Estimating Train Delays in a Large Rail Network Using a Zero Shot Markov Model

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Abstract—India runs the fourth largest railway transport network size carrying over 8 billion passengers per year. However, the travel experience of passengers is frequently marked by delays, i.e., late arrival of trains at stations, causing inconvenience. In a first, we study the systemic delays in train arrivals using n-order Markov frameworks and experiment with two regression-based models. Using train running-status data collected for two years, we report on an efficient algorithm for estimating delays at railway stations with near accurate results. This work can help railways to manage their resources, while also helping passengers and businesses served by them to efficiently plan their activities.

I. INTRODUCTION

Trains have been a prominent mode of long-distance travel for decades, especially in the countries with a significant land area and large population. India, with a population of 1.324 billion people in 2016, has a railway system of network route length of 66,687 kilometers, with 11,122 locomotives, 7,216 stations, that served 8.107 billion ridership in 2016 [2]. The Indian railway system is fourth largest in the world in terms of network size. However its trains are plagued with endemic delays that can be credited to (a) obsolete technology, e.g., dated rail engines, (b) size, e.g., large network structure and high railway traffic, (c) weather, e.g., fog in winter months in north India and rains during summer monsoons countrywide.

In this paper, we take the initial steps in understanding and predicting train delays. Specifically, we focus on the delays of trains, totaling 135, which pass through the busy Mughalsarai station (Station Code: MGS), over a two year period. We build an N-Order Markov Late Minutes Prediction Framework (N-OMLMPF) which, as we show, predicts near accurate late minutes at the stations the trains travel to. To the best of our knowledge, this is the first effort to predict train delays for Indian rail network. The closest prior work is by Ghosh et al. [4] [5] who study the structure and evolution of Indian rail network. The closest prior work is by Ghosh et al. [4] [5] who study the structure and evolution of Indian rail network. However, they do not estimate delays. Our analysis is complementary and agrees with the characteristics of the busiest train stations that they find. We now define the problem, outline contributions, and present our approach.

Problem Statement: Given a train and its route information, predict the delay in minutes at an in-line station during its journey on a valid date.

A. Contributions

Our main contributions are that we:

- as a first, present the dataset of 135 Indian trains’ running status information (which captures delays along stations), collected for two years. We plan to make it public.
- build a scalable, train-agnostic, and Zero-Shot competent framework for predicting train arrival delays, learning from a fixed set of trains and transferring the knowledge to an unknown set of trains.
- study delays using n-order Markov Process Regression models and do Akaike Information Criterion (AIC) and Schwartz Bayesian Information Criterion (BIC) analysis to find the correct order of the Markov Process. Most of the 135 trains follow 1-order Markovian Process.
- discuss how the train-agnostic framework can leverage different types of trained models and be deployed in real time to predict the late minutes at an in-line station.

The rest of paper is arranged as follows. We first discuss the data about train operation and its analysis in Section II and then present the proposed model in Section III. Next, in section IV we outline the experiments conducted with two different regression models: Random Forest Regression and Ridge Regression and give an exhaustive analysis of our results. Finally, we conclude with pointers for future research.

II. DATA PREPROCESSING AND ANALYSIS

This section gives details of train information we collected for a span of two years from site [10]. Table I gives the statistics.

A. Data Collection and Segregation

We considered 135 trains that pass through Mughalsarai Station (MGS), one of top busiest stations in India. For them, we collected train running status information (Train Data) over the period of March 2016 to February 2018. A train’s Train Data consists of multiple instances of journeys, where each journey has the same set of in-line stations that the train plies through. Table II has important fields of interest in Train Data.

| Table I | Data Statistics for 135 Trains Complete Data |
|---------|---------------------------------------------|
| Total number of trains considered | 135 |
| Total number of unique stations covered | 819 |
| Maximum number of journeys made by a train | 334 |
| Average number of journeys made by a train | 48 |
| Maximum number of stations in a train’s route | 129 |
| Average number of stations in a train’s route | 30 |

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Due to the infrequent running of trains, the amount of data collected for each of the trains greatly varied. Using the file size as a criterion, we selected Train Data of 52 frequent trains (henceforth mentioned as Known Trains), out of 135, as training data. The data of remaining 83 trains (henceforth mentioned as Unknown Trains) were used for testing and evaluating the transfer of knowledge through trained models.

Figure 1 pictorially illustrates the actual segregation of collected Train Data from March 2016 to February 2018 for 135 trains. One may recall that in traditional machine learning, the training and test data are drawn from the same set (or class). In contrast, we train our models on a seen set of Known Trains and test it on an unseen set of Unknown Trains, thus employing zero data of Unknown Trains for training, hence the term Zero-Shot. This problem setting is similar to Zero Shot Learning [8] where training and test sets classes’ data are disjoint. Figure 2 shows a train journey and related notations used in this paper.

