Modeling Arterial Travel Time with Limited Traffic Variables using Conditional Independence Graphs & State-Space Neural Networks

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Abstract

This paper presents travel time prediction models for both congested and non-congested conditions on urban arterial using only limited basic traffic data. The state-space notion of traffic processes and State-Space Neural Network (SSSNNet) models are used on simulation generated traffic data. Conditional Independence (CI) graphs are used to identify independence and interaction between observable traffic parameters thus only relevant ones can be used to predict travel time. Even with limited data, the predictive performance and computational efficiency of Conditional Independence Graphs coupled with State-Space Neural Networks are practically accurate. They also outperformed a traditional Artificial Neural Network model.

Keywords: Travel time, Urban arterials, Conditional Independence graphs, State space neural networks.

1. Introduction

The successful implementation of Advanced Traveler Information Systems (ATIS) and Advanced Traffic Management Systems (ATMS) requires collection of accurate data from extensive traffic surveillance systems. It also requires complex analysis of data for short-term forecasting of key traffic parameters like traffic flow and travel time. Travel time estimation and prediction is particularly important because it is a criterion in optimizing signal control settings and in route guidance systems (RGS) in ATIS projects.

Several research studies formulated travel time prediction algorithms for uninterrupted-flow freeways. For urban arterials, far less work has been completed probably because of the vastness of the arterial system, complexity of traffic behavior on arterials due to presence of signal control devices, and lack of sufficient traffic surveillance systems compared to freeways. This implies that travel time prediction on urban arterials should use lesser number of traffic parameters so that dependence on extensive traffic surveillance systems can be avoided. In addition, the stop-and-go phenomena of arterial traffic should be captured in the travel time prediction model.

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This paper relies on the state-space notion of the traffic pattern (explained later) which is found to be suitable to represent traffic states on urban arterials. Recurrent Neural Networks (RNN) along with Conditional Independence (CI) Graphs is used to analyze the complex relationship between travel time and observable parameters like speed, flow, occupancy, etc. The application of CI graphs revealed that average speed and queue length are sufficient parameters to predict travel time on arterials. This study is based on data collected from micro-simulation for a hypothetical linear arterial. It provides insights on the state-space dynamics of traffic conditions in both congested and non-congested conditions. A model for one-step (next five minutes) prediction of travel time along a section of arterial is also presented.

2. Literature review

The forecasting, or prediction of traffic parameters or performance measures, is concerned with a short-term prediction horizon (time window in which traffic conditions are predicted in the future) generally because of its dynamically evolving nature. There have been various research studies and models for travel time prediction for freeways. Similar research and models for urban arterials is still lagging behind. Vlahogianni et al. (2004) gives a critical discussion on the short-term traffic forecasting techniques for both freeways and urban arterials for different type of implementations like ATIS and ATMS. The discussion of methodologies for traffic forecasting identifies two broad categories: parametric and non-parametric techniques. Among other conclusions, this review asserts that the non-parametric modeling techniques like Artificial Neural Networks (ANN’s) are more promising for traffic forecasting problems and give robust and accurate models.

Zwet and Rice (2004) proposed a prediction scheme by means of linear regression with time-varying coefficients. The coefficients are subjected to the time of day and the time until start of a vehicle on a section. The varying coefficients show the dynamic behavior of the traffic which is captured by other advanced parametric and non-parametric techniques. Ishak and Al-Deek (2002) proposed a non-linear time-series approach to make short-term predictions of speed using the most recent speed profile at each loop detector station and then mathematically found travel time from speed. This study is based on freeways data and also presents statistical analysis to identify parameters like congestion index, rolling horizon, prediction horizon, and their interaction terms with the congestion index. Statthopoulos and Karlaftis (2003) proposed a multivariate time-series state-space model for traffic flow prediction on arterials and compared it with other time-series techniques like ARIMA. They noted that different model specifications are appropriate for different time periods of the day. Wu et al. (2004) used Support Vector Regression to predict travel time for highways in Taiwan. Chien and Kuchipudi (2003) applied Kalman Filtering to predict link and path-based travel time based on time-series data collected through wireless technologies on freeways. Skabardonis and Geroliminis (2005) presented models based on the kinematic wave theory to estimate travel times on arterial streets in real-time based on data commonly provided by system loop detectors and signal settings. The models provide accurate predictions but not generic enough; they require data for the specific location of study.

