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## Deep Learning Based Prediction Framework of User specific Mobility Patterns

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**Abstract:** Expanding unavoidable use of advanced cells and area based administrations around the globe has added to tremendous and quick development in versatility information. For the most part, the forecast objective fluctuates from various application situations. For the applications including asset designation and portability the executives, it is fundamental to anticipate the places of versatile clients sooner rather than later from many seconds to a couple of moments in order to make readiness ahead of time, which is really a direction forecast issue. In this paper, with the specific spotlight on multi-client multi-step direction forecast, we first plan a fundamental profound learning-based expectation system where the Long Short-Term Memory (LSTM) arrange is legitimately applied as the most basic part to take in client explicit versatility design from the client's recorded directions and foresee his/her development patterns later on. Spurred by the related discoveries in the wake of affirming and breaking down this essential structure on a model-based dataset, we extend it to a locale situated forecast conspire.

**Index Terms**-Trajectory Prediction, Multi-Step Prediction, Long Short-Term Memory, Sequence-to-Sequence, Machine Learning.

### I. INTRODUCTION

Expanding unavoidable utilization of PDAs and territory based organizations around the world has added to tremendous and quick advancement in compactness data. The colossal size of convey ability data gives new opportunities to finding the properties of human flexibility models and making adaptability estimates. In every practical sense, human convenience desire is basic in a wide extent of present day applications, going from modified proposition systems to transportation, urban orchestrating, and adaptability the board in the flexible correspondence structure. All around, the desire objective vacillates from different application circumstances. For the case of trades, it is fundamental to predict the spots of versatile customers soon from numerous seconds to a few minutes so as to prepare for convey ability the board and resource task. It is actually a course gauge issue where the bearing implies a period plan of positions with a fixed analyzing time stretch between each other. The specialists has proposed various versatility figure methodology, for example, visit plans mining, Markov-based models and other AI techniques, the vast majority of these methodologies are given to a discrete area desire which is really a multi-gathering issue, and not reasonable for foreseeing headings with fixed investigating time ranges. The reasons are as indicated by the going with. On one hand, for direction made out of discrete zone records, zones may save same for a couple back to back time-steps when the evaluating time stretch is essentially nothing, while zones may have a change between two near to time-steps when the seeing time go is gigantic. In this manner, they can barely reflect client improvement slants successfully. Obviously, for headings made out of a constant area brains, it is difficult to show the discretization granularity of course. By and large, high discretization granularity focal points to reflect client progression plans. Regardless, the gauge exactness may decrease with growing number of contender regions under high discretization granularity. In order to avoid the above issues, this paper embraces broad assessment for the procedures to envision headings made out of consistent bearings. Since it is actually a period course of action backslide desire issue, customary backslide counts, for instance, direct backslide and support vector backslide (SVR) are up-and-comer plans. What's more, autoregressive fused moving typical (ARIMA) is another backslide figuring. It is dedicated to taking care of gauge issues for long time game plan made out of numerical data with sum relationship, for instance, stock desire and traffic figure. In any case, the adaptability direction are consistently short groupings made out of two dimensional headings reflecting geographic zones, making ARIMA conceivably not adroit to the course want issue. Luckily, inside the structure of noteworthy learning, the Recurrent Neural Network (RNN) has demonstrated its inescapability in different time course of action issues not just in typical language arranging field (for example machine understanding, talk attestation ) yet similarly some different fields (for example traffic want precipitation figure ). As such, as the improved changes of regular RNN, Long Term Short Term Memory (LSTM) and Gate Recurrent Unit (GRU) are promising means the heading figure issue. Profiting by the most recent progression in noteworthy learning, this paper makes a wicked good assessment of the course want issue from both the single-client point of view and multiuser viewpoint. The significant obligations of this paper can be summed up as follows: We propose a LSTM-based single-client want structure and assess its introduction on a model-based dataset. Exploratory outcomes show the limit of LSTM to anticipate client's mobility dependent on pre-learning of the client's versatility structures. We additionally feature two or three difficulties (e.g., helpless hypothesis limit, disturbing screw up arrangement influence) of this client express want plot. To acclimate to these difficulties, we further relax up the customer unequivocal want plan to a locale arranged check plan and set forth a multi-client multi-step bearing want structure subject to the

Seq2Seq learning. Moreover, we acquaint a variable educator degree with control data moving in the course of action strategy. At last, we show likely that the proposed multi-client multi-step bearing guess structure can adequately coordinate the spoil get-together effect and improve as far as possible on a reasonable dataset.