B. Data Preparation

We define a data-frame as a collection of multiple rows with fixed number of columns. For our experiments we prepared two types of data-frames, with one type being a data-frame Table III for each station (henceforth mentioned as Known Stations), totaling 621 out of 819) falling in the journey route of Known Trains by extracting required information from Train Data Table II of respective trains (in whose route the station fell) to train the models. Another type consisted of only one data-frame Table V capturing certain information of all 819 stations; irrespective of whether they are in-line to Known Trains or Unknown Trains. We divided the journey data in 52 TrnsTrCv Data in ratio 4 to 1 to train and cross-validate the models and prepared data-frame (Table III) for the chosen 80% journey data. However we did not prepare any data-frames (Table III) for rest 20% of 52TrnsTrCv Data, 52TrnsTe Data and 83TrnsTe Data, thereby leaving them in their native format of Train Data Table III.

C. Data Analysis

Here we analyze the most important factors which drive our learning and prediction algorithm. As observed in Figures 3 and 5, the spikes in each month signify that mean late minutes at a station varies monthly (the colored dots are the individual late minutes during the month). This premise was verified with similar graphs obtained for other trains and their in-line stations. In Figures 6, 7, and 8 the dots represent the mean of late minutes at each in-line station during a train’s journey in a particular month. In Figure 6 we can see that the mean late minutes increase during journey up-till station BBS and later it decreases. We observed similar graphs for other trains and found that partial sequences of consecutive in-line stations characterize the delays during a train’s journey.

III. PROPOSED MODEL

In this section, we explain our proposed regression-based N-OMLMPF algorithm and its components. Regression is the task of analyzing the effects of independent variables (in a multi-variate data) on a dependent continuous variable and predicting it. In our setting, the independent variables are the ones mentioned in Table III and the dependent continuous variable to be predicted is the target late minutes (Stn0_late_minutes). Our regression experiments with low RMSE and significant accuracy under 95% Confidence Interval back our hypothesis to cast it as a Regression based problem. We used Random Forest Regressors (RFRs) and Ridge Regressors (RRs) as two types of individual regression models in N-OMLMPF to learn, predict, evaluate, and compare results.

For real-time deployment and scalability, we avoided building train-specific models. Hence we looked for entities which would help us to frame a train-agnostic algorithm as well as enable knowledge transfer from Known Trains to Unknown Trains. A train’s route is composed and characterized by the Stations in-line in its journey. Significant delays along a route which has more number of busy stations can be expected compared to the ones having lesser number of busy stations.

Through the analysis of multiple figures similar to the ones mentioned in subsection II-C we observed the following details about the delay at in-line stations during a journey:

- It highly depends on the months during which the journey is made. One can observe the variations during summer (Jun in Fig 3) and winter months (Dec in Fig 3).
- Partial routes of consecutive Stations can be identified during journey which either increase or decrease the delay at next stations (CNB → MGS → BBS in Fig 6).
- Stations with a high traffic and degree strength tend to be the bottleneck in a journey, thus increasing the overall lateness (MGS-a busy station in Fig 6 Fig 7 and Fig 8).
Fig. 2. Train Route of Train 12439. The above figure shows the route of train 12439 which starts at the station RNC and ends at the station NDLS. For current station MGS, 4 previous stations are considered; whose information we can use for preparing a 4-prev-stn data-frame (Table III). $Stn_i$ notation for $i^{th}$ previous station is used throughout this paper.

### TABLE III

| train_type | zone | is_superfast | month | weekday |
|------------|------|--------------|-------|---------|
| Is it Special, Express or Other? | What zone does the train belong to? | Is it super fast? | Month in which the journey is made | Weekday on which the journey is made |

| Obtained from [2] through train number (e.g. 13050 for Train 13050) | Obtained from actarr_date (Table III) |

The bold font texts are the columns in our prepared data-frame for each Known Station. Obtained from Open Government Data [4].

The above points suggest that multiple deciding factors (e.g. the month of travel, the sequence of stations during a journey etc.) determine the late minutes at a station considered. Since we sought to use Stations to frame a train-agnostic late minutes prediction algorithm and for knowledge transfer, we prepare a data-frame Table III for each of the Known Stations capturing the details mentioned. Later, we train $n$-Order Markov Process Regression models for each Known Station; described next.

### A. $n$-Order Markov Process Regression ($n$-OMPR) Models

The Markov Process asserts that the outcome at a current state depends only on the outcome of the immediately previous state. However if the current state’s outcome depends on $n$ previous states, we call it an $n$-Order Markov Process. Here we assert that the late minutes at a current target station depends on the details of its $n$-previous stations (henceforth mentioned as $n$-prev-stns). This notion is effectively captured in data-frame Table III where we capture general features of a train, day and month of a journey and the characteristics of the $n$-prev-stns along with that of the current target station. The idea is to learn $n$-OMPR models (Random Forest Regressors and Ridge Regressors) for each of the Known Stations using Algorithm I and later use those trained models to frame a train-agnostic late minutes prediction algorithm ($N$-...
OMLMPF Algorithm [2]. Regression models are trained on each of the Known Stations’ corresponding n-prev-stn data-frame Table III with the values of $n$ depending on the number of stations previous to it, subject to its positions during the journeys of multiple trains. This design will be clarified in section III-C. We used python sklearn.ensemble library [9] and sklearn.linear_model library [9] for learning Random Forest Regressor and Ridge Regressor models respectively.