There are significant studies related to the application of different types of ANNs. Mark and Sadek (2004) proposed an ANN model for freeways to predict experiential travel time under transient traffic conditions including incidents. They found that speed appears to be the most influential input variable for travel time prediction. A special type of Recurrent Neural Network (RNN) called State-Space Neural Network (SSSN) was used by Lint et al. (2002) for freeways travel time prediction using flow and speed. The study showed that the analysis of the internal states and weight configurations of SSSN could develop an internal model that is closely linked to the underlying traffic process.

Travel time prediction on urban arterials is still lacking efficient models. Sisiopiku and Rouphail (1994) presented a literature review of methods for travel time estimation on urban arterials. They noted the traffic parameters used by various researchers which influence travel time on arterials, and concluded that most of the models are link-specific rather than estimators of travel time on a section (path) level. Sisiopiku et al. (1994) proposed regression equations between travel time and percentage detector occupancy. No model for congested conditions which results into higher percentage occupancy is reported in this study. A recent study reported by Lin et al. (2004) decomposed total delay on an arterial into link delay and intersection delay. The model is based on the flow condition, the proportion of net inflows into the arterial from the cross streets, and the signal coordination level. This model relies on existing intersection delay formulas which are not suitable for over-saturated conditions.

The literature review suggests that applying a SSNN model like the one successfully used by Lint et al. (2002) for freeways, might be a good approach. The SSNN model is expected to capture the non-linear and complex relationship between traffic parameters and travel time on arterial sections.
3. Problem statement

Travel time is the experiential time required by a vehicle between two points on an arterial. This includes the flow, or running time on the link and delay incurred at the signalized intersections due to signal setting’s and, if applicable, interruptions due to downstream queues. Travel time can be predicted if sufficient data can be collected on a large enough number of predictor variables. It would preferable, however, if travel time can be accurately predicted using only a small number of variables.

The following groups of variables affect experiential travel time: 1) traffic flow conditions on arterials like average flow rate, average speed, average occupancy, storage on a link; 2) geometrics like link lengths, number of lanes and lengths of turning pockets; 3) signal control settings like cycle length, green time and offsets; 4) effect of signal control on traffic movement like queue lengths at signalized intersection; 5) other more complex variables like turning vehicle volumes, mid-block traffic, traffic composition, driver behavior, environmental conditions, presence of bottlenecks, incidents, etc.

For this study, among the above categories of variables travel time is taken to be dependent on average volume, average speed, average occupancy, storage, and maximum queue length. The other variables related to geometrics and signal settings are kept constant and hence, are not included directly as independent variables. The other complex variables mentioned earlier were also kept constant.

The collection of various traffic parameters like flow rate, average speed, average occupancy, etc. in the field depends on the availability of traffic detection instruments. Due to the impracticality of collecting all traffic parameters from traffic detection instruments, one objective of this study is to use a minimum number of traffic parameters and still predict travel time accurately. Synthetic data from micro-simulation is used for this purpose. Conditional Independence (CI) graphs is coupled with ANN to serve this purpose, and is explicitly described in subsequent sections.

The other aspect of the problem addressed here is the variation in the travel time profile between congested and non-congested conditions. A single SSNN model is obtained at the end which is able to learn both congested and non-congested conditions, and predict the travel time profile accurately in both types of conditions.

4. Experimental setup

In order to improve the understanding of interactions between traffic parameters and their effect on travel time on arterials, it is necessary that a wide range of experiments be conducted and an extensive amount of data be collected. This is not easy to do in the field using real world networks. Often microscopic traffic simulation platforms are used to simulate conditions of interest and generate necessary data. CORSIM, a well known and well documented micro-simulation traffic software, is used. The features of CORSIM that led to its use for this study are: 1) its ability to model time-varying traffic and control conditions in a sequence of ‘time periods’ specified by the user; 2) ability to simulate congested traffic flow conditions as compared to other empirical/analytical methods; 3) detailed output obtained with diverse measures of effectiveness (MOE’s) which helps to select suitable parameters for analyzing the problem at hand (Owen et al., 2000).

