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DEEP LEARNING ALGORITHMS FOR PREDICTING ROUTES OF SNOWPLOWS IN EU CITIES

Sydorchuk V. Deep learning algorithms for predicting routes of snowplows in European cities. Most cities are faced with annual snowfall but are finding it difficult to deal with their snow plowing activities. Even though winter road maintenance has been studied for many decades, most of the papers do not present models that can be scaled up to allow for incorporation of side constraints that are often met in practical applications. Subject of the paper: Comparison of deep learning algorithms for forecasting snowplow routes in European cities in terms of spatial analysis, routing and traffic flow. The study focuses on extending neural networks including Recurrent Neural Network (RNN), Convolutional Neural Network (CNN) and Graph Neural Network (GNN) to overcome the problematics of snowplow in urban setting. Temporal and spatial data are incorporated using sophisticated models such as Spatio-Temporal Graph Convolutional Networks (STGCNs) using examples that capture the capacity to control the changes in the snowplow routes in reaction to the real-time traffic flow and weather information. The report also looks at how transformer models among other emerging technologies could be harnessed to improve predictive accuracy as well as efficiency. Comparisons made to these other methods evaluating deep learning methods' benefits and drawbacks and their application to urban infrastructure and traffic flow. The results, therefore, point out that integrating these complicated formulas can go a long way in enhancing the efficiency and safety of snowplowing in the European cities to create better lit and safer transport networks.
Keywords. spatial modeling, route optimization, neural networks, urban infrastructure, traffic management

Сидорчук В.О. Алгоритми глибокого навчання для прогнозування маршрутів снігоприбиральної техніки в містах Євросоюзу. Алгоритми глибокого навчання для прогнозування маршрутів снігоприбиральних машин у європейських містах. Більшість міст стикаються зі щорічними снігопадами, а також із труднощами в управлінні снігоприбиральною технікою. Незважаючи на те, що зимове утримання доріг вивчається вже багато десятиліть, більшість робіт не представляють моделей, які можна масштабувати для врахування побічних обмежень, що часто зустрічаються в практичних застосуваннях. Предмет дослідження: Порівняння алгоритмів глибокого навчання для прогнозування маршрутів снігоприбиральної техніки в європейських містах з точки зору просторового аналізу, маршрутизації та транспортних потоків. Дослідження фокусується на розширенні нейронних мереж, включаючи рекурентні нейронні мережі (RNN), згорткові нейронні мережі (CNN) та графові нейронні мережі (GNN), для подолання проблематики снігоприбиральної техніки в міських умовах. Часові та просторові дані інтегруються за допомогою складних моделей, таких як просторово-часові графові згорткові мережі (STGCN), на прикладах, які демонструють здатність контролювати зміни в маршрутах снігоприбиральної техніки у відповідь на транспортні потоки в реальному часі та інформацію про погоду. У звіті також розглядається, як трансформаторні моделі серед інших нових технологій можуть бути використані для підвищення точності та ефективності прогнозування. Проведено порівняння з іншими методами, оцінено переваги та недоліки методів глибокого навчання, а також їх застосування до міської інфраструктури та транспортних потоків. Таким чином, результати показують, що інтеграція цих складних формул може значно підвищити ефективність і безпеку снігоприбиральної техніки в європейських містах для створення краще освітлених і безпечніших транспортних мереж.
Ключові слова: просторове моделювання, оптимізація маршрутів, нейронні мережі, міська інфраструктура, управління дорожнім рухом

The problem statement. Among the largest costs that regional or local authorities bear during winter to maintain the roads is removing snow and ice from the roads. That is why much emphasis is placed on the search for procedures to improve the distribution of resources since the possible cost-reduction benefits may be quite modest, while the overall benefit of their application can be very high. The priorities of concern in snow removal involve the people (the drivers, the mechanics, the supervisors,) the consumables (the road salt, the road sand, other chemicals used in combating ice and snow,) the equipment (the snowplows, the dump trucks, the supervisor trucks, and so on,) the financial aspect in terms of the wages for the people, the consumables, the equipment's maintenance and repair, and last, but not the One of them is the set of weather coefficients, and the other one is geographical data Forecasting implies numerous factors; they include the weather coefficients and the geographical indicators. And by resources – this is again something that you have to comprehend – where you are going to need it most, particularly if it comes to the points of snow drifts.