## II. RELATED WORK

### **Accomplishing high throughput with prescient asset allotment[1]**

Huge information investigation makes foreseeing human conduct conceivable, however it is muddled how to misuse the anticipated data for improving execution of remote systems. In this paper, we explore the capability of prescient asset allotment in supporting high throughput by abusing abundance assets. To this end, we expect that the solicitations and directions of portable clients and the normal asset utilization status of base stations can be anticipated inside a window. To completely utilize assets inside the forecast window and hold assets for the unusual traffic showed up after the window, we enhance an asset assignment intend to limit the maximal transmission consummation time. To help the base stations for client planning, we acquaint a technique with make a transmission arrangement. These two plans figure out where, when and what to transmit to the clients with how much assets. Reproduction results show that the prescient asset designation can give significant increase over non-prescient system as far as both system throughput and client experience.

### **Enormous information driven shrouded markov model based individual portability expectation at focal points[2]**

With the development of cell phones and area based administrations, client versatility expectation has become a basic empowering influence for a wide scope of utilizations, similar to area based publicizing, early admonition frameworks, and citywide traffic arranging. Various procedures have been proposed to either direct spatio-worldly versatility expectation or estimate the following spot. In any case, both produce various expectation execution for various clients and show horrible showing for certain clients. This paper centers around examining the impact of living propensities on the model of spatio transient estimates next place desire and picks one from two models for a person to accomplish persuading versatility figure at clients' focal core interests. Considering the secured Markov model (HMM), a spatio normal marker and a next-place pointer are proposed. Living affinities are investigated regarding entropy, whereupon clients are pressed into unquestionable get-togethers. With huge degree genuine smaller information got from a critical city, we separate the proposed HMM-based pointers and existing front line markers and apply them to various client social events. The outcomes show the sound introduction of the two proposed adaptability pointers, which beat the front line for different client get-togethers.

### **ARIMA model for arrange traffic forecast and oddity discovery**

This paper presents the utilization of an essential ARIMA model for arrange traffic forecast and oddity identification. Precise system traffic demonstrating and expectation are significant for organize provisioning and issue finding, however arrange traffic is exceptionally powerful. To accomplish better displaying and forecast it is expected to disengage irregularities from ordinary traffic variety. Therefore, we break down traffic signals into two sections ordinary varieties, that observe certain law and are unsurprising and, inconsistencies that comprise of unexpected changes and are not unsurprising. ARIMA investigation and displaying for arrange traffic forecast can recognize and distinguish volume abnormality or anomalies.

"LSTM: A hunt space odyssey,"

A few variations of the long momentary memory (LSTM) engineering for repetitive neural systems have been proposed since its initiation in 1995. As of late, these systems have become the cutting edge models for an assortment of AI issues. This has prompted a reestablished enthusiasm for understanding the job and utility of different computational parts of commonplace LSTM variations. In this paper, we present the principal huge scope examination of eight LSTM variations on three delegate undertakings: discourse acknowledgment, penmanship acknowledgment, and polyphonic music displaying. The hyperparameters of all LSTM variations for each errand were upgraded independently utilizing irregular pursuit, and their significance was surveyed utilizing the ground- breaking utilitarian Analysis Of Variance structure. Altogether, we sum up the aftereffects of 5400 exploratory runs ( $\approx 15$  long periods of CPU time), which makes our examination the biggest of its sort on LSTM systems. Our outcomes show that none of the variations can enhance the standard LSTM engineering essentially, and exhibit the overlook door and the yield actuation capacity to be its most basic segments. We further see that the examined hyperparameters are for all intents and purposes autonomous and determine rules for their productive change.

### **An overall examination of unpredictable waypoint and gauss markov flexibility model in introduction evaluation of manet[3]**

A portable specially appointed system (MANET) is a system comprising of a lot of remote versatile hubs that speak with one another without brought together control or set up framework. The versatility model speaks to the moving conduct of every portable hub (MN) in the MANET that ought to be reasonable. It is a vital part in the exhibition assessment of MANET. Irregular waypoint portability model is the main versatility model that has been generally utilized in the reenactment investigation of MANET notwithstanding some ridiculous development practices, for example, unexpected stop and sharp turn. While Gauss-Markov portability model has been demonstrated that it can take care of both of these issues. This project presents a relative multiplication examination of unpredictable waypoint and Gauss-Markov flexibility model on the presentation examination of MANET that uses extraordinarily designated on-demand partition vector (AODV) as the coordinating show. The outcomes show that both portability models are not diverse in the event that every MN is moving at human running velocity. In this way, it is proposed to utilize arbitrary waypoint portability model in light of its less computational overhead contrasting with Gauss-Markov versatility model. At the point when the speed of MNs is as high as quick autos, the exhibition result utilizing irregular waypoint portability model is huge not quite the same as Gauss-Markov versatility model. In this manner, Gauss-Markov portability model ought to be utilized. Also, various degrees of arbitrariness setting have no impact on the exactness of throughput and start to finish delay.

