When Should We Report the Traffic Jams of Today? A Case Study on a Swiss Highway Using Graph Neural Networks and Expert Knowledge

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Abstract: This case study manuscript details the conception and implementation of an artifact that uses floating car data to forecast average speeds on a segment of a Swiss national road. To consider the spatial and temporal dependencies when performing the predictions, the studied segment was modeled as a graph and as a time series problem. Subsequently, to obtain a prediction model, the data collected over a month and augmented to simulate the behavior during summer were used as the input to train a Graph Neural Network. After the evaluation of the results it was concluded that despite the considerable differences between the forecasted values and the reality, it was possible to perform such an implementation with limited data and resources. Moreover, a handful of traffic reporters still considered the results appropriate, and suitable.

1 INTRODUCTION

The definition of traffic congestion has different shades. It can be explained in terms of demand capacity, travel time delay, and cost (Aftabuzzaman, 2007). With demand capacity it is understood that travel demand exceeds the capacity of a road; from the perspective of travel time delay, traffic congestion means that the time needed to reach a destination is higher than the incurred under free-flow travel conditions; lastly, from the cost-related perspective, it is implied that the actual need of resources to go from one place to another is incremented. Regardless of the definition that one adopts, one thing they have in common is their consequences: a considerable increase in travel time and required resources.

Nowadays, traffic analysis and forecasting are a very relevant topic since it impacts not only citizens commuting or going on holiday but also the logistic planning of services. For companies, estimating the effects of traffic congestion on their supply chain has become critical to keep their operational costs low and to ensure the ever-growing demand for just-in-time delivery Pincay et al. (2020). Such facts have driven a growing interest in the field of traffic modeling not only from researchers but also from practitioners.

Furthermore, the availability of more data as well as the development of methods to process larger amounts of information have eased the development of systems able to provide travel time information to commuters and carriers. Usual data sources used for traffic analysis include sensors (e.g., traffic counters and loop detectors), on-site collected data, and floating car data (FCD) recorded from global positioning systems (GPS) devices (Mori et al., 2015; Zhou et al., 2012).

The usage of FCD for traffic and travel time modeling has been steadily increasing since it is a large and affordable source of information. The methods used to analyze and process FCD found in the literature include machine learning, fuzzy-based, probabilistic, and deep learning-based methods. Despite the satisfactory results that they offer, they require vast amounts of data and the availability of enough computational resources (Pincay et al., 2020; Zhu et al., 2020).

This manuscript presents the method and outcomes of a case study whose goal is to obtain a daily prediction of speed on a road segment of one of the

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main highways of Switzerland. To that end, an artifact following the principles of design science research in conjunction with a transdisciplinary approach was conceptualized. For the implementation of the artifact, FCD provided by the Here Developer platform[1] was processed and methods based on a Graph Neural Network (GNNs) were applied. Furthermore, traffic experts were included in all the stages of the development of the project.

This article is structured as follows: Section 2 introduces the concepts and related works on which this initiative is grounded. Then, the methods followed in the design of the artifact are described in Section 3. Section 4 presents the results of the implementation of the project. Lastly, Section 5 closes the curtains of this research effort with a summary and concluding remarks.

2 THEORETICAL BACKGROUND

This section introduces the theories and concepts used for the foundation of this research effort. Related work is also examined.

2.1 Traffic and Speed Prediction

According to Lin et al. (2005), the main components of a road traffic environment are humans, vehicles, and facilities (e.g., signaling, roads and streets). In this context, the facilities constitute the supply, and humans and vehicles are the traffic demand.

In regards to road traffic, it can be classified into two states: congested/jammed and uncongested/free flow (Treiber and Kesting, 2013). There are several traffic characteristics or variables that enable identifying the traffic in any of these two states. These variables are known as *traffic state variables*, being the most relevant the flow, vehicle density, and speed (Pincay et al., 2020).

Traffic and speed forecasting has been studied mainly through knowledge-driven and data-driven approaches. Knowledge-driven methods implement queueing theory and perform simulations about the user behavior in traffic; data-driven initiatives focus on the study of time series to enable the implementation of Auto-Regressive Integrated Moving Average (ARIMA) models for instance (Li et al., 2017).

Although ARIMA models remain popular they work only under stationary situations, which in traffic, is not always true. Thus, most recent efforts are directed towards designing and implementing neural network and deep learning-based methods, as a way of considering temporal and spatial structures in the definition of more reliable and accurate traffic prediction models.

