Analysis of Deep Neural Network based Road Distance Estimation

Jinsoo Moon
M2Cloud Inc.
Seoul, Korea
jinsoo.moon@m2cloud.kr

Sanghwan Lee
School of Computer Science
Kookmin University
Seoul, Korea
sanghwan@kookmin.ac.kr

***Abstract*—Accurate estimation of driving distances is essential for various location-based applications, such as vehicular routing. However, these distances often differ from direct geographic measurements based on latitude and longitude. Researchers have attempted to improve this through various methods, resulting in an average detour index of about 1.3. Yet, these methods may not effectively handle complex road networks, leading to the emergence of deep learning-based solutions. These deep learning approaches have shown promise, particularly with real road data. However, it is not clear why DNN based method works and does not work for different situations. Thus, we delve into understanding the behavior of deep neural network (DNN) methods for road network distance estimation. To be specific, we consider two distance types (Geodesic distance and graph based distance) and rigorously evaluating the DNN's performance. By conducting simulations and analyzing the results, it becomes evident that DNNs performs relatively well for the two distance types than other estimation method. Furthermore, we reveal that distance discontinuity significantly impacts accuracy. Hence, future DNN-based methods should prioritize "discontinuity" considerations for optimized performance and enhanced accuracy in road network distance estimation.**

***Index Terms*—DNN, Distance Estimation, Geodesic**

I. INTRODUCTION

The advent of modern technology has brought about significant changes in a multitude of industries and applications, not least of which is the way we estimate and utilize location-based data [1]. One such application is vehicular routing [2]. This service, integral to a wide array of sectors including logistics, food delivery, ride-sharing, and more, thrives on its ability to accurately determine driving distances between two locations. However, it is a well-documented fact that the geographical distance, calculated using traditional latitude and longitude coordinates, often does not mirror the actual driving distance [3]–[7]. This is due to various factors such as road type, physical obstacles, road rules, and more. Thus, there is a pressing need for a more advanced and reliable approach for driving distance estimation, particularly for applications involving complex road networks.

Many researchers offer methods for estimating driving distances using an inflation ratio, which involves multiplying the direct geographical distance by a factor of approximately 1.3 [4]. This approximation, albeit simple, has proven to be reasonably effective in a variety of scenarios and applications. Other researchers have proposed deep learning-based approaches [8], [9]. They propose DNN models and evaluate the model based on some real road traffic data set. Even though their works work well for certain data sets, it is not clear whether they will perform well for other environments with different road types, traffic type, etc. In other words, it is crucial to gain a deeper understanding of how the deep learning based approach behaves in different scenarios.

Thus, in this paper, we conduct an examination of a deep learning-based road network distance estimation method under carefully controlled conditions. To achieve this, we build a simple DNN model for distance estimation for geodesic distances and planar graph based distances. We generate distance data sets based on the two distance types and evaluate the performance of the DNN-based approach on each. By this, we can better understand the behaviour of the DNN based approach. This deeper understanding will contribute to the development of more accurate and efficient DNN based distance estimation models that can address the complexities of modern road networks effectively.

The rest of the paper is organized as follows. In Section II, we describe the background and review the related works. Section III describe the neural network model that we examine. We present the analysis results of the neural network based approach in Section IV. Lastly, the paper is concluded in Section V.

II. RELATED WORKS

In this section, we discuss previous studies that offer insights into the estimation of road distances. Since the advancement of deep learning technology, there has been many deep learning based approaches to estimate the road distances. [8] proposes a deep learning model, ST-NN (Spatio-Temporal Neural Network), which utilizes deep neural networks to jointly predict travel distance and time. The ST-NN model shows improved generalization compared to other existing methods, reducing mean absolute error by approximately 17% for travel time prediction. Furthermore, ST-NN demonstrates increased robustness to outliers in the dataset, making it a promising approach for accurate and efficient transportation

This research was partly supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (2022R1F1A1074672) and by a grant (22183MFDS436) from Ministry of Food and Drug Safety in 2023. Sanghwan Lee is the corresponding author.

management. ST-NN model is rather simple. Thus, it might be interesting to see whether a more complex model shows better performance. In this regards, [9] introduces a novel travel time estimation framework that combines transformer and convolutional neural networks (CNN) to enhance accuracy. The proposed framework includes a traffic information fusion component, incorporating GPS trajectory, real road network, and external attributes for comprehensive estimation. Additionally, a multiview CNN transformer component captures spatial information at multiple regional scales. Experiments demonstrate competitive mean absolute percent errors (MAPE) of 11.25% and 11.78%, outperforming state-of-the-art baselines in travel time estimation.

