is proposed.

(Krumm, Gruen and Delling, 2013),proposed a new algorithm for predicting a driver's Path based on a probabilistic prediction of the driver's destination. The proposed algorithm plans a Path. Roads on these Paths accumulate the probabilities of their respective destinations, giving higher probabilities to roads along the way to higher probability destinations. The algorithm is based on a single parameter that characterises how efficiently adriver drives. Once this parameter is computed, it does not require storing a history of trips, and it works in places a driver has never visited. The Path prediction algorithm in this case starts with probabilistic destination predictions for all intersections within a given range of the trip's start. For each candidate destination, the algorithm plans the fastest Path from the driver's current location and sums the probability of that destination over the Path's constituent road segments. While this requires many Path computations, our algorithm takes advantage of a new Path computation algorithm that computes a shortest path tree in a few tens of milliseconds on a regular PC. This algorithm is run every time the vehicle goes through a new intersection, resulting in a ranked list of future road segments. The algorithm depends on only one parameter, which characterises driving efficiency. After computing this parameter, it does not require storage of a driver's trip history, which is beneficial for privacy and beneficial for drivers in new locations. Our tests show that the prediction works well at eliminating large fractions of future candidate roads from consideration.Another extension is the possibility of timed predictions that estimate not only which roads the driver will encounter but also when they will be encountered. This would be useful for traffic jams that may clear by the time the driver arrives or for refuelling suggestions for when the vehicle is expected to be close to empty.

(Moreira-Matias et al., 2013),proposed a method to employ a learning model based on historical GPS data in a real-time environment. The major task was to predict the spatiotemporal distribution of the Taxi-Passenger demand in a short time horizon. They used a well known online algorithm: the perceptron. They were able to accomplish a satisfactory performance to output the next prediction using a short amount of resources. The authors in this case proposed a method to apply a complex learning model to build predictions about the taxi passenger demand in a real-time environment. They used a ARIMA model to an incremental one using the delta rule - a rule firstly introduced in the perceptionalgorithm which is able to update its weights step by step.

(Manasseh and Sengupta, 2013), presented a method for predicting the destination useful for applications including traffic safety, traffic mobility, and influencing driver behaviour. According to their study, current methods for predicting destination result in 72% accuracy if relying only on GPS traces. By providing accurate map data, the accuracy of prediction in current methods can reach 98% in best case scenarios has been tested in this paper. In their proposed method, given the current position of the driver, the position at which the driver was 5 min prior, the time of day, and the day of the week; the algorithm provides a prediction of the destination with a 1000m resolution. The Decision Tree with Pruning algorithm proves to be the most accurate resulting in an average 96 +/- 1.72 % accuracy of prediction across all subjects under testing. The work in this paper shows that predicting the destination of a driver with high accuracy is possible using the GPS trace data.

(Fogliaroni P., et. al., 2012) ,analyzed sequences of intersections of different types. Starting with sequences of lengthtwo and present a probabilisticmodel to derive statistics for longer sequences. They have validated theresults by comparing them with real frequencies. The data derived, when put together in a graph representation, allowed for looking for structurally similar areas in different regions by applying graph matching The first one is the algorithm conceived for subgraph isomorphism and is still today one of the most usedtechniques. It enumerates all (sub)graph matchings employing a tree search with backtrackingand forward checking. It basically creates the matching incrementally; at each step it triesto match a new node. If the matching fails it backtracks to the last matched subgraph. Theforward checking is used to prune the search space by looking at node adjacency. The morerecent algorithm presented in is based on a depth-first search strategy, also employinga set of forward-checking rules to prune the search space.

This work included other quantitative measurements such as the anglesformed by consecutive intersections or the distance betweentwo intersections. Similarly, one can also include qualitative spatial relations such as relativedirection, orientation, and visibility. Semantics can be included in different ways. For example, one may extend the model byconsidering not only intersections but also point of interests of a given types (e.g., recreationaland sightseeing features). Extending the representation in such a way would allow for semanticsimilarity analysis and search among different region.