[1]https://developer.here.com/

2.2 Artificial Neural Networks and Deep Learning

Artificial Neural Networks (ANN) or simply neural networks were conceived as a way of taking to the computational world how the human brain works: numerous neurons are interconnected and together they process information (Wang, 2003). They had proven to be useful and efficient to solve tasks where performing inferences from previous data are required. Current applications of ANNs include image segmentation, pattern recognition, face recognition, and prediction tasks, among others (Abiodun et al., 2018).

A special type of ANN is the deep neural network. The main difference with traditional ANNs is that deep neural networks are composed of a large number of layers. Current research is directed towards extending deep learning methods with approaches based on graph data aiming to consider the interaction between agents in the definition of prediction models. Such networks are known as Graph Neural Networks (GNNs) and their study is called *geometric deep learning* (Wu et al., 2020). There is a plethora of architecture definitions of GNNs; authors Wu et al. (2020) proposed a taxonomy to classify them: Recurrent Graph Neural Networks (RecGNNs), Convolutional Graph Neural Networks (ConvGNNs), Graph Autoencoders (GAEs), and Spatial-Temporal Graph Neural Networks (STGNNs).

Circulation on roads can be represented as a graph. For instance, locations along the way constitute the nodes and the weight of the edges correspond to the distance between places. The assumption that the circulation in a certain location at a certain time influences its neighboring places can also be made. Under this definition, the problem of forecasting the average speed over time based on GNNs is possible. The specific type of neural network that enables such reasoning is named Temporal Graph Convolutional Network (T-GCN). They capture both spatial and temporal dependencies among time series. This characteristic makes this type of ANN suitable for a broad range of spatiotemporal forecasting tasks (Bai et al., 2021).

2.3 Related Works

Previous publications dealing with the task of predicting vehicle speeds on the roads through GNNs are presented in this section.

Guo et al. (2019) proposed an attention-based spatial-temporal GNN to capture the dynamic spatio and temporal properties of traffic data simultaneously. According to the reported results, the method showed a superior accuracy than others used for traffic-related problems such as the ARIMA and Long short-term memory (LSTM). However, their solution was yet to be proved in larger-scale experiments.

Researchers Yu et al. (2017) proposed a deep learning framework implemented through the training of Spatio-Temporal Graph Convolutional Networks (STGCN). After conducting simulations on two real-life datasets they found that formulating the problem of traffic and average speed forecasting as a graph and convolutional structures enabled faster training with fewer parameters than other state-of-the-art approaches. Nevertheless, their framework needed further optimizations in its network structure to enable its application in large-scale industries.

Another initiative is by Li et al. (2017). They attempted to incorporate the spatial and temporal dependencies in traffic flow using Diffusion Convolutional Recurrent Neural Network (DCRNN). The studied segments were modeled as a graph, where the nodes corresponded to the speed measuring stations and the weight of the edges was the distance between the nodes. The diffusional nature architecture of the neural network enabled us to consider the effect of traffic over space and time to improve the results of the predicted speeds.

Lastly, Bai et al. (2021) proposed to use an Attention Temporal Graph Convolutional Network (A3T-GCN) as a means to model the short-time trend in time series by using Gated Recurrent Units (GRU) and a graph convolutional network to consider the spatial dependencies according to the topology of the road network. An attention mechanism was introduced to fine-tune the importance of different time points to improve prediction accuracy. The experimental results in real-world datasets demonstrated the effectiveness and robustness of the proposed method.

In contrast to the precedent work, this research effort presents the results of a transdisciplinary case study of speed predictions for traffic using floating car data collected over a month from one segment of one of the most important highways of Switzerland, augmented through statistical methods to simulate the behavior during summer, and used to train a GNN network implemented in Python. The goal is to demonstrate how adequate results can be obtained with limited computational resources, with relatively low amounts of data, and by incorporating expert knowledge in the design of the solution.

3 METHODOLOGY AND USE CASE

The development of this case study were guided by the principles of the design science research for information systems methodology with a transdisciplinary approach (i.e., incorporating practical experiences into the solution process (Hadorn et al., 2008)). This research methodology was selected because its application entails the development of an artifact while extending existing knowledge (Hevner and Chatterjee, 2010) and since this project was realized in a conjoined effort between academia and an industrial practitioner namely *Viasuisse AG*[2].