[10] addresses travel time estimation using deep learning, which has gained traction due to available large trip datasets. However, existing methods often disregard road network information. The proposed approach integrates road networks and historical data, enhancing performance, particularly with smaller training sets. Incorporating node embeddings and road distance leads to improved results, especially when road distance significantly differs from Vincenty distance. Experiments on real-world datasets highlight the method's efficacy.

While existing approaches offer sufficient accuracy in estimating travel distances and times, our paper shifts its focus to a specific question: the suitability of the neural network-based approach for various types of distances. Instead of solely focusing on accuracy, our objective is to investigate the specific domains in which this neural network based approach demonstrates superior performance. By doing so, we aim to identify the key characteristics of the road data set that play a crucial role in its success. Through this exploration, we seek to gain valuable insights into the important factors that contribute to the effectiveness of the new approach in specific scenarios.

III. Analysis Methodology of DNN based Distance Estimation

In this section, we delve into the specifics of our proposed analysis methodology. First, we describe the deep neural network (DNN) based road distance estimation method that we want to analyze. Then, we elucidate the key performance metric that we aim to focus in the evaluation. These metric serves as the benchmark against which the effectiveness and practicality of the DNN based method is measured.

In this road distance estimation problem, given specific input, the model's task is to learn a mapping from the coordinates of the two points (source and destination) to the actual road distance. In this paper, we rather focus on a simple neural network model, which is similar to the model proposed in [8]. The model is a simple feed-forward neural network structured as in (Fig. 1). The input layer consists of 4 neurons corresponding to the latitudes and longitudes of the two points. The model has 3 hidden layers. These layers are fully connected (dense) layers. The first layer has 50 perceptrons, the second hidden layer has 100 perceptrons, and the third hidden layer has 50 perceptrons. Each perceptron has a non-linear activation function, ReLU (Rectified Linear Unit) [11]. It should be noted that the model in this paper is slightly different from the model in [8], which has 20,100,20 perceptrons instead of 50,100,50. The output layer consists of one neuron, which gives the estimated road distance. Since our objective is to solve a regression problem, the activation function used for the output layer is *linear*. As a loss function, we use SmoothL1Loss() [12]. Furthermore, we use *mean* as the reduction function so that we want to minimize the mean of the smooth l1 loss of each sample. Thus, the smooth l1 loss is finally defined as $l(x, y) = mean(L)$. We use $\beta = 1.0$ and Adam optimization algorithm for training [13].

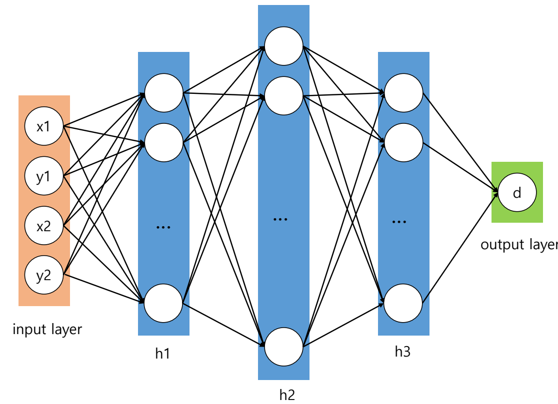

Fig. 1: Five layer deep neural network model. h1 has 50, h2 has 100, and h3 has 50 perceptrons.

The primary objective of this paper is to analyze a deep learning-based road network distance estimation method under controlled conditions. Essentially, the focus of the paper lies in exploring the relationship between the characteristics of the distance dataset and the performance of the model. As such, controlled datasets are utilized to provide a more controlled environment for the analysis, rather than relying solely on datasets collected from real-world scenarios. The two datance definitions are described as follows. Let $p_1 = (x_1, y_1)$ and $p_2 = (x_2, y_2)$ be the positions of two points.