The calibration of micro-simulation software with field data and its ability to simulate actual traffic conditions is in itself a separate topic of research. It was ensured that this study captures the randomness of traffic behavior in the field by varying the random seeds in various runs of CORSIM. Hence, the use of CORSIM is justified here and a validation is recommended should the proposed approach be used in real world networks.

A hypothetical linear arterial is constructed in TRAFED, the graphical input processor in CORSIM. This linear arterial is a typical urban arterial with three segments (as defined by the Highway Capacity Manual, HCM) separated by three signalized intersections. Turns were assumed to take place from separate bays with no interference from or onto through traffic (practically this means turns were ignored). Other traffic details such as signal timing and optimization are side issues to this presentation since the focus of the paper is the travel time modeling approach and the computational aspects of the models. Furthermore, the same control, geometrics, and traffic conditions are the same for the cases when CI graphs were used and when they were not used. The linear arterial used in the experiments is shown in figure 1.
Data was generated from 10 simulation runs for two sets of time-varying volume profiles. In the first set (Set #1) entry volumes ranged from non-congested condition to congested condition (300 to 2100 vehicles/hour/lane group); Set #2 is for entry volume varying from close to congested condition to over-saturated, then back again non-congestion (1300 to 2200 then back to 700 vehicles/hour/lane group). The varying of entry volumes was achieved over the time periods of the simulation run. Each simulation run was for 95 minutes. The output data is aggregated for each 5-minute interval thus 19 data patterns are identified from each run. The output and input parameters selected for each link are described as follows based on the definitions given by CORSIM: 1) output parameter: travel time (in sec/vehicle; obtained by dividing the total time (veh-min) by number of vehicle trips); and 2) five input parameters for each link: average flow (in veh per hr, obtained by dividing the vehicle trips by the simulation time), average speed (in miles per hr, obtained from total vehicle miles and total travel time), average occupancy (in vehicles, obtained from the summation of vehicle content on a link every 5 seconds for the entire simulation run), storage (in %, calculated by taking a constant (i.e., 6) times the adjusted vehicle length (i.e., a weighted average of all vehicle types on a link) divided by the lane length which includes full lanes and turning pockets), and maximum queue length by lane (in vehicle, which is the maximum queue length that was observed in a lane since the beginning of the simulation, i.e., 100 percentile). The data from CORSIM is collected for the input parameters for all three segments thus giving a total of 15 variables based on which travel time of the path or section (i.e. total travel time required to traverse the three segments) is predicted. CORSIM tracks individual vehicles in the simulation and then aggregates their data over the given time-period.

5. Conditional independence graphs-based selection of variables

The CI graphs are used to find the minimum required number of traffic parameters which significantly affect travel time, and to identify the rest (redundant parameters). A common approach to achieve this end is to formulate a correlation matrix among various variables affecting the process and determine their affect on the output variable by means of the correlation coefficients. However, when the input variables themselves are correlated, this approach becomes complex. The CI graphs approach, based on a matrix of partial correlation coefficients between different variables gives a simpler and more tractable graphical view of the interaction and independence among them.

The CI graphs method is a founding stone of a series of probabilistic graphical models like the Markov Networks and Bayesian Networks. The use of the CI graphs method is this research is only a facilitator or a mean to the process of predicting travel time using SSNN more efficiently. Doing more with less data, and do so more accurately, means lower costs and higher reliability.

The theory of independence and conditional independence between events or random variables and vectors is grounded into the foundations of probability and statistics theory. Random vectors $X$ and $Y$ are independent if and only if the joint probability density function, $f_{XY}$ satisfies $f_{XY}(x,y) = f_X(x)f_Y(y)$ for all values of $x$ and $y$. The
relationship is denoted by $X \perp_{\perp} Y$. The random vectors $Y$ and $Z$ are conditionally independent on $X$ if and only if $f_{YZ|X}(y,z;x) = f_{Y|X}(y;x)f_{Z|X}(z;x)$ for all values of $y$ and $z$ and for all $x$ for which $f_X(x) > 0$. This is written as $Y \perp_{\perp} Z|X$.