(Mikluščák, Gregor and Janota, 2012),presented Path prediction and destination prediction based on the past Paths are a missing piece in intelligent transport systems (ITS). These predictions can be useful in many areas: congestion prediction, traffic control, upcoming traffic hazards and targeting advertisements next to the roads are some of the obvious ones. Simply said, if we can estimate the future location of cars which are already on the road network, we will be able to estimate future congestions andupcoming traffic hazards. The GPS units in the new generation of smartphones provide a good data source for prediction algorithms. Google maps application already collects this data. This paper discusses several algorithms and methodswhich have been used in similar areas and a Path prediction method based on artificial neural networks using the past Paths of a vehicle.

When looking at the results concerning performance, the need for testing on real data becomes increasingly obvious. The results achieved for the highly stochastic dataset are not very good – the performance approaches 60%. This is to be expected: the theoretical maximum is in fact not much greater for the data in question. It is shown that with an increasing size of the training data set, the results become better: this can be ascribed to the fact that the ANN is able to make better guesses concerning the probabilities related to the stochastic process.

(Yuan J., et. al.2010.), discussed a smart driving direction system leveraging the intelligence of experienced drivers. In this system, GPS-equipped taxis are employed as mobile sensors probing the traffic rhythm of a city and taxi drivers' intelligence in choosing driving directions in the physical world. We propose a time-dependent landmark graph to model the dynamic traffic pattern as well as the intelligence of experienced drivers so as to provide a user with the practically fastest Path to a given destination at a given departure time. Then, a Variance-Entropy-Based Clustering approach is devised to estimate the distribution of travel time between two landmarks in different time slots. Based on this graph, we design a two-stage routing algorithm to compute the practically fastest and customized Path for end users. We build our system based on a real-world trajectory dataset generated by over 33,000 taxis in a period of 3 months, and evaluate the system by conducting both synthetic experiments and in-the-fieldevaluations. As a result, 60–70% of the Paths suggested by our method are faster than the competing methods, and 20% of the Paths share the same results. On average, 50% of our Paths are at least 20% faster than the competing approaches.
This research describes a system to find out the practically fastest Path for a particular user at a given departure time. Specifically, the system mines the intelligence of experienced drivers from a large number of taxi trajectories and provide the end user with a smart Path, which incorporates the physical feature of a Path, the time-dependent traffic flow as well as the users' driving behaviors (of both the fleet drivers and of the end user for whom the Path is being computed).

(Froehlich and Krumm, 2008), presented The trend of using the past observations for performing the relevant analysis is being used in many researches. This paper develops and tests algorithms for predicting the end-to-end Path of a vehicle based on GPS observations of the vehicle's past trips. We show that a large portion of a typical driver's trips are repeated. Our algorithms exploit this fact for prediction by matching the first part of a driver's current trip with one of the set of previously observed trips. Rather than predicting upcoming road segments, our focus is on making long term predictions of the Path. We evaluate our algorithms using a large corpus of real world GPS driving data acquired from observing over 250 drivers for an average of 15.1 days per subject. Our results show how often and how accurately we can predict a driver's Path as a function of the distance already driven

This work showed how the regularity of a driver's travellingbehaviour could be exploited to predict the end-to-end Path for their current trip. We made three primary contributions. First, we provided a methodology for automatically extracting Paths from raw GPS data without knowledge of the underlying road structure. Second, we presented a detailed discussion and analysis of repeat trip behaviour from a real world dataset of 14,468 trips from 252 drivers. Finally, we developed and evaluated two algorithms that used a driver's trip history to make Path predictions of their current trip. Although performance varies, we believe some application areas such as improving hybrid vehicle efficiency and dynamic traffic alert systems could still benefit from long-term Path predictions even with a degree of uncertainty.

(Das et al. 2019), proposed that Travel time estimation is a fundamental problem in transportationscience with extensive literature. The study of these techniqueshas intensified due to availability of many publicly available largetrip datasets. Recently developed deep learning based models haveimproved the generality and performance and have focused on estimatingtimes for individual sub-trajectories and aggregating themto predict the travel time of the entire trajectory. However, thesetechniques ignore the road network information. In this work, the authors proposed and studied techniques for incorporating road networks alongwith historical trips' data into travel time prediction. We incorporateboth node embeddings as well as road distance into the existingmodel. Experiments on large real-world benchmark datasetssuggest improved performance, especially when the train data issmall. As expected, the proposed method performs better than thebaseline when there is a larger difference between road distanceand Vincent distance between start and end points.