Five main phases encompassed the execution of this study: i) preliminary analysis, ii) data collection and augmentation; iii) training; iv) evaluation; and, v) visualization. Figure 1 depicts these phases and intermediate steps.

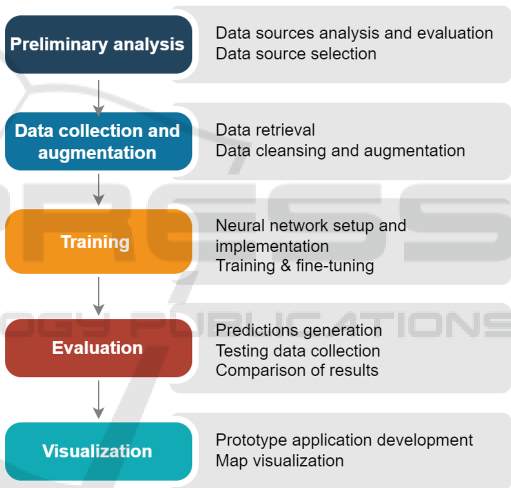

Figure 1: Methodology followed in the research project.

3.1 Preliminary Analysis

Selecting a suitable data source for the prediction tasks is crucial. Before starting the development of this project, different data sources that record information about traffic flow in Switzerland were evaluated:

- *Real-Time Data from Road Traffic Counters:* The open data platform for the mobility of Switzerland[3]offers real-time data from traffic sensors deployed through the main roads and highways of the country. The recorded data corresponds to the

[2]https://viasuisse.ch/

[3]https://opentransportdata.swiss/en/

average speed of vehicles that passed near the location of the sensor in the previous minute.

Aiming to evaluate the quality of the retrieved data, points of interest from the entire network were selected based on the location of traffic cameras. Access to those cameras was granted by our partner. After performing several observations of what was happening and reality and the data that was being retrieved, the researchers came to the conclusion that although this source offers data with fine granularity and is well documented, the results were not reliable enough to define a training set that meets the goals of this case study.

- *Traffic Message Channel-Based Records:* Traffic messages delivered through the Traffic Message Channel (TMC) technology (Gao and Wen, 2007) and processed by our partner company were also studied. Such messages record a variety of incidents that may cause traffic anomalies (e.g., traffic congestion, accidents, and road works) and they are reported by traffic monitoring responsible (e.g., road police and municipalities).

  This data source however recorded the duration of traffic anomalies and not the speed of the circulating vehicles, and thus, it was not suitable to reach the objectives of this work. Nevertheless, the TMC technology encodes points of interest over the highways in the form of a location code list expressed in the standard ISO 14819-3 (Arco et al., 2017). For instance, the $A1$ highway is composed of 151 locations (as per version 7 of the Swiss location code table) and each of them has a unique identifier (e.g., the location *Niederbipp* is identified by the location code 10256). The existence of such location codes helped in the definition of points of interest and to understand the traffic flow over the Swiss highways.

- *Floating Car Data from Here WeGo:* Here WeGo[4] is a navigation service operated by HERE Technologies that offers among others traffic and location services. Through an API for developers, HERE offers traffic flow data aggregated by location; this data contains information about the average speed and the tendency of traffic jams.

  Moreover, some tests were conducted to estimate the quality of this data source. The tests consisted of traversing a segment of interest and comparing what was happening while in a car and what the data being retrieved was showing. It was determined then that the average speed provided by the API was close to reality. Considering this fact and also that the speed can be aggregated by TMC location codes, the authors decided to use this data source to build our speed prediction artifact.

[4]https://wego.here.com/

3.2 Data Collection and Augmentation

With the selection of the data source, it was possible to proceed with the data collection.

Firstly, a segment of interest was defined. To that effect, discussions with traffic reporters (part of our partner company) were held. The goal of defining a segment of interest in this way is to later use the expertise of the reporters to corroborate the results of the speed predictions. The selected segment was part of the $A1$ highway, which traditionally is the one with the highest amount of traffic hours every year; the segment had a length of $50Km$ and encompassed 24 locations from *Verzweigung Härkingen* (TMC Location code 10041) until *Würenlos* (TMC Location code 11211).