Let $X = (X_1, X_2, \ldots, X_k)$ denote a vector of random variables, and $K = \{1, 2, \ldots, k\}$ the corresponding set of vertices. A graph is a Conditional Independence graph if there is no edge between two vertices whenever the pair of variables is independent given all the remaining variables. For example, taking $k = 4$ for $X = (X_1, X_2, X_3, X_4)$, assume that the following independence relations are identified among these variables: $X_1 \perp_{\perp} X_3 | \{X_2, X_4\}$, $X_1 \perp_{\perp} X_4 | \{X_2, X_3\}$, and $X_2 \perp_{\perp} X_4 | \{X_1, X_3\}$. The CI graph resulting from these relations is shown in figure 2. In figure 2, two variables which are conditionally independent, like $X_1$ and $X_3$, do not have any connecting edge in the graph and are also separated by the rest of variables. The resulting graph gives a picture of the pattern of dependence or association between the variables (Whittaker, 1990).

**FIGURE 2** A simple Conditional Independence graph for independence relations of four random variables.

If we can assume that the distribution of a vector of variables in the travel time prediction process is multivariate normal, then a sample mean and a sample variance-covariance matrix can be constructed from the simulation data. Since the correlation matrix is easier to interpret than the variance-covariance matrix, the sample correlation matrix for all 16 variables (15 independent and 1 dependent) in this process is formed.

When the inverse correlation matrix is scaled that its diagonal elements are unity, it gives a matrix which can be used to interpret and understand the independence and interactions between the different variables influencing the process at hand. For the convenience of presentation, the scaled inverse correlation matrix describing the independence and interaction between the five independent and 1 dependent variables of Link 1 for Set #2 data is presented in table 1. The off-diagonal elements of this scaled inverse correlation matrix are the negatives of the partial correlation coefficients between the corresponding pairs of variables given the remaining variables.

**Table 1** Scaled Inverse Correlation matrix for traffic parameters of a typical link

<table>
<thead>
<tr>
<th></th>
<th>Average Flow (vph)</th>
<th>Average Speed (mph)</th>
<th>Average Occupancy (veh)</th>
<th>Storage (%)</th>
<th>Maximum Queue Length (veh)</th>
<th>Travel Time (sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Flow (vph)</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Speed (mph)</td>
<td>0.75</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Occupancy (veh)</td>
<td>0.39</td>
<td>0.31</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Storage (%)</td>
<td>0</td>
<td>0</td>
<td>-1</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Maximum Queue Length (veh)</td>
<td>0.1</td>
<td>-0.1</td>
<td>0</td>
<td>-0.94</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Travel Time (sec)</td>
<td>-0.12</td>
<td>0.83</td>
<td>0</td>
<td>-0.17</td>
<td>-0.28</td>
<td>1</td>
</tr>
</tbody>
</table>

- shows Symmetric Matrix.
A unique and potent way to convey the information contained in this scaled inverse correlation matrix is a Conditional Independence (CI) graph. This graph is constructed with the vertices corresponding to the variables, and the two variables are connected with an edge only if the corresponding element in the scaled inverse correlation matrix is not too small (close to zero). For practical applications, like the travel time prediction problem at hand, any element less than 0.2 is taken as zero. Other thresholds may be used based on the specifics of the domain problem and based on relevant practical considerations. There are sophisticated methods to decide on how close a value should be to zero before it is considered “practically zero”. That discussion is beyond the scope of this paper but may be found in Whittaker (1990). The use of the 0.2 threshold here is solely based on practical considerations. The CI graph constructed with this assumption is shown in figure 3.

The CI graph presented here is interpreted with the use of the global Markov property of stochastic processes as follows: any two subsets of variables separated by a third subset is independent conditionally only on variables in the third subset. The application of this definition here leads to the conclusion that travel time is conditionally independent of average flow (or volume), average occupancy and storage when average speed and maximum queue length are given for this process. Finally, it can be concluded from this discussion that average speed and maximum queue length are minimum required parameters to predict travel time of a section and no further information contained in average flow, average occupancy and storage are necessary if the other two parameters are known.