### "SLAW: self-comparable least-activity human walk,"

Numerous exact investigations of human strolls have announced that there exist principal factual highlights ordinarily showing up in versatility follows taken in different portability settings. These include: 1) substantial tail flight and respite time circulations; 2) heterogeneously limited portability zones of people; and 3) shortened force law intercontact times. This paper reports two extra such highlights: a) The goals of individuals (or we state waypoints) are scattered in a self-comparable way; and b) individuals are bound to pick a goal closer to its current waypoint. These highlights are known to be compelling to the exhibition of human-helped portability systems. The fundamental commitment of this paper is to introduce a versatility model called Self-comparative Least- Action Walk (SLAW) that can deliver manufactured portability follows containing all the five measurable highlights in different portability settings including client made virtual ones for which no observational data is accessible. Making engineered follows for virtual conditions is significant for the presentation assessment of versatile systems as system fashioners test their systems in numerous different system settings. An exhibition investigation of portable steering conventions on manufactured follows made by SLAW shows that SLAW draws out the extraordinary presentation highlights of different directing conventions.

### "A LSTM organize for interstate direction expectation,"

So as to drive securely and effectively on open streets, independent vehicles should comprehend the aims of encompassing vehicles, and adjust their own conduct likewise. Whenever experienced human drivers are commonly acceptable at surmising other vehicles' movement up to a couple of moments later on, most ebb and flow Advanced Driving Assistance Systems (ADAS) can't perform such medium-term conjectures, and are generally restricted to high-probability circumstances, for example, crisis slowing down. In this article, we present an initial move towards steady direction expectation by presenting a long momentary memory (LSTM) neural system, which is able to do precisely foreseeing future longitudinal and horizontal directions for vehicles on expressway. Not at all like past work concentrating on a low number of directions gathered from a couple of drivers, our system was prepared and approved on the NGSIM US-101 dataset, which contains an aggregate of 800 hours of recorded directions in different rush hour gridlock densities, speaking to in excess of 6000 individual drivers

### Profound learning-based wise double availability for portability the board in thick system[4]

Ultra-thick framework sending has been proposed as a key strategy for achieving limit destinations in the fifth-age (5G) convenient correspondence structure. Regardless, the sending of more diminutive cells unavoidably prompts logically visit handovers, in this way making flexibility the chiefs all the all the more testing and decreasing the breaking point gains offered by the thick framework course of action. In order to totally gather the increments for adaptable customers in such a framework space, we propose a shrewd twofold accessibility instrument for convey ability the heads through significant learning-based adaptability desire. We first use LSTM (Long Short Term Memory) count, one of significant learning estimations, to pick up capability with every customer equipment's (UE's) versatility structure from its recorded bearings and envision its advancement inclines later on. Considering the looking at figure results, the framework will choose whether a handover is required for the UE. For the handover case, a twofold affiliation will be developed for the related UE. Along these lines, the UE can get the radio sign from two base stations in the handover strategy. Reenactment results watch that the proposed shrewd twofold accessibility instrument would altogether be able to improve the idea of organization of adaptable customers in the handover technique while guaranteeing the framework imperativeness efficiency.

### III. Proposed System:

In this paper, the significance of trajectory prediction and explore feasible approaches from both the single-user perspective and multi-user perspective. For single-user trajectory prediction, we propose a basic LSTM framework and experimental results on a model-based mobility dataset illustrate the superiority of LSTM to make predictions based on pre-learning of user-specific mobility patterns. For multi-user multi-step prediction, we further propose a region oriented prediction scheme and put forward an LSTM-based Sequence-to-Sequence (Seq2Seq) framework. The proposed framework has significant improvements on generalization ability and reduces error-accumulation..