A script written in the programming language `Python` was deployed on a server to retrieve the traffic flow data. The data was retrieved every 5 minutes during May of 2022 and for 30 days. The extracted data contained among other fields the timestamp, TMC location code, location name, and average speed.

Furthermore, since one month of data was not enough, the collected data was augmented to simulate a database of readings for the whole summer. To that end, the average of the speeds grouped by timestamp, location, and direction was computed and used to simulate the values for June, July, and August. The values were selected from a uniform distribution on the interval from a minimum value of 93% and a maximum 103% of the observed average speed.

3.3 Training

Once the data was available, the training stage took place. The goal of the training is to predict the future traffic average speed considering previously observed traffic flow from N correlated observed locations on the selected highway segment. In a similar manner, as proposed by Li et al. (2017), the monitored locations can be represented as a weighted directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{W}))$ where $\mathcal{V}$ corresponds to the set of nodes (the observed locations), $\mathcal{E}$ denotes the set of edges, and $\mathcal{W} \in \mathbb{R}^{N \times N}$ corresponds to a weighted adjacency matrix denoting the proximity of the nodes.

Furthermore, the training stage consisted of two main steps: Neural network setup & Implementation, and Training & fine-tuning of parameters. Details are presented below:

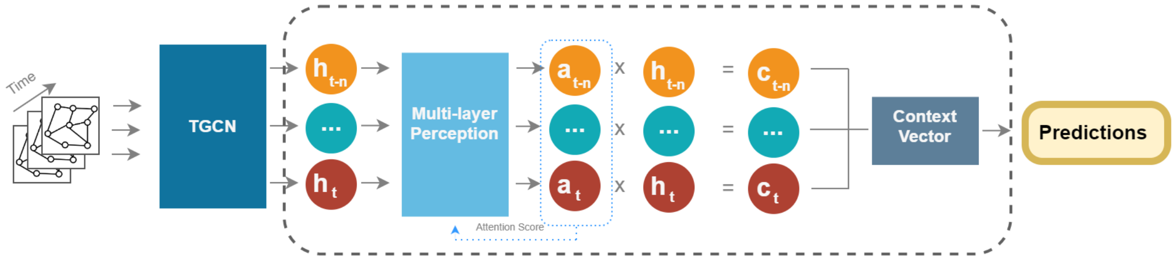

Figure 2: Architecture of the A3T-GCN Network. Adapted from Bai et al. (2021).

3.3.1 Neural Network Setup and Implementation

When modeling the traffic flow with GNNs, the problem takes the shape of a diffusion process over a directed graph. This abstraction enables the capturing of the stochastic nature of traffic dynamics (Li et al., 2017; Cowan and Jonard, 2004). Thus, the locations of the road segment are modeled into a graph network, where the traffic state on the different locations is depicted as the node attributes (i.e., the average speed at a certain time and day).

The A3T-GCN architecture proposed by Bai et al. (2021) was adapted to define the structure of the model to perform the speed forecasting task. The reason behind this choice was the good results they presented in their study and related literature and since our dataset had a similar structure. The characteristics of the A3T-CGN model are described as follows:

- The A3T-GCN is based on the T-GCN but uses attention.
- For the spatial aggregation a GCN structure is used. For the temporal aggregation a GRU.
- Historical time series are inputted to the T-GCN model, then *n* hidden states *h* are obtained. These hidden states cover spatiotemporal characteristics.
- The hidden states are fed into the attention model to determine a context vector that covers the traffic variation information: $a_{t-n}, \ldots, a_{t-1}, a_t$.
- Final results are computed using a fully connected layer.

Figure 2 illustrates the architecture of the A3T-GCN model applied.

3.3.2 Training and Fine-Tuning

The original dataset was split into 80% for the training process and 20% for testing purposes. The hyper-parameters to define included the learning rate (lr), *epochs*, and the number of hidden units.

The `Python` implemented neural network was trained using the Adam optimizer with learning rate annealing. The hyper-parameters were chosen using the Tree-structured Parzen Estimator (TPE) on the test set (Bergstra et al., 2011).

The data sample for the training consisted of 24 nodes; each node containing 2 features (speed and time). Each bucket of data contained 12 timesteps (12×5 min = 60 min). The edges attributes were defined on the distances between the locations and a threshold. This threshold was defined with the value of 4000 ($k = 4000$), meaning that the effects of low speeds on a location will have an effect up to the locations in the following 4000 *meters*. This distance was defined after holding meetings and discussions with traffic experts. Lastly, the neural network was trained in 30 epochs.