This work concentrates on the problemof travel time prediction of anygiven path. They have considered an existing state-of-theart method based on deep neural networks and incorporated into one of the grids. This eventually leads to querying in one of thegrids while mapping any trip data node to OSM node, thus reducingthe computation time.

3. Comparative Analysis of Existing Path Prediction Methodologies

Sr. No	Methodologies	Pros	Cons
1	Random Decision Forests (RDF), Support Vector Machine (SVM)	RDF achieves a TP@5FP of 59 % at a TTI of 2.88 s which performs better than support vector machine.	Not applicable for real-world conditions and live testing.
2	Improved Personalized Path recommendation and RM calculation method.	Algorithmtakespersonalpreference , real-time network congestion conditions and popularitypreference	
3	Machine learning for building personal driving Path knowledge system First order Markov chain model Intelligent dynamic Path prediction system	Re-direct the driver's intended Path when the driver deviates from the predicted Path. Accurate prediction and superior performance.	Information such as traffic flow, weather conditions and other conditions are not considered.
4	Macroscopic, closed-form reformulation of a standard microscopic consumption model.	Analytical and exact with respect to widely accepted microscopic model . Gains new insights that can lead to development of new consumption predictors for realistic vehicles.	Not suited to replace consumption models used in eco-routing . Not suitable for consumption prediction of realistic vehicles.
5	Novel mechanism Partial Matching	Precision of 76.9%. Predicts places that have never been visited by the user	

		before.	
6	Autoregressive Input-Output HMM	Accuracy is 80% in real-time	
7	Improved Dijkstra's algorithm	Provides reasonable shortest Path for drivers.	
8	Intelligent Trip Modelling System (ITMS) through Machine Learning	Performance of ITMS is robust when Cross-region variance is considered	It cannot be used where traffic sensors are unavailable.
9	Road networks Map matching	Algorithm runs faster , by two folds without affecting the accuracy of the output.	
10	Time-Expanded Network (TEN) TEN-based mathematical programming problem Pareto optimal solution fuzzy programming	Algorithmtakespersonalpreference , real-time network congestion conditions and popularitypreference Usedforregionswithdifferentsizes	
11	Hidden Markov Model(VSW method)	Higher accuracy when compared to Fixed Sliding Window(FSW)	Interpolating trajectory points should be considered rather than shortest path.
12	Instance-Based Learning(IBL)	Accuracy stands out 87% at middle of trip.	Accuracy is relatively low at beginning of trip.
13	A* algorithm	When long distance is considered Performance is high. The model is automatic Predicts both destination and road segments.	Traffic jams and multiple traffic choice is not considered.
14	Vehicle Terminal is designed along with usage of TCP/UDP protocols.	CPU usage rate is 66.164% and disk busy percentage is 4.99%.	
15	Variable-order Markov Models (VMMs) Probabilistic Suffix Tree (PST)	Enormous impact of different traffic conditions are taken into consideration .	Poor scalability as the approach is centralized.

		40% next road segments are predictable , with a confidence weight of 60%.	
16	Hidden Markov Model (HMM)	Accuracy is above 98% for all transition that are Forced transitions.	Accuracy drops to 70% when Unforced transition is considered.

Table.1: Comparative Analysis of Existing Path Planning Algorithms

4. Path Planning Approach

a. Real time Data Collection

Successful development of effective real-time traffic management and information systems requires high quality traffic/Path information in real-time. We also require the state-of-the-art of traffic and general mobility sensory technology and a suite of methods for data pre-processing and cleaning for real-time applications. A proper traffic data acquisition, preprocessing, transformation and integration until data advanced processing and transfer is needed. Even though the comprehensive use of historical traffic data and assignment models to support the most part of online services and operations, real-time data is extremely important to promote models' accuracy.

b. Architecture for Real Time Path prediction

In the past decades, a variety of models and algorithms have been developed to predict arrival times or travel times. The most widely used ones can be classified into the following categories: historical average models, regression models, machine learning models including artificial neural network (ANN) models and support vector machines (SVMs) models, Kalman filtering-based models, and dynamic models. Historical average models are based on the historic data and able to predicate the travel times through previous trips. These models will be practical, useful, and reliable when the traffic flow is relatively small and stable. Regression models use a multivariate statistical technique for examining the linear correlations between a set of independent variables and a single dependent variable.