### IV. Framework:

#### LSTM-BASED SINGLE-USER PREDICTION FRAMEWORK

The thought is to utilize one LSTM to peruse the info arrangement, each timestep in turn, to acquire huge fixed-dimensional vector portrayal, and afterward to utilize another LSTM to remove the yield succession from that vector. In the model-based dataset, various clients ordinarily have particular versatility designs, making the portability forecast issue to be client explicit. Along these lines, so as to make versatility expectations for a client, the most basic advance is to set up a particular portability model which completely speaks to the client's portable example from his/her chronicled directions. The forecast procedure includes three significant advances. To start with, the given direction is handled by a completely associated (FC) input layer with 128 neurons so every two-dimensional organize is planned to a 128-dimensional feature tensor. At that point, the prepared arrangement is sent to the principle part of the portability model, a profound intermittent neural system shaped by three stacked LSTM layers each with 128 neurons. Each LSTM layer takes the yield of the past layer as information and feeds its yield to the following layer. At long last, a FC yield layer with 2 neurons maps the yield of the last LSTM layer at each time-step  $i$  to a two-dimensional facilitate  $\tilde{p}_{i+1}$  as the anticipated area of whenever step, and subsequently we get the expectation grouping  $\tilde{p} = \{\tilde{p}_2 \tilde{p}_3 \dots \tilde{p}_T + 1\}$ . The preparation objective is to limit the separation mistake between the anticipated area and the real area. In this manner, we pick the Mean Square Error (MSE) as the misfortune work and embrace Backward Propagation Through Time (BPTT) calculation to refresh the system boundaries. At last, the client's versatility design is spared in the portability model as system boundaries and the forecast of future direction can be finished dependent on the prepared portability model. In this part, we assess the expectation execution of the proposed structure on a client's directions from the model-based dataset. The preparation settings are appeared in Table II. The length of every direction is 360min at one-minute granularity. So as to completely gain proficiency with the client's portable example, during the preparation procedure, we take the total direction aside from the latest possible time (for example  $\{p_1 p_2 \dots p_{359}\}$ ) as information



and push the time-arrangement forward one moment as standard yield (for example  $\{p_{2p3} \dots p_{360}\}$ ). During the test procedure, following one-hour perception, we first make single-step expectations given the client's genuine situation at each time-step. At that point, so as to assess the forecast exhibition exhaustively, the instance of multi-step expectation where the genuine position turns out to be quickly inaccessible is additionally thought of.

#### Multi-user multi-step prediction framework :

Multi-client multi-step forecast vows to bring loads of critical benefits. Right off the bat, it takes into account more viable close ongoing asset pre-designation. Be that as it may, it needs to manage the irritating blunder amassing impact. Besides, the speculation capacity of the forecast model across clients additionally makes it practical to rapidly perform direction expectation for any client. Thirdly, the calculation overhead of preparing a model for every client independently can be altogether decreased. Accordingly, we consider this present reality client development situation and propose a multi-client multi-step direction forecast structure. It tends to be seen that however the direction originates from various clients, most directions have comparable momentary attributes following topographical requirements in a little region given a constrained direction term. This rouses us to concentrate on the common development designs in a particular zone (e.g., 3 to 5 full scale base stations as opposed to singular development designs when making expectations for numerous clients. Along these lines, we expand the client explicit expectation plot for singular clients to an area arranged multi-client forecast conspire. Besides, so as to diminish the mistake collection impact for multi-step forecast, we propose a Seq2Seq structure which can decouple the direction highlight extraction process and the expectation procedure, in this way making the decoder more spotlight on worldwide data of the information succession and overlook the nearby blunders.

We set up a Seq2Seq structure dependent on the LSTM encoder-decoder design to catch the transient relationship inside the direction like speed or course. All directions in the particular region are used for the system to secure the mutual transient versatility designs brought about by geological imperatives. In particular, the information arrangement is the perception direction  $\{p_1 p_2 \dots p_T\}$  and the yield arrangement is the forecast of target direction  $\{p_{T+1} \dots p_{T+K}\}$ . Since the objective direction likewise contains development data and expected geological qualities, we blend two distinct systems as the last preparing methodology to utilize the portable data contained in the preparation information:

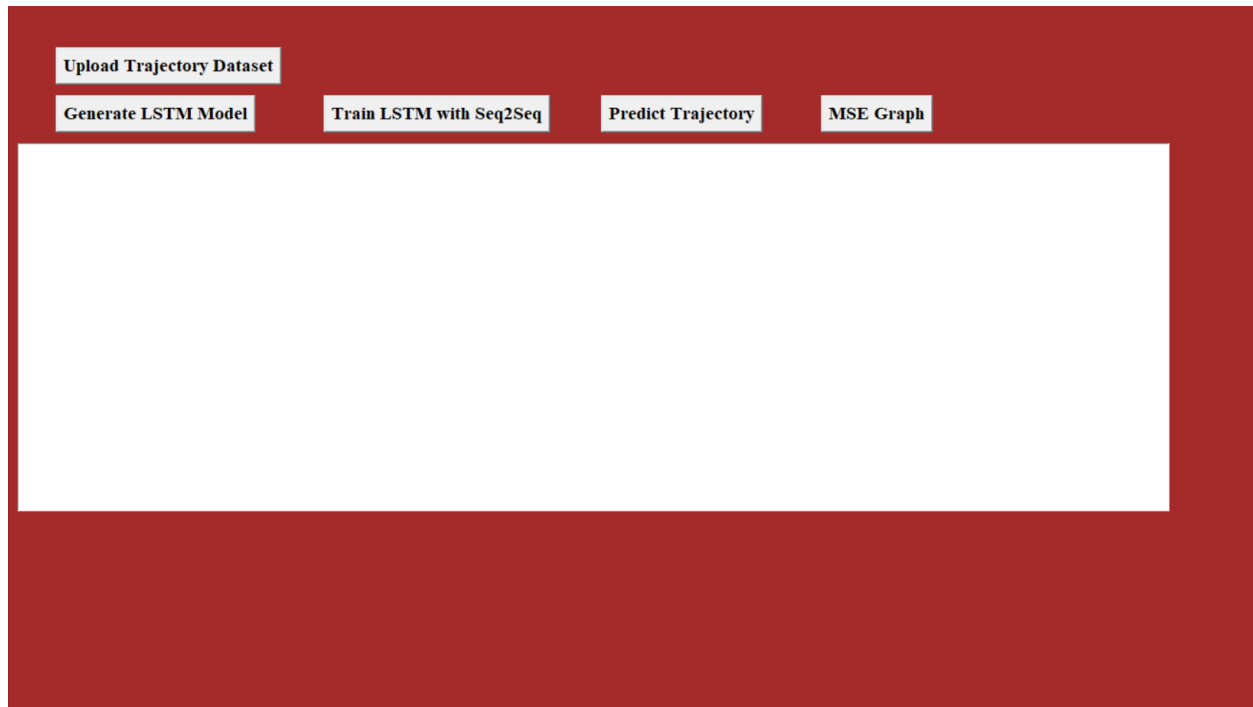
The principal case is equivalent to the auto-backward model where the inaccurate yield of the past advance is filled in as the contribution of the following stage. Thusly, the decoder can be more spotlight on worldwide data of the information direction and overlook the neighbourhood expectation blunders, in this way improving the coordination of the whole system. For the other case, the objective succession moved one stage forward is filled in as the contribution of the decoder to learn greater development data and expected geological attributes. So as to amplify the forecast exhibition, we acquaint an instructor proportion with balance the two cases. The multi-user multi-step prediction framework consists of the following two neural networks

**1) Encoder Neural Network:** It comprises of one FC input layer with 128 neurons followed by two LSTM layers stacked each with 128 neurons. The information arrangement is the given direction  $\{p_1 p_2 \dots p_T\}$ . The info layer is answerable for changing the 2-dimensional area  $p_i$  into a 128-dimensional element tensor to catch the intricate structure of the direction information. The yield is then taken care of into the LSTM stack with two layers. After  $T$  recursive updates in the two LSTM layers, their most recent cell states are resolved and gone to the decoder.

