Application Of Viterbi Algorithm For Efficient Transportation Forecasting

Manas Kumar Yogi, Koondrapu Koushik Sri Sai, Afreen Jaha

Abstract: This paper discusses a novel application of probabilistic models which can uncover a hidden sequence of states thereby helping us predict the transportation needs during time where people will travel in huge numbers. We advocate the application of Viterbi algorithm for serving our purpose. The Viterbi algorithm has been already applied in various domains with remarkable efficiency forcing us to think about its role in supporting development of robust prediction models for railway transport. Our paper enlightens the strength of Viterbi algorithm and how its efficiency is comparable to other prediction models which considers the standard factors only limiting their conclusive prediction power. The experimental results prove that our proposed strategy improves prediction accuracy significantly than other forecasting models.

Index Terms: Transportation forecasting, Viterbi algorithm, Hidden Markov Model, Prediction.

1 Introduction

Transportation forecasting is the process of calculating number of people using a particular mode of transport.. For instance, a forecast may result in calculating the number of vehicles/people travel on a road or bridge etc. It begins with the collection of data on current traffic. These are used for several key purposes in transportation policy, planning, and engineering. In the late fifties has traditionally followed the four-step model or urban transportation planning (UTP) and implemented it on the mainframe computers[1]. Following the four-step model as root to our model we've built an algorithm which solves this problem. The four steps of the UTP are

I. Trip Generation
II. Trip Distribution
III. Mode Choice
IV. Route Assignment

. In addition to identify the forecasting, it is important to note that forecasting infuse every step. For forecasting such traffic for a user, we have come up with a model which uses the Viterbi Algorithm to predict the traffic, for instance who uses railway mode of transportation. Here our model takes input data such as vehicle availability, mode of transport, climate effect, ride fares, journey history of the user. The criteria and decisions of the above factors that we have taken into consideration are applied to the Viterbi algorithm to get the accurate traffic prediction.

2 I. PROPOSED MECHANISM

2.1 About Viterbi algorithm

This algorithm is the best dynamic programming algorithm to find the series of unrevealed states which is known to be Viterbi path[3]. In programming everything is updated in day to day life similarly the name Viterbi path is changed and the new name that is evolved is convolution code. The Viterbi algorithm is used in decoding the Viterbi path or convolutional code. This algorithm is also known as maximum sum or maximum product algorithm. This algorithm is highly applied in fields like converting speech to text, recognition of speech and in many other fields[4]. This model is focused to forecast the effect of transport network over the future locations and then the effect of these new locations over the transport demand.

2.2 Importance of Viterbi algorithm

A Viterbi algorithm finds valid Viterbi code from a received signal. A Viterbi algorithm looks for the current state of the signal and the series of previous states to decide what the most likely true value of the current state is. It is particularly effective in preventing errors in digital communication over wireless and other transmission media[5]. The complexity of the algorithm is easily estimated: Memory: the algorithm needs M storage locations, one for each state, where each location must be capable of storing a length L(m) and a truncated survivor listing S(m) of the symbols Computation: in each unit of time the algorithm must make M2 additions at most, one for each existing transition, and M comparisons among the M2 results[6]. In the existing work the modeling processes considering the standard factors which direct prediction in the context of transportation forecasting. The factors used as model components are the

I. Vehicle availability
II. Time of the day
III. The season of the year
IV. Climate conditions

Hidden factors:

1. Climate of the day is hidden factor which can be derived from which month it is.

2. The occupancy of the vehicle can be derived from time of the day. During rush hour 8am to 6 pm IST the occupancy level will be high and vice versa.

The existing model need huge amount of historical data for transportation forecasting. Also, the prediction accuracy has been observed to be in the range of 60% to 80%. Our propose

- *Author name is Manas Kumar Yogi currently working as Asst. Prof. Department of Computer Science in Pragati engineering college, India. E-mail: manas.yogi@gmail.com*
- *Co-Author name is Koondrapu koushik srisai currently pursuing B.Tech 3rd year in computer science and engineering in Pragati engineering college, India. E-mail: koushiksrisai999@mail.com*
- *Co-Author name is Afreen jaha currently pursuing Btech 3rd year in computer science and engineering in Pragati engineering college, India. E-mail:afreenjaha20052000@gmail.com*

technique tries to increase this accuracy level above 80%. For this we propose a dynamic programming approach for determining the most likely hidden factors to help for the purpose of transportation forecasting. For this we use an extension of the hidden Markov model (HMM)which is called Viterbi algorithm.