B. k-Nearest Neighbor (k-NN) Search

Unknown Stations (USs) are the ones which, along with the Known Stations (KSs), build the journey route of Unknown Trains. Since we made Unknown Trains’ data Zero Shot, data-frame Table III is not prepared for USs, thus we do not have n-OMPR models for them. Hence, we look for a KS which is best similar to the current target US with respect to features stated in Table IV whose model could be used to approximate the predicted late minutes at the US. We employ k-NN search algorithm (Algorithm 3) to fulfill this objective. A two-step k-NN search is applied since latitude and longitude data are semantically different from traffic and degree strength data. We used python sklearn.neighbors library [9] with default options.

C. Example

In our example, let there be five Known Trains ($K_{T_i}$) routes and two Unknown Trains ($U_{T_j}$) routes with dummy stations $K_{S_\alpha}$ and $U_{S_\beta}$ to explain our proposed framework, where $K_{S_\alpha} \forall \alpha \in (a..q)$ and $U_{S_\beta} \forall \beta \in (r..w)$ are Known Stations and Unknown Stations, respectively. Figure 9 shows the train route map where source stations are colored green.

**$K_{T_i}$ Journey:** $K_{S_a} \rightarrow K_{S_b} \rightarrow K_{S_c} \rightarrow K_{S_d} \rightarrow K_{S_e} \rightarrow K_{S_f}$
Algorithm 1: Training n-OMPR Models

**Input:** List Of Known Stations (KS): \(< KS_1, ..., KS_M >\)

**Output:** n-OMPR Models for Known Stations

for \(i = 1; i <= 5; i+ = 1\) do
  
  \(ipsi_{list} \leftarrow \text{Initialize empty list (stores stations having i-OMPR models)}\)

end

for \(V \text{ stn}_k \in \text{Known Stations} \) do
  
  for \(i = 1; i <= 5; i+ = 1\) do
    
    \(df \leftarrow \text{Get stn}_k\text{'s i-prev-stn data-frame (Table III)}\)
    
    if \(df\) is not empty then
      
      \(mdl_{i_{stn}} \leftarrow \text{Train RFR & RR Models on} df\)
      
      \(ipsi_{list} \leftarrow \text{Save} ipsi_{list} + \text{stn}_k\)
    
    end
  
  end

end

for \(i = 1; i <= 5; i+ = 1\) do
  
  \(\text{Save} ipsi_{list}\)

end

- \(KT_3\) Journey: \(KS_g \rightarrow KS_h \rightarrow KS_i \rightarrow KS_c \rightarrow KS_j\)
- \(KT_3\) Journey: \(KS_m \rightarrow KS_a \rightarrow KS_b \rightarrow KS_c \rightarrow KS_h \rightarrow KS_i\)
- \(KT_3\) Journey: \(KS_m \rightarrow KS_a \rightarrow KS_b \rightarrow KS_c \rightarrow KS_h \rightarrow KS_i\)
- \(KT_3\) Journey: \(KS_g \rightarrow KS_h \rightarrow KS_i \rightarrow KS_c \rightarrow KS_a \rightarrow KS_q\)
- \(UT_1\) Journey: \(KS_q \rightarrow US_r \rightarrow KS_i \rightarrow US_u \rightarrow US_t \rightarrow KS_j\)
- \(UT_2\) Journey: \(US_u \rightarrow US_v \rightarrow KS_b \rightarrow KS_m \rightarrow US_w \rightarrow KS_j\)

Fig. 9. Visual view of example trains routes \(KT_3\) and \(UT_2\). Starting stations are highlighted.

Algorithm 2: N-OMLMPF for Known Trains and Unknown Trains (here the value of \(N\) is set as 3 \(\Rightarrow\) limit the models up to 3-OMPR models)

**Input:** Train number \(tr_{train}\), in-line stations list \(stn_{jrny}\), journey route information (Table III), \(ipsi_{list}\)

**Output:** A list \(lms_{stn}\) of predicted late minutes at each station during the journey

for \(i = 1; i < \text{length}(stn_{jrny}); i+ = 1\) do
  
  \(crnt_{stn} = stn_{jrny}, At(i)\)
  