At the moment, AI is recasting enumerable practices in any discipline in a way that machines can learn from exposure, create, and solve problems regarded hitherto as requiring intelligence. AI has been conceptualized over 60 years ago and the development of technologies and product based on AI and interest in these technologies and applications have witnessed a number of fluctuations. Several factors have contributed to a recent revival of interest in AI over the last decade: more computational capabilities, more and/or larger mass storage devices, and advances in the computational formalization of AI techniques including a subfield of this area, ML [1]. AI has been received warmly by the public and policy makers with signs of huge possible benefits in terms of productivity, resource management and people's quality of life. In the banking and financial sector, artificial intelligence is crucial for high-frequency stock trading and fraud detection. AI is utilized in national security for object/threat recognition and cybersecurity. Artificial intelligence (AI) is utilized in the medical field to evaluate patient data, assist in diagnosis, and forecast which treatments will work best for each patient [2].

With potentially revolutionary effects, the current generation of AI subfields and methodologies is ready to expand into the transportation environment. By utilizing cutting-edge technologies like shared mobility services, automated vehicles (AV), connected vehicles (CV), and accessible transportation capabilities, the Intelligent Transportation Systems (ITS) Joint Program Office (JPO) and its modal partners have taken the lead in addressing fundamental issues in mobility, safety, and equity. The United States Department of Transportation (USDOT) has significantly increased its research and development of artificial intelligence (AI) in the past few years [3]. The Federal Highways Administration (FHWA), Federal Aviation Administration (FAA), and Federal Railroad Administration (FRA) are a few of the USDOT's modal administrations that have led the way in using AI technologies for mission execution. Data fusion, anomaly detection, safety analysis, and video analytics have all been applied using AI. For instance, the development of AI technologies for the collection of copious amounts of traffic data, including safety data, to recognize patterns and link seemingly unrelated data streams, and for video analytics to assist in predicting driver behavior in various driving scenarios, was funded by the Federal Highway Administration's Exploratory Advanced Research Program [4]. The use of AI to the development of prediction methods and assessment instruments is being studied by the FHWA's Traffic Analysis Tools (TAT) Program [5]. More than $16 million in awards were recently given out by the FHWA's Advanced traffic and Congestion Management Technologies Deployment (ATCMTD) Program to develop AI-powered solutions for multimodal traffic management [6]. Using artificial intelligence (AI) and unmanned aerial systems (UAS), FRA is creating a suite of technologies for predictive analytics and intrusion detection [7]. Other government organizations are investigating the use of artificial intelligence (AI) in citizen-facing services. These organizations include the Federal Transit Administration (FTA), the Federal Motor Carrier Safety Administration (FMCSA), and the Pipeline and Hazardous Materials Safety Administration (PHMSA) [8].

Having effective and timely snow management in the European countries can be an important concern specifically during cold season because heavy accumulation of snow can hinder the life within urban environment, mobility and in extreme cases even endanger lives. The conventional ways employed in planning snowplows routes are usually slow and ineffective and can in many a times fail to meet the dynamic conditions of the urban environment such as, traffic jam, closed roads, and differences in the intensity of snowfalls. This requires the enhancement of better ways to improve on the functionality of snowplow, in order to free the priority sectors and areas much faster [9].

The problem under consideration is the development of deep learning models that will allow determining the optimal routes for snowplows in the context of spatial configurations of big city environments. The problem is to combine spatial modeling with the techniques of route optimization with the help of neural networks to analyze the data on historical snow, traffic and available spatial layouts. These algorithms should therefore have the ability of coping with the volatility of the urban environment; provide turn by turn route guidance based on the current and future state of the roads [10].

However, one should mention that traffic management data should be incorporated to avoid interruptions during the procedure of snow clearing. This was attributed to the need for the growth of neural networks that would be capable of handling spatial data so as to deliver proper and dependable route estimations. In overcoming these challenges, the proposed deep learning models assets organizing the operation of snowplows, reducing response time and thereby improving the fluidity of cities during snow conditions for a safer and more sustainable environment in the European cities.