6. SSNN Development based on conditional independence graphs

State Space Neural Network (SSNN) is a generic form of Recurrent Neural Networks (RNN) where the hidden neurons define the state of the network (Haykin, 1999). Like RNN, SSNN serves two functional purposes: associative memories and input-output mapping.

The SSNN used in this study is similar to the Simple Recurrent Neural Network (SRN) proposed by Elman (1990) and used by van Lint et al (2002). The primary feature of SSNN that makes it useful for travel time prediction is that its hidden neurons represent the ‘state’ of a link $X_i (t+1)$ at any time instant ‘$t+1$’ and are connected to a context layer $(X_i (t))$– state of the link at previous time instant ‘$t$’ and inputs $U_i (t)$ (representing the prevailing traffic conditions during previous time interval $\{t-1,t\}$). The hidden layer and the context layer together provide ‘dynamic memory’ that captures the temporal behavior of traffic parameters on an arterial link. The various
hidden neurons arrayed in the hidden layer get their input from their individual link and hence contribute to the ‘space’ modeling of traffic parameters in a section or a path (figure 4).

In mathematical terms, the dynamic behavior of a system, assumed to be noise free, is described by the following pair of non-linear equations:

\[
x(n+1) = \varphi(W_a x(n) + W_b u(n)) \\
y(n) = C \cdot x(n)
\]

where, q is number of unit delays used to feed the output of the hidden layer back to the input layer (order of the model); m number of input variables; p number of output variables; \(x(n)\) a q-by-1 vector denoting the state of a nonlinear discrete-time system; \(u(n)\) an m-by-1 vector denoting the input applied to the system; \(y(n)\) a p-by-1 vector denoting the corresponding output of the system; \(W_a\) a q-by-q matrix; \(W_b\) a q-by-(m+1) matrix; \(C\) a p-by-q matrix; and \(\varphi\) is a nonlinear mapping function.

FIGURE 4 State-Space Neural Network Structure employed in this study.

Another way to view the state-space notion of a traffic process can be through the application of a CI graph as seen in Whittaker et al. (1997).

There are two SSNN models tried in this study. They are distinguished by the traffic parameters chosen as inputs to the ‘state’ of the model. One SSNN had all five traffic parameters for each link each as input node without
using the CI graph (call this SSNN #1 model). In SSNN #2, the CI graph approach was used to select the input traffic parameters. In this case only the average speed and queue length emerged as inputs. The average speed here is for the entire link, not for a point, and was estimated using regression based on relevant traffic data.

6.1 Training and testing data sets

The training and testing data sets each consist of the data outcomes of 5 runs: three runs of Set #1 and two runs from Set #2. There are 19 patterns in each run thus 95 data patterns are obtained. One requirement of the State-Space approach of modeling is that the patterns be presented sequentially--i.e. in a certain time order and not randomly fed as in the case of static Back Propagation neural networks (BNN). The arrangement of Set #1 and #2 (as specific time-sequence sets) was introduced randomly in the training and testing data groups to ensure the obtained model is not dependent on the presentation of Set #1 or #2. In other words, the commencement of congested and non-congested conditions in the training and testing data is random.

After selecting the training and testing data, a linear transformation function was applied to the training and testing data to convert it into a common range of 0.1-0.9. After training and testing of the SSNN, the transformed results were retrieved in their original form by applying a reverse linear transformation function. Matlab 7.0 was used for training and testing of data.

7. Results and discussion

Three measures of performance were used to assess the SSNN models: correlation coefficient ($R^2$) between target and predicted values of travel time, Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Two types of SSNN models were produced: SSNN #1 is the conventional SSNN model used in other studies, and SSNN #2 where CI graphs were used to select the input traffic parameters. The comparison between the two models reflects the value of the CI graphs when used with neural networks to improve the latter’s efficiency.