3.4 Evaluation

The evaluation was conducted using 20% of the available data. The loss and Mean Squared Error (MSE) were used to define how accurate the trained model was. Moreover, the prediction for a whole day was obtained and the predicted average speed of several locations was compared to what really happened, this helped us to have a closer-to-reality appreciation of the results.

The results were then shared with the traffic experts and contrasted with their day-to-day insights.

3.5 Visualization

The results of the daily predictions were shown through a web heatmap. Moreover, some insights about the daily predictions are also depicted.

4 RESULTS

This section presents the artifact's implementation results built upon the methods explained in Section 3.

A script written in `Python` was used to perform the data collection and another one was written in `R`

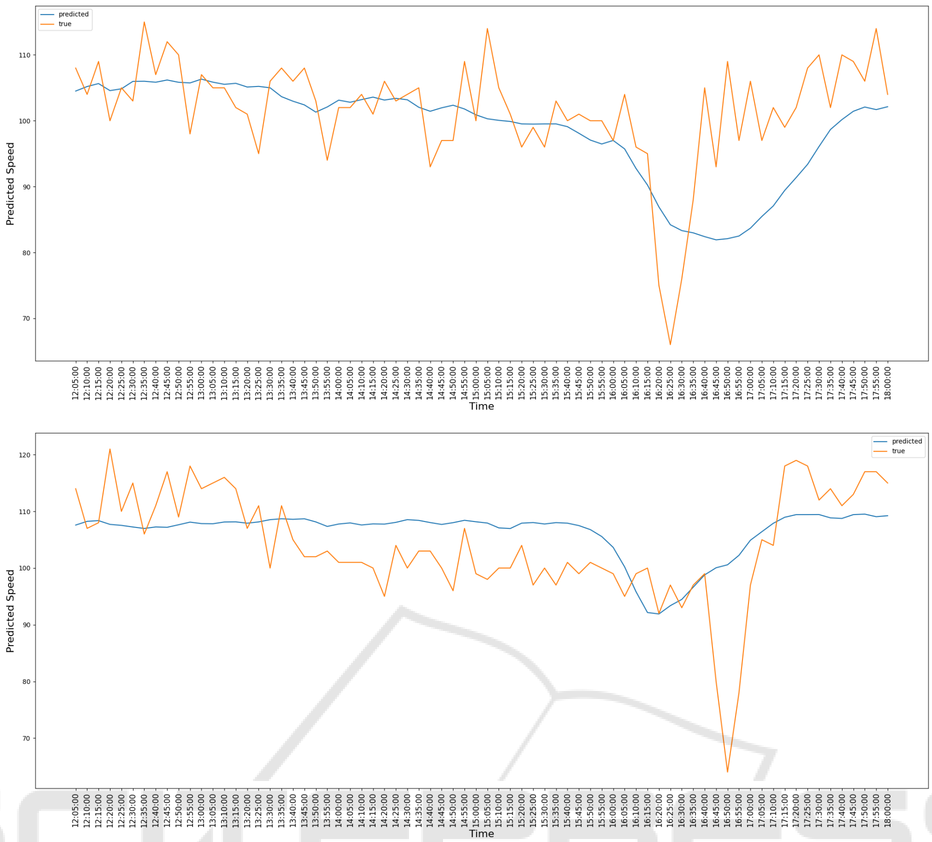

Figure 3: Predicted and real speeds for the locations of Kölliken Süd (top) and Verzweigung Härkingen (bottom) for the 1st. of September 2022 between 10H00 and 18H00.

to augment and simulate the data. The neural network model was implemented with the deep learning framework `PyTorch Geometric Temporal`. Introduced by Rozemberczki et al. (2021), this framework was implemented with the existing libraries of the `PyTorch` ecosystem, temporal snapshot generators for batching, and streamlined neural network layer definitions. The library `Folium` was used to create the heatmap presenting the results.

4.0.1 Dataset Conformation

The data source used to conform the dataset was the FCD obtained from HERE; moreover, the data were collected during May 2022 and augmented to simulate readings for the whole summer of 2022 (until August 2022). Furthermore, only the average speeds in the direction west to east were taken into consideration.