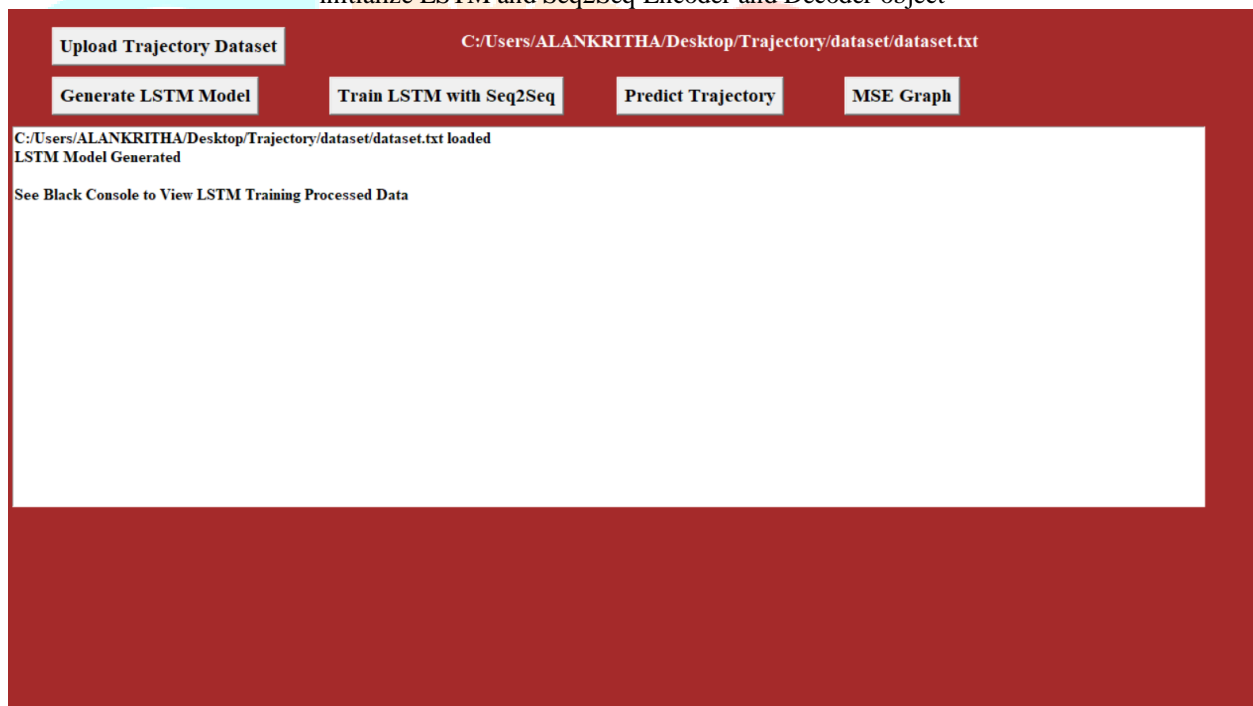
**2) Decoder Neural Network:** It comprises of one FC input layer with 128 neurons, two stacked LSTM layers each with 128 neurons, and one FC yield layer with 2 neurons. The LSTM layers are introduced by the encoder state vectors ( $h_T, c_T$ ). The main contribution of the decoder arrange is  $p_T$ , the last estimation of the info succession for the encoder organize. For the preparation procedure, we utilize the educator proportion to control the contribution of the following stages. In particular, we create an arbitrary number somewhere in the range of 0 and 1. In the event that the arbitrary number is bigger than educator proportion, the contribution of the following  $K - 1$  stages will be  $\{\tilde{p}_T + 1 \tilde{p}_T + 2 \dots \tilde{p}_T + K - 1\}$ , the anticipated ss estimation of the past advances. Otherwise, the objective yield grouping moved one stage forward  $\{p_T + 1 p_T + 2 \dots p_T + K - 1\}$  will be the info grouping for the following  $K - 1$  stages.

In order to show results, we used python programming language in which the detail results will be shown. First upload trajectory dataset which contains user id steps latitude values longitude values after uploading the dataset it is necessary to map dataset to LSTM model, each timestep in turn, to acquire huge fixed-dimensional vector portrayal, and afterward to utilize another LSTM to remove the yield succession from that vector and then train LSTM with Seq2Seq framework shows accuracy results in percentage and then predict the trajectory by giving inputs of specified user id latitude longitude values, users next predicted sequences locations is shown. MSE Graph' to get Mean Square Error Graph between LSTM and Existing GRU technique we can see with LSTM less prediction error is there compare to existing technique. In MSE graph x-axis contains algorithm name and y-axis contains error rate

## V. RESULTS



After uploading dataset and we can see LSTM model generated. Then 'Train LSTM with Seq2Seq' to train uploaded dataset with initialize LSTM and Seq2Seq Encoder and Decoder object



```

(54, 9, 9)
Model: "model_1"

Layer (type)                 Output Shape                 Param #   Connected to
-----
input_1 (InputLayer)         (None, None, 9)             0
input_2 (InputLayer)         (None, None, 9)             0
lstm_1 (LSTM)                 [(None, 512), (None, 1069056) input_1[0][0]
lstm_2 (LSTM)                 [(None, None, 512), 1069056 input_2[0][0]
                                     lstm_1[0][1]
                                     lstm_1[0][2]
dense_1 (Dense)              (None, None, 9)             4617      lstm_2[0][0]
-----
Total params: 2,142,729
Trainable params: 2,142,729
Non-trainable params: 0

None
Epoch 1/10
54/54 [=====] - 2s 30ms/step - loss: 82.9850 - accuracy: 0.3457
Epoch 2/10
54/54 [=====] - 0s 9ms/step - loss: 55.7021 - accuracy: 0.8313
Epoch 3/10
54/54 [=====] - 1s 9ms/step - loss: 47.1328 - accuracy: 0.8601
Epoch 4/10
54/54 [=====] - 1s 10ms/step - loss: 42.4645 - accuracy: 0.7798
Epoch 5/10
54/54 [=====] - 1s 10ms/step - loss: 39.2537 - accuracy: 0.7428
Epoch 6/10
54/54 [=====] - 1s 11ms/step - loss: 36.7426 - accuracy: 0.8827
Epoch 7/10
54/54 [=====] - 1s 12ms/step - loss: 35.6255 - accuracy: 0.9444
Epoch 8/10
54/54 [=====] - 1s 11ms/step - loss: 34.8738 - accuracy: 0.9424
Epoch 9/10
54/54 [=====] - 1s 11ms/step - loss: 34.1775 - accuracy: 0.9444
Epoch 10/10