- Geodesic distance (*D1*): The distance between two nodes is defined as the distance on the globe [14].
- Delaunay triangulation with nearest point (*D2*): we first generate k random landmarks in an area and conduct the Delaunay triangulation among the landmarks. The distance between two points, p_1 and p_2 is defined as the Euclidean distance from p_1 to the nearest landmark of p_1 + the distance from p_2 to the nearest landmark of p_2 + the shortest distance over the Delaunay triangulated graph between the two landmarks.

For the performance metric of the evaluation, we consider the (absolute) relative error ϵ between estimated road distance $\hat{r}$ and the actual road distance r. The relative error is defined as follows.

$$\epsilon = \frac{|\hat{r} - r|}{r} \tag{1}$$

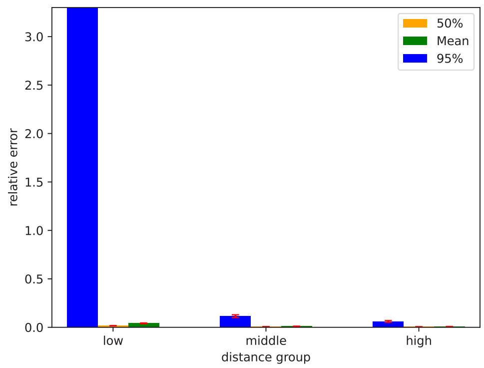

Fig. 2: Estimation of Geodesic Distances with DNN

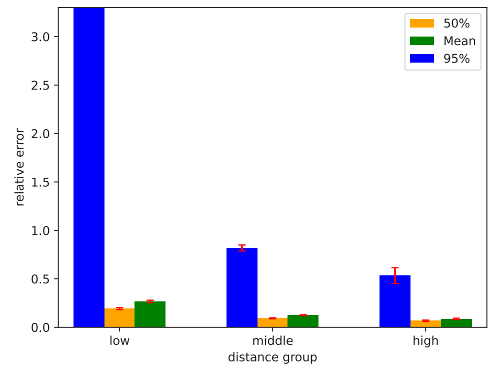

Fig. 3: Estimation of Distances by Delaunay triangulation with Nearest Point

IV. Analysis Results

In this section, we investigate the performance of the DNN based road distance estimation method over the two distance definitions. For the evaluation, we first generate the synthetic distance data sets for the two distance definitions. Then, we train the deep neural network with varying sizes of training data sets. We vary the size from 10,000 to 50,000. The size of the test data set is fixed to 10,000. We conduct the evaluation 15 times, each time with a different set of randomly selected landmarks and src-dest pairs. This allows us to establish confidence intervals and demonstrate the robustness of the repeated evaluations. During this evaluation, we add the estimation result of the simple linear regression method, which basically exploits detour index of 1.3. Even though we add linear regression method, it does not mean that the linear regression is the state of the art estimation method till now. Rather we just want to show that the simple linear regression method may not work for some distance definitions, which justifies the necessity of more sophisticated methods. Furthermore, it should be noted again that the main focus of this paper is to show the performance differences of DNN based method for different kinds of distance definitions.

Even though the Earth looks flat, it is actually a globe. So to better measure the direct distance between two points, we need to use Geodesic distance instead of Euclidean distance. For that matter, we generate random points in spherical coordinates with radius 1. The latitudes are uniformly randomly generated from $-90°$ to $90°$. The longitude are uniformly randomly generated from $-180°$ to $180°$. It should be noted that through this random selection, the points near poles are more frequently chosen. Fig. 2 shows the estimation performance over the Geodesic distances. We divide the set of actual distances into 3 groups: low, middle, high. To define the group, we find the maximum of the output values. Then, we create three groups with intervals of one third of the maximum value. Then, we compute the statistics (mean, 50th percentile and and 95th percentile) of the errors in each group. It is quite clear that except the low group, the estimations are very accurate.