The final dataset used for the training and the testing was composed of approximately 211 800 records, which registered the timestamp, TMC location name, code, and average speed at the moment of the reading. To construct the sensor graph, the distance between the 24 studied locations was computed and used to build an adjacency matrix applying a thresholded Gaussian kernel (Shuman et al., 2013).

4.1 Training and Validation

The training was conducted on a Windows computer with 32 GB of RAM memory and with an Intel (R) Core i7 processor.

A learning rate $lr = 0.001$ and 30 training epochs were set for the training process. During the first training epoch, an MSE of 1.0497 was obtained; after all the training epochs were executed, the MSE was 0.327 and 0.2947 on the testing set.

The speed forecast for the 1st. of September 2022 between 10H00 and 18H00 was later obtained. These values were used to compare with the actual records of the day. Two locations were selected to that end: *Kölliken Süd* und *Verzweigung Härkingen*. These locations were selected after consulting with the traffic professionals; the location Kölliken Süd is a rather straight sub-segment whereas the Verzweigung Härkingen is rather a complex road junction where multiple roads meet.

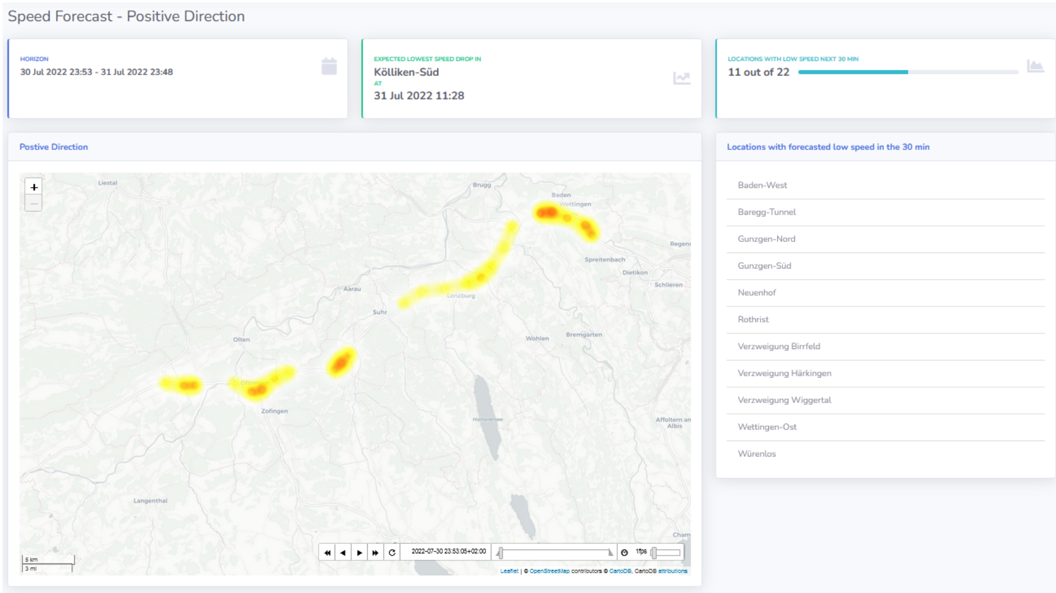

Figure 4: Example of the visualization results for the traffic prediction on the studied segment; besides a heatmap depicting the low speeds, some stats are also provided.

These results are depicted in Figure 3; for Kölliken Süd (see Fig. 3 top), the predictions follow very well the tendency of the real values, which can be interpreted as encouraging results. On the other hand, in the outcome for the Verzweigung Härkingen (see Fig. 3 bottom), the differences are more evident.

To get an expert opinion about the obtained predictions, discussions with traffic experts working at our partner company were held. From their point of view, the results are promising and they reflect what they observe on a regular Thursday. Moreover, for their daily activities, when they have to report traffic incidents they always have to verify on-road cameras and decide whether an incident is going to be solved soon or if it is going to last for a longer period. *"Having such daily predictions will help us to make our job more effectively"* manifested one of the participants in the discussion; *"Even if the predicted speeds differ from the real values, having an indicator of an approximate time when a sudden reduction could happen is also useful"* manifested another.

In light of these results, one can say that despite the 0.2947% MSE on the validation set seeming high at first glance, the predicted speed values can still be practical when assisting traffic reporters to report incidents in a faster and more agile manner.