  \(\triangleright\) Station at \(i^{th}\) position

  if \(crnt_{stn}\) is at position \(i = 1\) then
    
    \(df_{stn} \leftarrow \text{Prepare} crnt_{stn}\text{'s 1-prev-stn row data-frame (Table III) using Table III with late\_mins\_Stn}_{1}\text{ set as lms}_{stn},At(0)\)
  
  else if \(crnt_{stn}\) is at position \(i = 2\) then
    
    \(df_{stn} \leftarrow \text{Prepare} crnt_{stn}\text{'s 2-prev-stn row data-frame (Table III) using Table III with late\_mins\_Stn}_{2}\text{ set as lms}_{stn},At(0)\)
  
  end

end

\(lms_{stn},At(i) \leftarrow \text{Predict late minutes at crnt}_{stn}\text{ for} df_{stn}\text{ using} mdl_{crnt}_{stn}\)

\(\triangleright\) crnt_{stn} is at position \(i \geq 3\) during the journey

\(df_{stn} \leftarrow \text{Prepare} crnt_{stn}\text{'s 3-prev-stn row data-frame (Table III) using Table III with late\_mins\_Stn}_{3}\text{ set as lms}_{stn},At(i-2)\text{ and late\_mins\_Stn}_{2}\text{ set as lms}_{stn},At(i-3)\)

end

end

\(lms_{stn},At(i) \leftarrow \text{Predict late minutes at crnt}_{stn}\text{ for} df_{stn}\text{ using} mdl_{crnt}_{stn}\text{ model}\)

end

Algorithm 3: k-NN search framework to get a Known Station best similar to any type of Station (\(k\) set to 10)

**Input:** A Station \(stn_s\), Valid \(ipsi_{list}\) of Known Stations

**Output:** A nearest Known Station \(stn_{KS}\)

\(stn_{KS}^{KS} \leftarrow \text{Get k-NN Known Stations to} stn_s\text{ among stations in} ipsi_{list}\text{ on the basis of Latitude and Longitude}\)

\(stn_{KS}^{alt} \leftarrow \text{Get k-NN Known Stations to} stn_s\text{ among stations in} ipsi_{list}\text{ on the basis of Degree and Traffic}\)

Return the first station among \(stn_{KS}\)

1) Data Preparation and Training: We collect Train Data Table III for each of the seven trains and divide them into two categories: Known Trains \((KT_i \ \forall \ i < 1..5)\) and Unknown Trains \((UT_j \ \forall \ j < 1..2)\) based on the amount of data collected for each train. After the actual segregation of collected data as showed in Fig. 1, we prepare n-prev-stn
data-frame Table III for each \( KS_n \) using \( KT_i \)’s Table III data.
- Preparation of n-prev-stn data-frames Table III for \( KS_n \): We prepare a 1-prev-stn data-frame for \( KS_n \) owing to Train \( KT_j \) only since it has \( KS_m \) as one station previous to it. It is navigated by \( KT_1 \) also, but it is the source station there, thus has zero stations previous to it.
- Preparation of n-prev-stn data-frames Table III for \( KS_n \): We prepare a 1-prev-stn data-frame for \( KS_n \) owing to trains \( KT_1 \), \( KT_2 \), \( KT_3 \) and \( KT_4 \) since it has a valid set of one station previous to it and a 2-prev-stn data-frame owing to train \( KT_3 \), as it has two stations previous to it.
- Preparation of n-prev-stn data-frames Table III for \( KS_n \): We prepare a 1-prev-stn data-frame for it owing to Train \( KT_1 \), \( KT_3 \) and \( KT_5 \) as they have a valid one station previous to \( KS_n \) during the journey. Another 2-prev-stn data-frame is prepared for it owing to Train \( KT_1 \) and \( KT_3 \), and a 3-prev-stn data-frame owing to Train \( KT_3 \).

Similarly, for each of the Known Stations, we prepare valid n-prev-stn data-frames Table III depending on the number of stations previous to them during the journey of Known Trains. Later we use those n-prev-stn data-frames to train n-OMPR models (RFR and RR) for each Known Station as explained in Algorithm 1. While training the models, we also maintain a list of stations ipsi\( \text{stn} \), which stores the names of stations (code) which have \( i^{th} \)-OMP models. For example, in context of all five Known Trains here, the stations in \( 1^{st} \text{ipsi\( \text{stn} \)} \) are \( (KS_o, KS_e, KS_d, KS_s, KS_f) \). Similarly, for each of the Known Trains, we prepare valid n-prev-stn data-frames Table III depending on the number of stations previous to them during the journey of Known Trains.