3 PROPOSED ALGORITHM

```
function  TFV(V_O,S_S,α,S_O,T_P,E_P) : out
for state s in [1,2,3,4,…….,n] do
V1[s,1] = αs* E_Ps.S_O 1
V2[s,1] = 0
end for
for obs o in [2,3,4,5,….,t] do
for states in[1,2,3,4,….,n] do
        V1[s,o] = max(V1[n,o-1]*T_Pns* E_Ps.S_O1)

        V2[s,o] = arg max(V1[n,o-1]*T_Pns* E_Ps.S_O1)
end for
end for
mt  = arg max(V1[n,t]
outt =  S_Sm t
for i in [t,t-1,t-2,t-3,…..,2] do
mi-1 = V2[mi,i]
outi-1 = S_Sm i-1
end for
        return out
end function.
```

4 EXPLANATION

The proposed algorithm produces Viterbi path as out that are series of states where outn belongs to the state space (S_S). It also produces the observations

$S\_O = (S\_O_1, S\_O_2, S\_O_3, \dots, S\_O_t)$ where S_O_n belongs to V_O.(where n is the number of Viterbi observations.

In this Nxn vector is initialized:

- For each and every value $V_1[s,o]$ in V_1 holds the probability of the path that produces S_O.
- For each and every value $V_2[s,o]$ of V_2 holds the probability of the path for all o, where s is in between 2 and t

These are incremented by order of (n*(o+ s)).

$V_1[s,o] = \max(V_1[n,o-1]*T\_P_{ns}* \; E\_P_{s.S\_O1})$

$V_2[S,O]=\text{ARGMAX}(V_1[N,O-1]*T\_P_{NS}* E\_P_{s.S\_O1})$.

5 INPUT

The veterbi observations
V_O= {V_O1,V_O2,……,V_ON}

- S_S which represents the state space of the problem where S_S = {S_S1,S_S2,S_S3,…….S_Sn}
- A vector of initial probabilities α ={α1,α2,……..,αn} where α1 holds the probability of out1==S_S1
- A series of observations S_O = {S_O1,S_O2,…,S_Ot} so that S_Ot == n , when V_On is the observed at a particular time t.
- T_P represents a nxn vector that holds the probability of the transitions from one state to another.
- E_P represents a kxn vector that holds the probability of observation S_O from some state in S_S.

6 OUTPUT

The output will be the unrevealed states out={out1,out2,out3,………,outN}.

7 EXAMPLE

Consider a state space where all passengers are either choosing to travel by train or not. Our algorithm takes input of the standard factors (like vehicle availability, time of the day, the season of the year and the climatic conditions) and predicts whether the train will be chosen by the passenger for transport. The probabilities of the standard factors and inputs for the Viterbi algorithm are given as below:

```
V_O = (‘ Availability’ ,’ Time’ ,’ climate’)


S_S = (‘ will_travel ’,’ will_not_travel ’)


α = {‘will_travel’ : 0.6,
     ’will_not_travel’ : 0.4}
T_P = { ‘will_travel’:{‘will_travel’:0.7’,
                       ’will_not_travel’:0.3},
        ‘will_not_travel’:{‘will_travel’:0.4,
                       ’will_not_travel’:0.6}
      }
E_P ={‘will_travel’:{‘availability’:0.5,
                     ’time’:0.4,
     ’climate’:0.1},
‘will_not_travel’:{‘availability’:0.1,’
                     time’:0.3,
                     ’climate’:0.6}
      }
```

In the above input the α represents the initial probability that a person travels by train. The T_P represents the transition of condition from will_travel to will_not_travel and there is a probability of 0.3 that the person will not travel by train tomorrow. E_P represents how each standard factor effecting the condition, will_travel and will_not_travel.

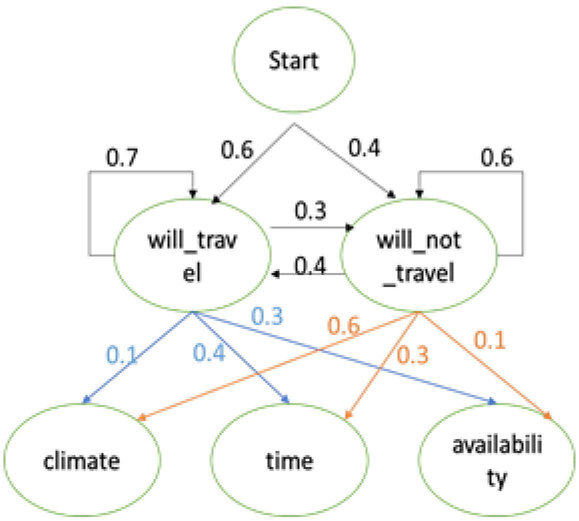

Fig.1. *Viterbi states with path probability for travel forecast*

8 EXPERIMENTAL RESULTS

We have conducted experimental studies on a specific train Kakinada Port-Visakhapatnam passenger/57255 train number and obtained estimation regarding the count of daily passengers traveling in that route by railway authorities. We have assumed the travel probabilities accordingly. After application of Viterbi algorithm, we have obtained the following results which has been represented by a graph. In the graph we have indicated number of t travelers forecasted in x-axis and the probability of selecting the railway transport on the y-axis. Our experiments shows that the Viterbi algorithm predicts at a rate which is better than other forecasting methods. We infer that the hidden factors which effect the choice of a traveler is used in our proposed technique which enhances the prediction accuracy of our model. We observe that as the hidden probability increases the chance that the person will travel by a train also increases .So, on that basis we have found an increasing trend in the graph which represents the fact that as hidden probability increases the number of travelers opting a railway route and a specific train also increases. The graph drawn between number the travelers and the probabilities of selecting the railway transport will be as below:

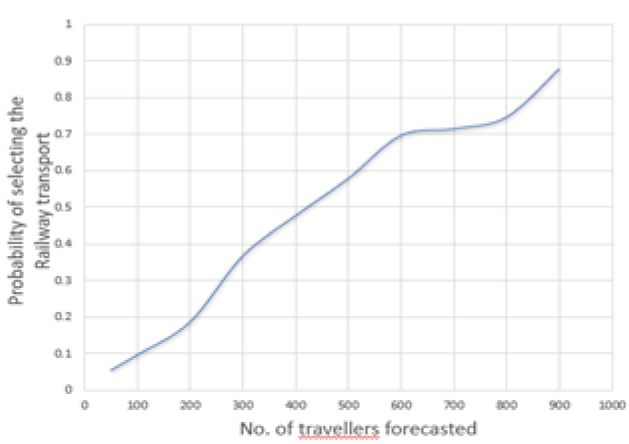

Fig. 2: *Plot of Travelers forecasted versus probability of Viterbi model*

Table I: *Probability analysis of different transport forecast models*

Sl. no.	Ridership Estimation	RP Probability	SP Probability	RP-SP Probability	Viterbi Model Probability
1	200	0.521	0.489	0.627	0.810
2	400	0.597	0.535	0.679	0.829
3	600	0.639	0.582	0.717	0.858
4	800	0.682	0.611	0.769	0.887
5	1000	0.697	0.646	0.793	0.893

From the above observations probability of estimation using Revealed Preference(RP) model, Stated Preference(SP) model and RP-SP model[9][10] is relatively low when compared with Viterbi model. If we consider the least travellers from the above observations the prediction using Viterbi model is 35.67% greater than RP model, 39.62% greater than SP model, 22.59% greater than RP-SP model. If we consider the number of travellers as 1000 then the prediction using Viterbi model is 21.94% greater than RP model, 27.65% greater than SP model,11.19% greater than RP-SP model. By using Viterbi algorithm, the rate of prediction has been increased. As the number of travellers increases the probability of ridership estimation is increased from 0.810 to 0.893 when the travellers are increased from 200 to 1000 respectively. The prediction using the Viterbi model will produce better output when compared with different models like-RP,SP,RP-SP models. If we plot a graph for the above observations it will be as below:

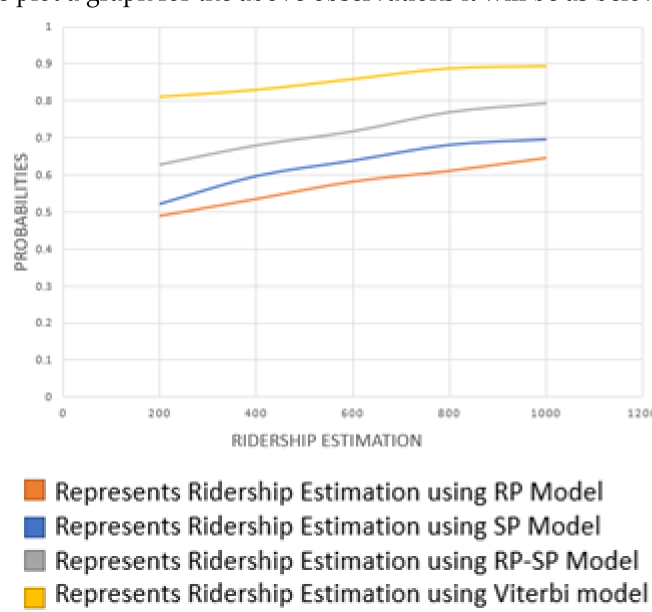

Fig.3. *Plot of Ridership estimation versus probabilities of different models*

9 CONCLUSION

Our paper advocates the novel utilization of Viterbi algorithm for decisive transportation forecasting. We have used the probabilistic approach of prediction to shape the forecasting model which takes into account the hidden factors related to the choice of a travel mode of a person. The Viterbi algorithm has helped us greatly to scale the projections of forecasting thereby making the prediction model robust, Our proposed mechanism can help the concerned authorities to take measures to handle the amount of unexpected rush of passengers. Authorities can also plan to put into service extra trains in the route or attach extra bogies to popular train service. These all depends on various hidden aspects which propels the Viterbi algorithm to predict the traveler's choice. We conclude with a comparative analysis and prediction rate of existing techniques against our proposed mechanism and find that our proposed mechanism edges past with a better accuracy rate when number of passengers increases significantly.

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