4.1.1 Visualization

A dashboard-like web interface was implemented to present the results of the speed predictions. The interface had two main parts: a heatmap and some indicators. The heatmap had the goal of depicting the locations with the lower speeds during the day whereas the indicators were designed to provide a better overview of the locations where the low speeds were predicted and the times when this was happening. Figure 4 presents an example of the described. Moreover, the prototype was intended to help traffic reporters in their duties and not drivers on the road. Therefore, a richer interface was preferred instead of a simplified one.

5 SUMMARY AND CONCLUSIONS

Nowadays, convenience is the currency to buy users' attention and thus decides whether a service remains relevant or not. As Kano Noriaki stated, over time delightful innovation becomes another basic need. As a result, the expectations of users grow accordingly to the technical standards set by the industry. Providers of traffic information itself are facing demands for more and more precise data to route from A to B. It has not been long ago that general information about major traffic jams on national highways broadcasted in 30-minute intervals over radio channels was enough.

This transdisciplinary research/applied project presents the results of a case study that attempts to demonstrate how speed predictions on highways can be obtained without a large amount of data and with limited resources but by exploiting deep learning methods and including experts' knowledge in the development. This project was completed in five stages: i) preliminary analysis; ii) data collection and augmentation; iii) training; iv) evaluation; and iv) visualization of results. The preliminary analysis allowed us to identify the most reliable data source to predict speed on the roads; a collection and cleansing process was conducted and an augmentation of the data took place afterward. The overall dataset was conformed of average speed readings every 5 minutes from May to August of 2022 of a segment on the $A1$ motorway in Switzerland. A training process of a neural network architecture based on GNNs took place then followed by an evaluation process based on different metrics and experts' opinions. Lastly, the speed predictions were depicted on a heatmap through a web interface.

The methodology applied and the usage of GNN models proved to be suitable for the task of forecasting speeds. Although there is still plenty of room for improvement, it was shown that with a relatively small amount of data and limited computer resources, it is still possible to obtain predictions. As expressed by the traffic experts that analyzed the results provided, even when these are not as accurate as one could wish they are still useful to ease the task of traffic reporting. Aspects such as a gradual or sudden change of speed might be an indicator that a traffic perturbation will occur. Regardless of the related work, this research project is characterized by its practical nature, transdisciplinarity, and the real data used for the implementation. The methods presented could guide similar studies in which the involvement of people is key to solving a rather complex problem.

The pressure of meeting expectations multiply in the logistics branch by the factor of ever-growing pressure on the prices and thus on the cost a product is allowed to cause. The supply chain of commodities has been optimized to a very high extent. Goods nowadays usually do not rest for a very long time at a storage facility since storing creates cost. Capacities of trucks and containers are being maxed out in order to waste as little as possible. At the same time, the goods need to be delivered just in time, in order to not cause delays, which are again cost relevant. The demands from users directly, as from industrial stakeholders, i.e. logistic suppliers, exceed the capabilities pure and accessible data can provide. In a hypothetical situation: Even if all the data available would be accessible for one solution that could perform the analysis in order to provide such information, it would consume way too much energy and storage space. Ecological ethics would heavily be violated by predictions for mainly fuel-based vehicles.

From a sustainable business perspective, we are urged to perform with the same efficiency as the logistic suppliers with their trucks and containers, in terms of using data. We must find ways to make the most sense out of data in order not to overproduce senselessly but still provide precise outcomes. The results of this study might still not have used the most ecologically sustainable of methods but it is a first step taken in the right direction. At the same time, it is a clear indicator, if not proof, that transdisciplinary research allows for finding viable solutions more efficiently. We must be aware that business and science are not two separate silos, but act as chain links. Science has no value to humans if it is not made accessible to the greater public. This happens by forming products. At the very same time, business needs real innovation in order to prosper. This study shows that joint forces of both areas are the future of business as of science.

Future work will focus on gathering more data to capture seasonality and to improve the models with the further tuning of parameters and training cycles. other aspects to be addressed are the inclusion of unexpected events (e.g., accidents and the presence of objects or animals on the road) to adjust the predictions. Lastly, the visualization dashboard must be also improved and enriched with maybe the inclusion of linguistic summaries (Pincay et al., 2021) as a means of addressing the uncertainty and imprecision of the predicted values.

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