2) Prediction of Late Minutes for Train Journeys: We explain N-OMLMPF algorithm (Algorithm 2) here with the help of above train examples. We employ a feed-forward method for late minutes prediction at each of the in-line stations where the late minutes predicted for the \( n \) previous stations and their other details are incorporated in current target station’s n-prev-stn row data-frame. (A row data-frame consists of only one row of Table III). 

a) Known Trains Late Minutes Prediction: Stations in-line during the journeys of cross-validation set and the test set of Known Trains consist of only Known Stations for which we have trained models saved from Algorithm 1. The column entries in n-prev-stn row data-frame (Table III) for the current station at which late minutes are to be predicted are filled accordingly as explained in the table, except \( Stn_0 \_late\_minutes \) since we aim to predict it here. Say for train \( KT_3 \)’s cross-validation or test data, we predict late minutes at each station. As per the execution steps of Algorithm 2 the late minutes at:
- \( KS_m \) is assumed to be 0 since it is a source station thus list \( lms_{\text{stn}} \) is \( < 0 \).
- \( KS_i \) is predicted through \( mdl^{KS_i}_{3} \) since we have this 1-OMPR model trained over the 1-prev-stn training data-frame for \( KS_i \). We fill the 1-prev-stn row data-frame for \( KS_i \) with \( Stn_1 \) set as \( KS_m \) and late minutes at \( Stn_1 \) set as the first entry in \( lms_{\text{stn}} \) i.e. 0. Say the predicted late minutes at \( KS_i \) is 5, hence \( lms_{\text{stn}} \) extends to \( < 0, 5 \) >.
- \( KS_n \) is predicted through \( mdl^{KS_n}_{2} \) as we have this 2-OMPR model trained for it. The first and second entry in \( lms_{\text{stn}} \) list, (0 and 5) are used as late minutes at station \( Stn_2 \) and \( Stn_3 \) respectively in the 2-prev-stn row data-frame for station \( KS_n \) to predict the late minutes at it; say 10 minutes. So the list \( lms_{\text{stn}} \) becomes \( < 0, 5, 10 \) >.
- In a similar fashion, we keep feed-forwarding the predicted late minutes at previous stations to predict the late minutes at \( KS_n \), \( KS_s \), and \( KS_l \) through 3-OMPR models \( mdl^{KS_n}_{3}, mdl^{KS_s}_{3}, \) and \( mdl^{KS_l}_{3} \) respectively.

b) Unknown Trains Late Minutes Prediction: We choose train \( UTS_2 \) for explaining Algorithm 2 to predict late minutes for Unknown Trains’ in-line stations. The late minutes at:
- \( UTS_n \) is assumed to be 0 since it is the source station. Thus the late minutes list \( lms_{\text{stn}} \) is initialized with \( < 0 \).
- \( UTS_n \) is predicted as follows. We do not have a trained 1-OMPR model (neither RFR nor RR) for \( UTS_n \) since it is an Unknown Station, thus not in 1\( \text{ipsi\( \text{stn} \)} \). Hence, via Algorithm 3 we find a Known Station nearest to it among the ones in 1\( \text{ipsi\( \text{stn} \)} \) which have a 1-OMPR model (RFR and RR), say station \( KS_n \) is found. Next, the 1-prev-stn row data-frame prepared for \( UTS_n \) with \( UTS_n \) set as \( Stn_1 \) is fed to the model \( mdl^{KS_n}_{1} \) to predict late minutes at \( UTS_n \), say 10 minutes. Thus \( lms_{\text{stn}} \) list extends to \( < 0, 10 \) >.
- \( KS_m \) is predicted through model \( mdl^{KS_m}_{3} \) with \( Stn_1 \), \( Stn_2 \) and late minutes at \( Stn_3 \), late minutes at \( Stn_2 \) set as \( UTS_n, UTS_n \) and 10, 0 respectively; say 15 minutes is predicted, thus the list \( lms_{\text{stn}} \) becomes \( < 0, 10, 15 \) >.
- \( KS_l \) is predicted as follows. It can be noticed from above set of Known Trains journey that we do not have a valid trained model \( mdl^{KS_l}_{3} \) in spite of the current target station being a Known Station since no 3-prev-stn data-frame for station \( KS_l \) could be prepared from any of the Known Trains. So we choose a station among 3\( \text{ipsi\( \text{stn} \)} \) which is best similar to \( KS_m \) through Algorithm 3 (say station \( KS_s \) is chosen). Thus \( mdl^{KS_s}_{3} \) is used to predict the late minutes (say 40 minutes) on the row data-frame for \( KS_s \) with \( Stn_1, Stn_2, \) and \( Stn_3 \) being \( KS_n, UTS_n \), and \( UTS_n \) respectively with corresponding late minutes as 15, 10, and 0. Thus the list becomes \( < 0, 10, 15, 40 \) >.
- \( UTS_n \) is predicted through a 3-OMPR model; say \( mdl^{KS_n}_{3} \) where \( KS_l \) is obtained through Algorithm 3 for \( UTS_n \). The 3-prev-stn row data-frame for it has \( KS_m, KS_n, UTS_n \) set as \( Stn_1, Stn_2, \) and \( Stn_3 \) respectively.
- \( KS_s \) is predicted through model \( mdl^{KS_n}_{3} \) on its 3-prev-stn row data-frame with \( UTS_n, KS_m, \) and \( KS_n \) set as \( Stn_1, Stn_2, \) and \( Stn_3 \) respectively.