The research purpose formulation. The purpose of this work is to consider and design the deep learning algorithms that can be used for the forecast of the snowplow paths in the European cities, thus improving the effectiveness of the snow management in the urban environment. Through the adoption of important ideas like spatial modeling, route optimization, neural networks, and traffic management, the report is meant to offset the dynamism of urban environment during snow events as a challenge. The objective is to give an understanding of how the use of such high-level mathematical algorithms can be utilized to enhance the functionality of snowplows to allow snow clearance within the shortest possible time on essential sections. This report also wishes to stress on the necessity of including present road traffic information and city infrastructure plan in to the derationing process in order more effectively guide the snowplows within the cities with least or no disturbance of the general traffic flow. By this way, the report wants to bring new inputs related to the applicability of the deep learning and spatial modeling in the field of the management of the urban infrastructures so as to create the basis for building smarter and safer cities that are capable to address extreme climate conditions with more effectiveness and accuracy.

The latest research and publications analysis. There is a good deal of research available on the use of geographic information systems (GIS) in transportation asset management, the incorporation of databases and expert systems, and the fundamentals of applying optimization approaches. Recent papers in the field of expert system development include [11] work, which integrated GIS information to optimize visiting nurse routing [12], optimization of Sears service van routing using operations research techniques and GIS, which resulted in $42 million in annual savings. [11] have combined a GIS database with a knowledge base for toxin cleanup in the context of municipal public works projects. and the integration of GIS with other datasets for managing public transportation has been demonstrated [13].

Expert systems are an AI technique that various transportation researchers have employed. For instance, an intelligent system for choosing deicing material for winter road maintenance has been created [14]. Geographical and demographic information may be utilized to project future transportation needs in Switzerland. Making decisions about how to improve the transportation infrastructure depends on this demand estimate. Individuals are categorized based on the daily commutes they take. The data is first sorted using a decision tree approach, and the classification is then further refined using a support vector machine (SVM). Both models are based on supervised neural networks. To create a forest, many de-correlated decision trees are integrated using a decision tree. The accuracy of the results increases with the number of trees. This technique assigns a classification based on the distinct attributes of each x-tree [15, 16].

The main research material presentation. Due of the abundance of operational data on snowplow operations, these issues may be data-driven resolved using predictive machine-learning (ML) algorithms. In this work, we used the widely used machine learning approach known as random forest (RF) to forecast snowplow vehicle performance, which was measured by the rank of major repair times. Support vector machines (SVM) are another machine learning approach. Both models were applied to the fleet of snow plough trucks operated by the Utah Department of Transportation, and it was shown that RF performs better in terms of prediction accuracy than linear SVM. Furthermore, by identifying critical performance characteristics, a feature significance analysis using the RF model can assist transportation organizations in improving their truck replacement strategies. Finally, an example of applying the created prediction model with RF indicates the threshold of labor intensity to stop trucks' performance from rapidly declining in different types of working conditions. When compared to life-cycle cost evaluations from earlier research, the prediction model presented here can assist transportation authorities in setting more appropriate fleet replacement priorities [17].

Presentation of main material. Introduction to Route Optimization and Neural Networks

In European cities, precise organization and logistics of snowplows during winter is something very important for traffic safety and road usability. It involves the forecast, of routes that would take least time and use less fuel while at the same time covering all or most of the important areas. Conventional approaches of route planning do not consider traffic conditions, weather and other conditions in cities and infrastructure. One of the most successful subtypes of deep learning, namely recurrent neural networks, can also accommodate these components into the models [18].

The Methodology of Neural Networks applied to Spatial Analysis and Traffic Control

Artificial neural networks operate on the principles of the biological neural networks and have become popular in spatial modeling because of their capability of developing complex patterns from large data sets. For example, in the case of selecting the best route for snowplow, the neural networks can take data regarding the weather forecast, historical traffic data or configuration of the road networks and come up with an optimized route. With respect to the time-series data such weather patterns and the traffic flow which are vital in the anticipation of the route to be followed by the snowplow, the long short term memory networks which are a class of the Recurrent neural networks can be implemented. Since bidirectional LSTM networks are used, the direction of data can be seen, and using this data, much more precise route recommendations can be obtained [19, 20].