The Task is to design an efficient model for the real time Path prediction for the E-taxies. The new design would concentrate on surpassing the existing drawbacks in the recent models available for prediction of real time Path.

c. Creating the real time information dataset

Successful development of effective real-time traffic management and information systems requires high quality traffic/Path information in real-time.

The inputs to considered in the proposed models include the following factors.

(1) Source and destination Paths. At different time of day the e-taxi travel Paths are. Thus, the factor Paths should be considered as an input of the models.

(2) Road Segment. Different road segments have different number of intersections (signalized or un-signalized), road segment length, traffic conditions, and traffic flow composition. All these differences can result in the changes of travel Paths. Thus, road segment should be a factor in the models, which is expressed as segment.

(3) Tiem_stamp. The time to navigate the Path.

(4) Travel_ID.

d. Path Prediction: Given the current location of a taxi, we need to identify the shortest Path to an anticipated customer. This problem is different from identifying the region with the highest pick-up probability. since we need to incorporate the balance between distance travelled and the chances of picking up a customer.

5. Conclusion

Dynamic Path Prediction techniques and algorithms suggest a constraint based path or a Path from a given source to a destination. The suggested and predicted path helps a user to minimize the travel time, less congestion, economical and fuel efficient ride. In this research work we have done the exhaustive survey on the various Path prediction methodologies, techniques, algorithms and the approaches selected, presented, described and used by research community in the field of Path recommendation and prediction. Various Existing methodologies that are existing with its pros and cons have been tabulated in one of the section of this article which concludes that the Path planning and prediction can be more efficiently implement through Machine learning and its approaches.

References:

[1] Petrou, P., Tampakis, P., Georgiou, H., Pelekis, N. and Theodoridis, Y., 2020. Online Long-Term Trajectory Prediction Based on Mined Route Patterns. Lecture Notes in Computer Science, pp.34-49.

[2] Tu, W., Mai, K., Zhang, Y., Xu, Y., Huang, J., Deng, M., Chen, L. and Li, Q., 2021. Real-Time Route Recommendations for E-Taxies Leveraging GPS Trajectories. IEEE Transactions on Industrial Informatics, 17(5), pp.3133-3142.

[3] Malik and Kim, 2019. Optimal Travel Route Recommendation Mechanism Based on Neural Networks and Particle Swarm Optimization for Efficient Tourism Using Tourist Vehicular Data. Sustainability, 11(12), p.3357.

[4] Simmons, R., Browning, B., Yilu Zhang and Sadekar, V., 2006. Learning to Predict Driver Route and Destination Intent. 2006 IEEE Intelligent Transportation Systems Conference.

[5] Arnab Kumar Laha, SayanPutatunda, Real time location prediction with taxi-GPS data streams, Transportation Research Part C: Emerging Technologies, Volume 92, 2018,

[6] Sudhanva, M., Kishore, S. and Dixit, S., 2017. Personalized dynamic route prediction using machine learning: A review. 2017 International conference of Electronics, Communication and Aerospace Technology (ICECA).

[7] Wu, L., Hu, S., Yin, L., Wang, Y., Chen, Z., Guo, M., Chen, H. and Xie, Z., 2017. Optimizing Cruising Routes for Taxi Drivers Using a Spatio-Temporal Trajectory Model. ISPRS International Journal of Geo-Information, 6(11), p.373.

[8] Katrakazas, C., Quddus, M., Chen, W. and Deka, L., 2015. Real-time motion planning methods for autonomous on-road driving: State-of-the-art and future research directions. Transportation Research Part C: Emerging Technologies, 60, pp.416-442.

[9] Ye, N., Wang, Z., Malekian, R., Lin, Q. and Wang, R., 2015. A Method for Driving Route Predictions Based on Hidden Markov Model. Mathematical Problems in Engineering, 2015, pp.1-12.