IV. Experiments and Result Analysis

The N-OMLMPF Algorithm 2 was executed on three sets of data, namely Cross-validation Data of Known Trains, Test Data of Known Trains and Test Data of Unknown Trains as mentioned in Figure 1 for different values of \( N \) (in N-OMLMPF).
We enumerate four detailed experiments below, which were conducted with both RFR and RR models individually:

1) Exp 1: We ignored `tfc_of_Stn_i`, `deg_of_Stn_i` and `Stn_dfs` columns from data-frame Table III since these features are implicitly captured in `Stn_code`. Experiment was conducted on dataset 52TrnsTrCv.

2) Exp 2: We ignored the `Stn_code` columns from data-frame Table III as `tfc_of_Stn_i`, `deg_of_Stn_i` and `Stn_dfs` numerically capture the property of station codes. This was done for `Unknown Trains` case because we did not have partial consecutive in-line station path of KSs and USs (hence no `Stn_code`) due to the test data being Zero-Shot. The experiment was conducted on 83TrnsTe data after learning the prediction models from 52TrnsTrCv data to assess the transfer of knowledge from `Known Trains` to `Unknown Trains`.

3) Exp 3: We conducted Exp 2 again on 52TrnsTrCv data, where results similar to that obtained in Exp 1 for cross-validation data endorse our notion of vice-versa representation of stations, as done in Exp 1 and Exp 2.

4) Exp 4: We conducted Exp 2 on 52TrnsTe data with prediction models learned from 52TrnsTrCv data.

After conducting the experiments we analyzed the results to evaluate the performance of trained models and to determine the optimum value of $N$ (in N-OMLMPF). For brevity, we do not present the detailed results for all 135 trains, but do justice by presenting 4-OMLMPF output on test data of few trains in Tables V, VI, VII (negative numbers in tables indicate a very important conclusion. Random Forest Regressors (which are an ensemble of multiple decision trees) very well model the deciding factors (in Table III) compared to Ridge Regressors, thus the results state that the prediction of late minutes is effectively a decision-based regression task.

A. Performance Evaluation of Models

We begin by noting again that a train’s `Train Data` consists of multiple instances of journeys, where each journey has the same set of stations that the train plies through. For each in-line station during a train’s journey, we calculated monthly 68%, 95%, and 99% Confidence Intervals (CI) around the mean of late minutes in a month, considering the train’s complete `Train Data` with outlier late minutes removed by Tukey’s Rule [6]. For each train’s cross-validation/test `Train Data`, the percentage of the number of times the predicted late minutes for an in-line station fell under each matching CI was calculated. Then we averaged out all the percentages (calculated for each train) in different experiments enumerated above. Table VIII shows the corresponding figures. In Table IX we present the mean Root Mean Square Error (RMSE) values for few `Known Trains` and `Unknown Trains` obtained from their Test Data, where RMSE for a journey was calculated between the predicted late minutes and the actual late minutes. It is to be noted that reported results in Table VIII and IX are inclusive of journeys where the train actually got late at the source station, but these details could not be captured by our models due to their scarce occurrences.

Preliminary analysis of CI and mean RMSE observations showed that RFR models outperformed RR models. However, for sake of completion, we present CI observations of RR models for some selected experiments in Table VIII. The scattering of individual late minutes at a station during a month; as observed in Figures 3,4 and 5 suggests to consider CI95 (or higher) since the late minutes are not closely centered around mean but cover a wider distribution around it. Under RFR Models column in Table VIII, the figures in CI95 columns for Exp 1 and Exp 3 suggest that at an average we were able to predict late minutes at in-line stations during cross-validation journey data of `Known Trains` for approximately 62% times within 95% CI (say accuracy is 62%). Figures in Exp 2 under both RFR and RR Models columns in Table VIII for `Unknown Trains`’ test data do not seem promising, but since these results are for Zero-Shot trains for which significant amount of data is not available, the observations are appreciable. One should also note here the low mean RMSE values for `Unknown Trains` in Table IX. The higher accuracies (around 56% and 66% for CI95 and CI99) for `Known Trains` test data in Exp 4 column under RFR Models column compared to that under RR Models column signify a very important conclusion. Random Forest Regressors (which are an ensemble of multiple decision trees) very well model the deciding factors (in Table III) compared to Ridge Regressors, thus the results state that the prediction of late minutes is effectively a decision-based regression task.