```

In above black console we can see LSTM generation process and in below screen we can see it accuracy also

```

C:\Windows\system32\cmd.exe
dense_1 (Dense)              (None, None, 9)             4617      lstm_2[0][0]
-----
Total params: 2,142,729
Trainable params: 2,142,729
Non-trainable params: 0

None
Epoch 1/10
54/54 [=====] - 2s 30ms/step - loss: 82.9850 - accuracy: 0.3457
Epoch 2/10
54/54 [=====] - 0s 9ms/step - loss: 55.7021 - accuracy: 0.8313
Epoch 3/10
54/54 [=====] - 1s 9ms/step - loss: 47.1328 - accuracy: 0.8601
Epoch 4/10
54/54 [=====] - 1s 10ms/step - loss: 42.4645 - accuracy: 0.7798
Epoch 5/10
54/54 [=====] - 1s 10ms/step - loss: 39.2537 - accuracy: 0.7428
Epoch 6/10
54/54 [=====] - 1s 11ms/step - loss: 36.7426 - accuracy: 0.8827
Epoch 7/10
54/54 [=====] - 1s 12ms/step - loss: 35.6255 - accuracy: 0.9444
Epoch 8/10
54/54 [=====] - 1s 11ms/step - loss: 34.8738 - accuracy: 0.9424
Epoch 9/10
54/54 [=====] - 1s 11ms/step - loss: 34.1775 - accuracy: 0.9444
Epoch 10/10
54/54 [=====] - 1s 11ms/step - loss: 33.7082 - accuracy: 0.9547
LSTM Accuracy: 94.44%

```

we can see LSTM with Seq2Seq got 94.44% accuracy. Now LSTM and Seq2Seq model is train and we can predict user's location on 'Predict Trajectory'. After enter the input of users current latitude, longitude and user\_id to predict next sequences. This details we can give from dataset and dataset has all this details. For example see below dataset values

```

1 user_id,steps,latitude,longitude
2 0.0,1.0,12.7752321543,7.27912389126
3 0.0,2.0,12.375348446,7.92350535049
4 0.0,3.0,9.3867438893,7.06433007152
5 0.0,4.0,7.89244161096,6.53927851215
6 0.0,5.0,5.76674400374,7.18365997137
7 0.0,6.0,6.58755793128,6.41994861229
8 0.0,7.0,7.32418581497,5.91876303289
9 0.0,8.0,7.02953466149,4.5822681545
10 0.0,9.0,7.02953466149,5.17891765378
11 10.0,1.0,12.419546119,7.19678626036
12 10.0,2.0,12.2187624044,7.78890122345
13 10.0,3.0,9.80767410855,6.8256702718
14 10.0,4.0,7.36227999981,6.76910789927
15 10.0,5.0,5.30245797191,7.23282389012
16 10.0,6.0,5.99699283367,6.45073572645
17 10.0,7.0,7.93642881887,5.96935891043
18 10.0,8.0,7.53465092459,4.52761506036
19 10.0,9.0,7.45572650848,5.17891765378
20 20.0,1.0,12.0640705488,7.11444862946
21 20.0,2.0,12.062386828,7.65429709641
22 20.0,3.0,10.2286043278,6.58701047209
23 20.0,4.0,6.83232885377,6.9989372864
24 20.0,5.0,4.83817194007,7.28198780886
25 20.0,6.0,5.40621727095,6.48152284062
26 20.0,7.0,8.54867182277,6.01995478797
27 20.0,8.0,8.0397671877,4.47320062603

```

After giving above input details we will get next predicted sequences

Upload Trajectory Dataset

Generate LSTM Model

Train LSTM with Seq2Seq

Predict Trajectory

MSE Graph

C:/Users/ALANKRITHA/Desktop/Trajectory/dataset/dataset.txt

C:/Users/ALANKRITHA/Desktop/Trajectory/dataset/dataset.txt loaded

LSTM Model Generated

See Black Console to View LSTM Training Processed Data

Predicted Sequences of users next steps are :