Some of the developments in CNN for Modeling Spatial Dependence

CNNs have in the past been utilized in image processing but current being employed in traffic and urban planning. In snowplow route optimization, one of the most important factors is the spatial dependency feature; CNNs can therefore be employed to capture this feature. For instance, the road network can be limited to grids [21], and CNNs can then identify spatial hieroglyphs of each grid, for example, road density, interconnection, and traffic. Nevertheless, standard CNNs fail to handle non-Euclidean geometries such as a road network, which has given rise to GCNs [22]. GCNs generalize CNNs for working with graphs and can be used for the modeling of transportation networks for they are based on graphs using intersections and road segments [23].

Spatio-temporal models for dynamic route prediction has been proposed

The features such as spatial and temporal models should be combined in order to design a good dynamic route prediction in the snowplow infrastructure. Similarly, Spatio-Temporal Graph Convolutional Networks (STGCNs) capitalize on the GCNs and LSTM networks to model traffic and road conditions spanned spatially and temporally. This mixed model may facilitate the estimation of traffic capability and road access in real time, by which means the snowplows may alter their pathways responding to the current circumstances.

Case Study: Implementation in EU Cities

Some of the large European cities have already ventured into deploying these contemporary forms of neural network models of traffic and routing. For example, when employing LSTM and CNN models, cities can predict not only the find the routes for snowplows but to estimate the amount of time it will take to clear the snow. They are built from data sets which consist of previous traffic information, weather data and actual traffic pattern information and has enhanced the efficiency and safety of the roads.

New Happenings and Future Direction

New work demonstrates the ability of Transformer models that employ attention mechanisms in capturing dependency structures in traffic data. These models have been found to perform better than the conventional RNNs with regards to traffic flow predication, and hence could be implemented in snowplow route optimization in the future. Further, real time information streams, social media feeds along with the IoT sensors is becoming popular in use. For example, tweeting about road conditions can be used in improving models used to predict states thereof.

Table 1. Comparison of Neural Network Models for Route Prediction [9, 11, 19, 20, 23]

Model Type	Strengths	Weaknesses	Application in Snowplow Route Optimization
LSTM Networks	Handles time-series data effectively	Requires large datasets	Predicting traffic flow and weather impact
CNNs	Extracts spatial features from grids	Limited in non-Euclidean structures	Initial spatial modeling
GCNs	Models graph structures of road networks	Computationally intensive	Advanced spatial dependency modeling
STGCNs	Combines spatial and temporal data	Complex implementation	Real-time dynamic route optimization
Transformer Models	Captures complex data dependencies	High resource requirements	Future applications in route prediction

Comparative Analysis of Deep Learning Techniques for Traffic Prediction

The method of machine learning nonlinear models is still being used in traffic prediction mostly in the city center where factors like congestion, closing of some roads, and events are likely to occur. Below is a deeper explanation of some of the most prominent techniques: Below is an elaboration of some of the more common techniques that have been described above:

Recurrent Neural Networks (RNNs)

Use Case

The other reason why use of RNNs is suitable when modeling traffic flow is because they are suitable for sequence prediction, which is especially useful when predicting the next traffic in the subsequent time steps. They are meant for data that is in some way a function of time, for example traffic density as a function of the time of day or vice versa and weather changes.

Strengths

RNNs can operate over time, that is, RNNs can 'learn' order or the temporal dimension of phenomena. This is important in the projection of current traffic pattern trends brought about by the elements of traffic flow.

Limitations

RNNs have issues like vanishing and exploding gradient which might affect its training for the particular long-range dependencies. This results to them being less efficient when used for estimating traffic over longer times intervals majoring components such as LSTM (Long Short-Term Memory).

Temporal Convolutional Networks (TCNs)

Use Case

To the RNNs, there are TCNs which are well known to be used in sequence modeling. They use convolutional layer that helps to capture temporal dependencies and it awards them the ability to use many sequences at once.

Strengths

It is far better than the RNN in that it poses no problem of vanishing gradient even for long sequences of information input. These are less sequential in computing and as such are faster to train and more scalable as compared to most of the deep learning models.

Limitations

However, it is need to mention some problems about TCNs: they require much computational resources and can have some difficulties with the some immensely complex temporal relations that can be met in traffic data.

Therefore, although they provide some advantages, TCNs require much computational power and cab encounter difficulties in some, very complex temporal relations that one can encounter in traffic data.

Multilayer Perceptron (MLP)

Use Case

MLPs are simple neural networks confined usually for and used primarily for classification and regression tasks. In traffic prediction, MLPs are able to map simpler dependent variables and the sort of independent variables as the impact of weather on the rate of flow of traffic.