The best SSNN #1 and #2 model are obtained after trials with different learning rate, momentum constant values. A learning rate and momentum constant value of 0.001 and 0.9, respectively, were found to give the best generalized SSNN #1 model. Similarly, the learning rate and momentum constant values of 0.005 and 0.9, respectively, gave the best generalized SSNN #2 model. The comparison between the two models, for both training and testing data sets, is shown in table 2 using the three noted measures of performance.

| SSNN Model | Training Set Results |  |  
|---|---|---|---|
|  | $R^2$ | MAE (sec.) | MAPE (%) |
| SSNN #1 | 0.96 | 9.4 | 3.7 |
| SSNN #2 | 0.99 | 5.9 | 2.3 |

| SSNN Model | Testing Set Results |  |  
|---|---|---|---|
|  | $R^2$ | MAE (sec) | MAPE (%) |
| SSNN #1 | 0.95 | 11.4 | 4.4 |
| SSNN #2 | 0.98 | 7.5 | 2.9 |

The SSNN #2 model, which is based on the CI graph selection of variables, has better prediction capability than the conventional SSNN models. A plot showing the actual travel time patterns fed to the SSNN #2 and the travel time pattern predicted by the model for the testing set is shown in figure 5. It is clear from the testing set results that SSNN #2 was able to capture the dynamics of traffic thus predicting travel both for both congested and uncongested conditions. A point worth noting here is that unlike other proposed models, a single SSNN is able to understand the dynamics of traffic flow, hence travel time, and then generalize for both congested and non-congested conditions intertwined with each other. In other words, the proposed model did not simply memorize the patterns but rather understood the logic or governing relationships between the input data and the output (travel
time) that it accurately predicted travel time of conditions (patterns) it did not see before. This is important for the field applications; a single model can predict travel time throughout the day even with widely varying traffic patterns and without adjusting any time-dependent coefficients.

Figure 6 and 7, respectively, show the distribution of MAE and MAPE for the testing travel time patterns of the SSNN #2 model. The MAE and MAPE are uniformly distributed with no inclination towards congested or non-congested conditions. This again shows that the proposed model is able to reliably predict travel time for both type of varying traffic conditions.

The efficiency of the SSNN #2 model is attributed to the fact that the CI graph identified redundant traffic parameters prior to feeding the input data to the neural networks model and hence improved the performance of the neural network in two ways: it increased the computational efficiency perhaps by reducing the confusion potential. Moreover, the CI graph improved the understanding of the analyst about the behavior of the problem at hand by uncovering the independence and interaction between the potential input variables.

![Image of Travel Time Patterns](image1)

**FIGURE 5** Travel time patterns for actual testing and prediction of testing set for SSSNN #2 model based on CI graph.

![Image of Mean Absolute Error (MAE) vs. Target Testing Travel Time Pattern](image2)

**FIGURE 6** Mean Absolute Error (MAE) plot in prediction of testing travel time pattern for SSNN #2 model based on CIG graph.
8. Conclusions and recommendations

Travel time prediction on urban arterials is a complex process with non-linear relationships between observable traffic parameters like average flow, average speed, queue lengths, etc., & experiential travel time. The state-space dynamics of traffic behavior in an urban arterial can be captured accurately by using a generic class of Recurrent Neural Networks known as State-Space Neural Networks (SSNN’s). A pre-processing of observable traffic parameters is required to minimize the input parameters. A statistical technique which is the underlying foundation of graphical models for applied multivariate statistics called the Conditional Independence (CI) graph was used with neural networks. The analysis of independence and interaction of underlying observable traffic parameters and resulting travel time increased the computational efficiency and predictive performance of the SSNN. A single SSNN model with the CI graph is proposed here as a starting point for travel time prediction on urban arterials. The model worked well and efficiently for both congested and non-congested traffic conditions. The proposed model is reliable and uses traffic parameters that can be collected from most traffic detection instruments. Some earlier research findings aimed at estimating or predicting traffic parameters like average speed and queue length from basic available data like flow rate, signal control settings, and geometrics of the arterials (Gang-Len & Chih Chiang, 1995). The present study can be juxtaposed with earlier findings thus accurate travel time prediction can be achieved using basic available data in the field. This objective is achievable by coupling the Conditional Independence graph approach with the State-Space Neural Networks, a combination that provides considerable insight into the underlying phenomena. It is recommended that further evaluations and improvements of the proposed approach be conducted. In this pursuit, the likes of the models presented here should be used on more complex network conditions. Testing and refinements based on real world data and networks is essential.

References