B. Determination of Optimum value of $N$ in N-OMLMPF

We executed Algorithm 2 with values of $N \in (1,.5)$, but which one truly captures the Markov Process property of delays along a train’s journey? To answer this we employ two common model selection criterion [1]: Akaike Information Criterion (AIC) and Schwartz Bayesian Information Criterion (BIC) to choose the statistically best regression model.

\[
AIC = n \times \ln\left(\frac{SSE}{n}\right) + 2p \tag{1}
\]

\[
BIC = n \times \ln\left(\frac{SSE}{n}\right) + p \times \ln(n) \tag{2}
\]

where $n$ stands for the number of observations used to train a model, $SSE$ is the Squared Sum of Errors (between predicted late minutes and the actual late minutes) and $p$ is the number of parameters in the model (number of columns in formatted data-frame Table III). Lower the score, better the model. The count of the number of times a run of N-OMLMPF (for a particular value of $N$) yielded the least AIC and BIC scores among all five runs for each train in all four experiments is noted in Table X. In Table X we see that delays along journey undertaken by 40.38% to 67.30% of `Known Trains` under related experiments follow a 1-Order Markov Process since 1-OMLMPF scores minimum AIC and BIC score among other frameworks. Similarly 71.08% to 81.93% of `Unknown Trains` follow a 1-Order Markov Process. Rest of the trains follow a higher order Markov Process with diminishing indications. However lower cumulative RMSE scores (summed over all trains) obtained for 3- and 4-OMLMPF under different experimental settings suggest to use them for real-time deployment.
TABLE V
PREDICTED LATE MINUTES FOR Known Train 22811 TEST DATA (OBTAINED FROM 4-OMLMPF WITH RFR MODELS)

| Stations: | BBS | CTC | JJKR | BHC | BLS | KGP | BQA | ADRA | GAYA | MGS | CNB | NDL | KOR |
|-----------|-----|-----|------|-----|-----|-----|-----|------|------|-----|-----|-----|-----|
| Actual Late Minutes: | 0 | 2 | 8 | -1 | 13 | 25 | 19 | 18 | 9 | -21 | -5 | 6 | 15 |
| Predicted Late Minutes: | 0 | 2.75 | 6.83 | 0.01 | 17.44 | 16.52 | 11.22 | 17.65 | 1.94 | 16.01 | -8.77 | -0.25 | 12.26 | 23.10 |

TABLE VI
PREDICTED LATE MINUTES FOR Known Train 12326 TEST DATA (OBTAINED FROM 4-OMLMPF WITH RFR MODELS)

| Stations: | NDLM | ANSB | RPAR | SIR | UMB | SRE | MB | BE | LKO | BSB | MGS | PNB | KIU | JAJ | JSME | ANN | KOAA |
|-----------|------|------|------|-----|-----|-----|----|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Actual Late Minutes: | 0 | 3 | 4 | -11 | 0 | -6 | 15 | 55 | 30 | 10 | 18 | 10 | 11 | 0 | 7 | 3 | 5 |
| Predicted Late Minutes: | 0 | 9.38 | 7.87 | -2.43 | 3.61 | 0.50 | 26.13 | 36.14 | 29.42 | 32.14 | 20.38 | 3.296 | 6.87 | -3.80 | 17.55 | 14.30 | 13.91 |

TABLE VII
PREDICTED LATE MINUTES FOR Unknown Train 12356 TEST DATA WITH 3 Unknown Stations (OBTAINED FROM 4-OMLMPF WITH RFR MODELS)

| Stations: | JAT | PTK | JRC | LDK | UMB | SRE | MB | BE | LKO | RBL | JAIS | AME | PBH | BOY | BSB | MGS | DNR | PNB | KJP |
|-----------|-----|-----|-----|-----|-----|-----|----|----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Actual Late Minutes: | 0 | 8 | 3 | 0 | -5 | -15 | -10 | -1 | 30 | 41 | 51 | 57 | 74 | 111 | 75 | 123 | 130 | 120 | 120 |
| Predicted Late Minutes: | 0 | 10.19 | 10.74 | 10.17 | 11.60 | 11.97 | 27.24 | 34.63 | 28.45 | 40.15 | 41.29 | 42.94 | 60.71 | 72.51 | 75.25 | 70.50 | 74.45 | 67.95 | 71.80 |