Strengths

They are also easy to implement and unlike some of the more complex HLLs are not computationally very intensive. They are still applicable when the relations in the data are not of a relatively high degree of complexity.

Limitations

An MLP would be insufficient in estimating traffic, especially if the data acquisition is in the form of a sequence because MLPs are incompetent of processing such forms of data. What they cannot do, however, is modelling temporal dependencies, which other examples of models such as the Recurrent Neural Networks (RNNs) or Temporal Convolutional Networks (TCNs).

Graph Neural Networks (GNNs)

Use Case

Intersection and road segments can be viewed as nodes and links respectively and data such as the road networks of cities are an input to GNNs. This makes them suitable for problems where there are dependencies in space i.e. where at least some of the operations require argument values that are dependent upon the value of the previous operation's argument.

Strengths

They can include the topology of the network in a road map and thus enable prediction of the flow of traffic and congestion in any given area of a city. They do well in problems where traffic movement is most endangered by the current layout of the network.

Limitations

GNNs are very flexible with very high non-linearity and, therefore, are very resource demanding networks to train. They also work best when they are well implemented by people with a good knowledge of graph theory; thus, they have rather steep learning curves, especially when it comes to general traffic prediction tasks

Transformers

Use Case

At present, Transformers which has become famous in natural languages processing are considered for traffic prediction due to the capability of attention-based mechanisms to take care of long-range temporal dependencies.

Strengths

Compared to Recurrent Neural Networks or Temporal Convolutional Networks, the Transformers have a higher potential of capturing nonlinear features of data; therefore, it might be more suitable for forecasting of some data. They also have certain very useful features – they can take complete sequences in one go, which as you know is faster.

Limitations

Issues of transformer interference arise in the case of an absence of the data and computational power in traffic managing systems which is necessary for their support. They also serve newer in this area, so their use is still in the process if being discovered and being experiment.

Table 2. Comparative Analysis of Deep Learning Techniques for Traffic Prediction

Technique	Use Case	Strengths	Limitations	Example in Snowplow Routing
Recurrent Neural Networks (RNNs)	Predicting sequential data (e.g., traffic over time)	Captures temporal dependencies	Prone to vanishing gradient issues	Traffic flow prediction
Temporal Convolutional Networks (TCNs)	Traffic flow prediction using sequence data	Handles long sequences with parallelism	High computational resources	Medium to long-term predictions
Multilayer Perceptron (MLP)	Basic traffic prediction and classification	Simple and efficient for small datasets	Limited in handling sequential data	Initial route planning
Graph Neural Networks (GNNs)	Analyzing road networks as graphs	Handles non-Euclidean data effectively	Complex model structure and training process	Road network analysis
Transformers	Advanced traffic prediction with attention mechanisms	Captures complex dependencies effectively	High resource consumption	Future application potential

The shown above tables additional provide an elevated and accurate representation of the fundamental parameters, compare methods and data fundamentals necessary to derive and evaluate deep learning models specifically tailored to the optimization of snowplow route. They demonstrate that within the same problem, different model can be used according to the state of the context of the city 's infrastructure and the type of data with which one has to operate in. All these are very important in rendering and finally implementing right course of action of snow removal policy that would have least inconvenience and maximum safety to the public in winter in the cities of Europe.

Conclusion and prospects for further research. Each of the earlier explained deep learning methods has its own strengths and weaknesses, and, therefore, the methods can be used in traffic prediction and route planning in the following manner. Even today, there is a very high demand to work with and improve RNNs, and their derivatives LSTM because of their ability to work with sequences. Despite TCNs improving so much the ability to handle sequences of significant length, GNNs enable to capture intrinsic spatial relations present in road networks. Auto encoder is the basic model and Transformer is the state of the art with relatively high resource requirement. The choice of this model is very much influenced by the selected traffic prediction mission or task, the nature or the complexity of data and computation power available. Deep learning algorithms especially neural networks have been applied especially in snowplow routes, it is a pioneering example of improved urban structure information management.

Indeed, through the use of spatial modeling and, traffic data, these models present a dynamic and effective way to deal with winter impacts on the European city. This becomes even more apparent as more innovative models such as transformers are integrated more into the system where diverse data feed is embraced to improve the accuracy of the predictions.

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