Next Location Latitude : 12.375348446

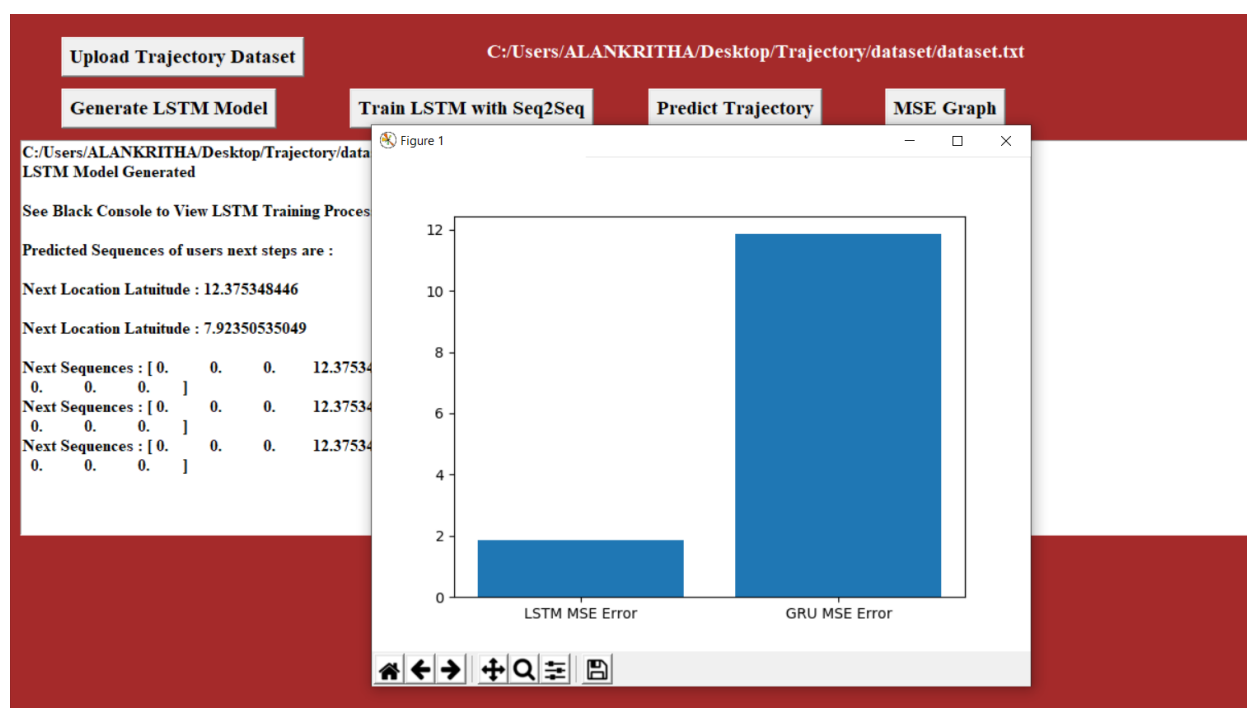
Next Location Latitude : 7.92350535049

Next Sequences : [ 0. 0. 0. 12.37534845 7.92350535 0. 0. 0. 0. ]

Next Sequences : [ 0. 0. 0. 12.37534845 7.92350535 0. 0. 0. 0. ]

Next Sequences : [ 0. 0. 0. 12.37534845 7.92350535 0. 0. 0. 0. ]

In above screen we got next locations latitude and longitude values from above output values u can ignore all zeroes and see only latitude and longitude values as users next predicted sequences locations. Now on 'MSE Graph' to get Mean Square Error Graph between LSTM and Existing GRU technique



In above graph we can see with LSTM less prediction error is there compare to existing technique. In above graph x-axis contains algorithm name and y-axis contains error rate

## VIII.CONCLUSION:

In this paper, we research the noteworthiness of direction expectation and investigate possible methodologies from both the single-client point of view and multi-client viewpoint. For single-client direction forecast, we propose a fundamental LSTM structure and trial results on a model-based portability dataset outline the prevalence of LSTM over make expectations dependent on pre-learning of client explicit versatility designs. For multi-client multi-step expectation, we further propose an area situated forecast plan and set forward a LSTM-based Seq2Seq structure. Examinations on a practical dataset show that the proposed structure outflanks the other contending approaches, which exhibit its extraordinary speculation capacity for multi-client forecast just as vigor and steadiness for multi-step expectation. Our present work doesn't consider the semantic setting in the direction like the purpose of interests due to the restriction of information. For future work, we intend to join our calculation with some semantic data to improve the forecast exhibition.

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