TABLE VIII
CONFIDENCE INTERVAL (CI) OBSERVATIONS FOR DIFFERENT EXPERIMENTS

| Random Forest Regressor (RFR) Models | Ridge Regressor (RR) Models |
|-------------------------------------|----------------------------|
| Exp 1 (Avg %age) | Exp 2 (Avg %age) | Exp 3 (Avg %age) | Exp 4 (Avg %age) | Exp 2 (Avg %age) | Exp 3 (Avg %age) | Exp 4 (Avg %age) |
| CI68 | CI95 | CI68 | CI95 | CI68 | CI95 | CI68 | CI95 | CI68 | CI95 |
| 1-OMLMPF | 34.65 | 61.37 | 70.47 | 5.90 | 14.73 | 18.51 | 33.67 | 61.03 | 70.21 | 27.60 | 55.41 | 65.37 | 4.97 | 12.87 | 17.29 | 22.34 | 44.30 | 55.71 |
| 2-OMLMPF | 33.28 | 61.36 | 70.85 | 5.72 | 14.17 | 18.41 | 33.72 | 61.03 | 70.65 | 27.51 | 56.32 | 66.87 | 5.34 | 12.65 | 16.80 | 22.81 | 43.67 | 56.59 |
| 3-OMLMPF | 32.86 | 62.21 | 71.42 | 6.00 | 14.79 | 18.81 | 33.80 | 62.13 | 71.58 | 27.81 | 55.89 | 66.98 | 4.89 | 12.46 | 16.76 | 22.71 | 44.05 | 55.67 |
| 4-OMLMPF | 34.39 | 62.53 | 71.74 | 5.66 | 14.96 | 18.97 | 33.69 | 61.57 | 71.49 | 27.82 | 55.80 | 66.82 | 4.66 | 12.55 | 16.35 | 21.85 | 43.89 | 55.83 |
| 5-OMLMPF | 34.77 | 62.70 | 72.10 | 5.51 | 14.52 | 18.75 | 33.45 | 62.03 | 71.96 | 27.95 | 56.20 | 67.07 | 4.61 | 12.43 | 16.16 | 21.85 | 43.87 | 55.18 |

V. Conclusion and Future Work

Our objective was to predict the late minutes at an inline station given the route information of a train and a valid date. The significant accuracy results in Table VIII for Known Trains’ and Unknown Trains’ data demonstrates the efficacy of our proposed algorithm for a highly dynamic problem. We also determine experimentally and statistically that the delays along journey for most of the trains follow a 1-Order Markovian Process, while other few trains follow a higher order Markovian Process. Reasonably low RMSE results obtained for Unknown Trains in Table IX also show that we were able to transfer knowledge from Known Trains to Unknown Trains. The N-OMLMPF algorithm is so designed that it can leverage different types of prediction models and predict delay at stations for any train, thus it is train-agnostic. With just 1.2% of total trains in India, our approach was able to cover more than 11.3% of stations, thereby illustrating scalability. There are many avenues for future work: (a) one can expand the data collection and extend the analysis to trains India-wide, (b) one can also explore other approaches like time series prediction and neural networks. In particular, Recurrent Neural Networks (RNN) have the property of memorizing past details and predicting the next state. The prediction of delays along stations is inherently dynamic which implicitly calls for an online learning algorithm to continuously learn the changing behavior of railway network and delays. Thus one can attempt to develop an Online RNN algorithm for it. One can also consider predicting delay of trains in other countries.

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### TABLE IX

| Known Trains | Unknown Trains |
|--------------|----------------|
| Trains       |                |
| 12305        | 12361          |
| 12815        | 13131          |
| 13151        | 22811          |
| 22409        | 22955          |
| 18612        | 12141          |
| 15635        | 22308          |
| 02310        | 04401          |
| 04821        | 03210          |
| 12307        | 13151          |
| 13195        | 22409          |
| 15635        | 03210          |

**Number of Journeys**

| Known Trains | Unknown Trains |
|--------------|----------------|
| 16           | 2              |
| 14           | 1              |
| 39           | 6              |
| 84           | 1              |
| 19           | 6              |
| 83           | 3              |
| 28           | 4              |
| 14           | 28             |
| 47           | 2              |
| 25           | 3              |
| 13           | 1              |

**Mean RMSE**

| Known Trains | Unknown Trains |
|--------------|----------------|
| 87.12        | 89.38          |
| 96.61        | 82.34          |
| 88.26        | 62.84          |
| 82.34        | 82.34          |
| 53.71        | 44.72          |
| 44.72        | 29.42          |
| 39.71        | 11.75          |

**Notes:**

- **Trains** row consists of unique Train Numbers.
- **Number of Journeys** row denotes the number of journeys undertaken by the corresponding train in its Test Data.
- **Mean RMSE** row presents the average of the RMSEs of all journeys. For example, Train 12305 covered 16 journeys with a mean RMSE of 87.12.

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### TABLE X

| Random Forest Regressor Models | BIC Analysis | AIC Analysis |
|-------------------------------|-------------|-------------|
|                               | Exp 1 | Exp 2 | Exp 3 | Exp 4 | Exp 1 | Exp 2 | Exp 3 | Exp 4 |
| 1-OMLMPF                      | 32    | 68    | 35    | 29    | 21    | 59    | 31    | 23    |
| 2-OMLMPF                      | 7     | 7     | 9     | 14    | 9     | 12    | 9     | 10    |
| 3-OMLMPF                      | 9     | 5     | 6     | 5     | 12    | 7     | 7     | 11    |
| 4-OMLMPF                      | 4     | 3     | 1     | 4     | 8     | 2     | 3     | 6     |
| 5-OMLMPF                      | 0     | 0     | 1     | 0     | 2     | 3     | 2     | 2     |

The figures in each cell denote the number of times an N-OMLMPF scored minimum score among other runs, e.g. in **BIC Analysis** column for Exp 1, 1-OMLMPF scored minimum BIC score for 32 trains among other runs.

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