We evaluate the performance of the DNN based approach for distances based on Delaunay triangulation graphs (*D2*). Fig. 3 shows the relative errors for the distances of Delaunay triangulation with Nearest Point. The number of nodes for the Delaunay triangulation is 30. As can be seen in Fig. 3, the mean and media relative errors of the DNN based method is less than 0.2. The 95th percentiles are also below 0.5. However, these errors are much higher compared to the Geodesic distance case. The reason is that for the distances of the Delaunay triangulation with nearest point, there are some cases where small difference in the position may occur large actual distance. However, for Geodesic distance , the difference is usually proportional to the offset of the positions.

Carefully analyzing the results, we conclude that the difference in performance comes from the degree of how much output change is incurred by the input change. To be specific, we expect that if the input change is small, the output change is small. Similarly, if the input change is large, the output should change large. Since DNN can be considered as a sort of linear regression model, if the data set shows this kind of linear behavior, the DNN model may work well. However, if the data set does not show linear behavior, DNN may not perform well.

For distances based on Delaunay triangulation graphs (*D2*), consider Fig. 4. The Delaunay triangulation has three points at $(0,0),(6,0),(0,6)$. There are three other points at $(4,5),(5,4),(6,1)$. The distance between $(4,5)$ and $(6,1)$ is $\sqrt{17}+6\sqrt{2}+1 \approx 13.6$. However, the distance between $(5,4)$ and $(6,1)$ is $\sqrt{17}+1 \approx 5.1$. This is because the nearest points in Delaunay triangulation of the two points, $(4,5)$ and $(5,4)$, are different even though the two points are close. Such ”discontinuity” actually affects the performance of DNN based distance estimations.

It is also needed whether the road distances actually show high ”discontinuity”. For that matter, we examine real road data sets. We collect 123 truck routes from a drug delivery services in Korea. The total number of destinations in the routes is 1090. Thus, in each route, there are in average 8.9 destinations. Fig. 5 shows the travel distance and the

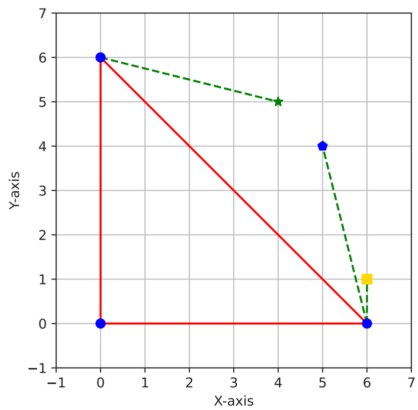

Fig. 4: Example of Delaunay triangulation with nearest points: Two close points have very different distance to a third point.

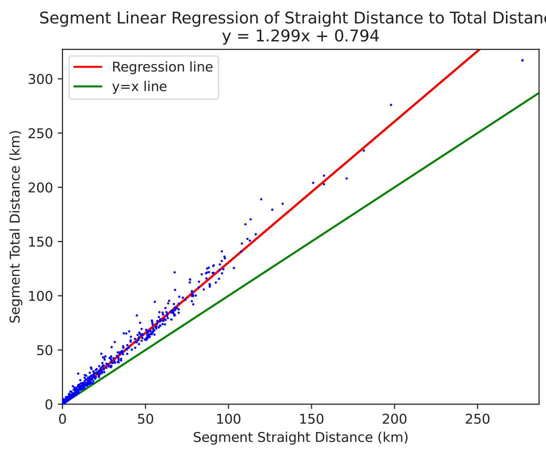

Fig. 5: Geographic distance vs. Travel Distance

geographic (straight) distance pairs. To be specific, Fig. 5 shows the distributions of distances of each segment in a route. The evident slope of approximately 1.3 in the plot confirms the consistent findings of previous studies [4], [5], [15]. This clear linearity suggests the promising potential of DNN models for accurately estimating travel distances. However, the inaccuracies may come from some discontinuities such as rivers and mountains that disconnect two area. Thus, to improve the distance estimation of current systems, it is necessary to remove the effect of discontinuity.

V. Conclusions

The road distances play a crucial role in many location-based applications, particularly in the context of the vehicular routing problem. However, traditional methods relying solely on direct geographic distances calculated by latitude and longitude fail to accurately represent road distances on real road networks. Estimating road distances is therefore paramount for the success of such services. Previous research has focused on developing efficient methods for estimating road distances and has reported an inflation ratio of approximately 1.3 between road distances and direct distances. Furthermore there are DNN based approaches to improve the accuracy of the estimation.