[10] Wang, H. et al. International Journal of Science and Research (IJSR), 2015. Real Time Based Recommendation System for Taxi Ride Sharing. 5(5), pp.617-621.

[11] Dong, H., Zhang, X., Dong, Y., Chen, C. and Rao, F., 2014. Recommend a profitable cruising route for taxi drivers. 17th International IEEE Conference on Intelligent Transportation Systems (ITSC).

[12] Ji-hua, H., Ze, H. and Jun, D., 2013. A Hierarchical Path Planning Method Using the Experience of Taxi Drivers. Procedia - Social and Behavioral Sciences, 96, pp.1898-1909.

[13] Krumm, J., Gruen, R. and Delling, D., 2013. From destination prediction to route prediction. Journal of Location Based Services, 7(2), pp.98-120.

[14] . Moreira-Matias, L., Gama, J., Ferreira, M., Mendes-Moreira, J. and Damas, L., 2013. On Predicting the Taxi-Passenger Demand: A Real-Time Approach. Progress in Artificial Intelligence, pp.54-65.

[15] Manasseh, Christian, and Raja Sengupta. “Predicting Driver Destination Using Machine Learning Techniques.” IEEE Xplore, 1 Oct. 2013, ieeexplore.ieee.org/document/6728224/similar.

[16] Paolo Fogliaroni, Marvin Mc Cutchan, Gerhard Navratil, Ioannis Giannopoulos, “Unfolding Urban Structures: Towards Route Prediction and Automated City Modeling”, ACM, 2012.”

[17] Miklušćák, T., Gregor, M. and Janota, A., 2012. Using Neural Networks for Route and Destination Prediction in Intelligent Transport Systems. Telematics in the Transport Environment, pp.380-387.

[18] J. Yuan, Y. Zheng, C. Zhang, W. Xie, G. Sun, H. Yan, and X. Xie,“ T-Drive: Enhancing Driving Directions with Taxi Drivers’ Intelligence,” Proc.18th SIGSPATIAL Int’l Conf. Advances in Geographic Information Systems (GIS), 2010

[19] Froehlich, Jon, and John Krumm. "Route Prediction from Trip Observations." SAE Technical Paper Series, 14 Apr. 2008, 10.4271/2008-01-0201
[20] Das, Soumi, et al. "Map Enhanced Route Travel Time Prediction Using Deep Neural Networks." ArXiv:1911.02623 [Cs, Stat], vol. VI, no. II, 6 Nov. 2019, arxiv.org/abs/1911.02623.
[21[Dr.AarushiKataria, Dr. Naveen Nandal and Dr. Ritika Malik, Shahnaz Husain -A Successful Indian Woman Entrepreneur, International Journal of Disaster Recovery and Business ContinuityVol.11, No. 2, (2020), pp. 88–93

[22]Kumar, S. (2020). Relevance of Buddhist Philosophy in Modern Management Theory. Psychology and Education, Vol. 58, no.2, pp. 2104–2111.
[23]Roy, V., Shukla, P. K., Gupta, A. K., Goel, V., Shukla, P. K., & Shukla, S. (2021). Taxonomy on EEG Artifacts Removal Methods, Issues, and Healthcare Applications. Journal of Organizational and End User Computing (JOEUC), 33(1), 19-46. http://doi.org/10.4018/JOEUC.2021010102

[24]Shukla Prashant Kumar, Sandhu Jasminder Kaur, Ahirwar Anamika, Ghai Deepika, MaheshwaryPriti, Shukla Piyush Kumar (2021). Multiobjective Genetic Algorithm and Convolutional Neural Network Based COVID-19 Identification in Chest X-Ray Images, Mathematical Problems in Engineering, vol. 2021, Article ID 7804540, 9 pages. https://doi.org/10.1155/2021/7804540
[25]Aarushi, Naveen Nandal, Parul Agrawal. AN EXPLORATORY RESEARCH IN PRODUCT INNOVATION IN AUTOMOBILE SECTOR. JCR. 2020; 7(2): 522-529. doi:10.31838/jcr.07.02.98