In this paper, the main focus is on thoroughly examining a deep learning-based road network distance estimation method under controlled conditions. Preliminary simulations show that the DNN-based method performs well across the two distance definitions. By carefully analyzing the evaluation results, we find that the discontinuity in the distances is a critical determinant of its performance. Consequently, future DNN-based road network distance estimation methods should carefully consider the discontinuity to optimize overall performance and develop more accurate and efficient distance estimation models for complex modern road networks.

References

[1] H. Huang, G. Gartner, J. M. Krisp, M. Raubal, and N. V. de Weghe, "Location based services: ongoing evolution and research agenda," *Journal of Location Based Services*, vol. 12, no. 2, pp. 63–93, 2018. [Online]. Available: https://doi.org/10.1080/17489725.2018.1508763

[2] K. Braekers, K. Ramaekers, and I. Van Nieuwenhuyse, "The vehicle routing problem: State of the art classification and review," *Computers & Industrial Engineering*, vol. 99, pp. 300–313, 2016. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0360835215004775

[3] R. Mariescu-Istodor and P. Fränti, "Fast travel-distance estimation using overhead graph," *Journal of Location Based Services*, vol. 15, no. 4, pp. 261–279, 2021. [Online]. Available: https://doi.org/10.1080/17489725.2021.1889058

[4] X. Chen and Y. Chen, "Quantifying the relationships between network distance and straight-line distance: applications in spatial bias correction," *Annals of GIS*, vol. 27, no. 4, pp. 351–369, 2021. [Online]. Available: https://doi.org/10.1080/19475683.2021.1966503

[5] F. P. Boscoe, K. A. Henry, and M. S. Zdeb, "A nationwide comparison of driving distance versus straight-line distance to hospitals," *The Professional Geographer*, vol. 64, no. 2, pp. 188–196, 2012. [Online]. Available: https://doi.org/10.1080/00330124.2011.583586

[6] J. Brimberg, J. H. Walker, and R. F. Love, "Estimation of travel distances with the weighted l_p norm: Some empirical results," *Journal of Transport Geography*, vol. 15, no. 1, pp. 62–72, 2007. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0966692306000044

[7] S. T. Waller, S. Chand, A. Zlojutro, D. Nair, C. Niu, J. Wang, X. Zhang, and V. V. Dixit, "Rapidex: A novel tool to estimate origin-destination trips using pervasive traffic data," *Sustainability*, vol. 13, no. 20, 2021. [Online]. Available: https://www.mdpi.com/2071-1050/13/20/11171

[8] I. Jindal, T. Z. Qin, X. Chen, M. Nokleby, and J. Ye, "A unified neural network approach for estimating travel time and distance for a taxi trip," *arxiv.org*, 10 2017. [Online]. Available: https://arxiv.org/pdf/1710.04350.pdf

[9] F. Liu, J. Yang, M. Li, and K. Wang, "Mct-tte: Travel time estimation based on transformer and convolution neural networks," *Scientific Programming*, vol. 2022, 04 2022.

[10] S. Das, R. N. Kalava, K. K. Kumar, A. Kandregula, K. Suhaas, S. Bhattacharya, and N. Ganguly, "Map enhanced route travel time prediction using deep neural networks," *CoRR*, vol. abs/1911.02623, 2019. [Online]. Available: http://arxiv.org/abs/1911.02623

[11] "Relu," https://pytorch.org/docs/stable/generated/torch.nn.ReLU.html.

[12] "Smoothl1loss," https://pytorch.org/docs/stable/generated/torch.nn.SmoothL1Loss.html.

[13] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," 2017.

[14] "geopy," https://geopy.readthedocs.io/en/stable/.

[15] R. H. Ballou, H. Rahardja, and N. Sakai, "Selected country circuity factors for road travel distance estimation," *Transportation Research Part A: Policy and Practice*, vol. 36, no. 9, pp. 843–848, 2002. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0965856401000441