Time-Aware Contrastive Representation Learning for Road Network and Trajectory

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Keywords: Contrastive Learning, Mutual Information, Transformer, Hard Negative Sampling.

Abstract: Modeling and learning representations for road networks and vehicle trajectories is essential for improving various Intelligent Transportation System (ITS) applications. Existing methods often treat road network and trajectory data separately, focus only on one, employ two-step processes that result in information loss and error propagation, or ignore temporal dynamics. To address these limitations, we propose a framework called Time-Aware Contrastive Representation Learning for Road Network and Trajectory (TCRLRT). Our approach introduces an end-to-end model that simultaneously learns road network and trajectory representations, enhanced by a temporal encoding module that captures temporal information and a synthesized hard negative sampling module to enhance the discriminative power of the learned representations. We validate the effectiveness of TCRLRT through extensive experiments conducted on two real-world datasets, demonstrating improved performance over baseline methods across multiple downstream tasks. The results highlight the advantages of joint representation learning with temporal modeling and hard negative sampling, leading to robust and versatile representations.

1 INTRODUCTION

Vehicle technology and intelligent transportation systems (ITS) (Yangxin Lin and Ma, 2017) are key to enhancing safety, efficiency, and sustainability. A fundamental challenge within ITS is to accurately model and understand the interactions between road networks and vehicle trajectories. Effective representation learning (Yoshua Bengio and Vincent, 2013) for road networks and trajectories transforms complex spatial-temporal data into machine-interpretable formats, facilitating various applications such as travel time estimation, traffic speed inference, route prediction, etc.

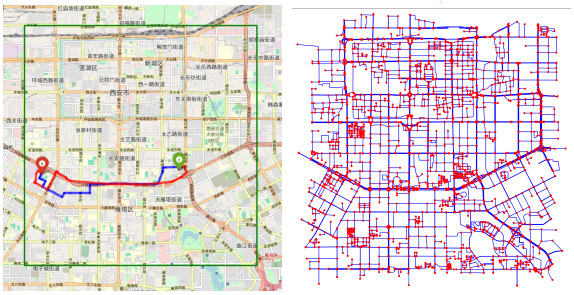
A road network can be described as a type of graph structure that represents the interconnected layout of road segments, encompassing both the topological structure and additional contextual details about the connections between these segments. On the other hand, a trajectory represents sequential data composed of successive road segments that capture spatial and temporal movement patterns, embedding the dynamic nature of mobility and the associated semantics. The structural and temporal characteristics of road networks and vehicle movements can be captured through representation learning methods, and the learned representations can be directly used in a variety of downstream tasks by fine-tuning.

Most existing representation learning models either focus solely on road networks or trajectory data (Tobias Skovgaard Jepsen and Nielsen, 2019; Ning Wu and Pan, 2020; Meng-xiang Wang and Yu, 2019). Treating them separately leads to ignoring the valuable inter-relations between them. 1 Recent approaches have demonstrated that integrating road network representations into trajectory learning, or vice-versa leads to more robust representations (Peng Han and Zhang, 2021; Yile Chen and Ellison, 2021; Yu Zheng and Ma, 2009). Existing methods often adopt a two-stage approach, where they first learn the representation of one aspect and then use it as a foundation for the other. However, this type of approach leaves room for error propagation between the stages and can not directly define the objectives to learn the cross-scale relationship between road network and trajectory.

Contrastive learning (Ting Chen and Hinton, 2020) has recently emerged as a promising technique in semi-supervised settings, leveraging cross-scale information to learn the inter-related representations effectively, by maximizing their mutual information (Philip Bachman and Buchwalter, 2019). JCLRNT

Sikder, A. I. S. and Nower, N.
Time-Aware Contrastive Representation Learning for Road Network and Trajectory.
DOI: 10.5220/0013297700003941

In *Proceedings of the 11th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS 2025)*, pages 498-505
ISBN: 978-989-758-745-0; ISSN: 2184-495X



(a) Two different trajectories. (b) Extracted road network.

Figure 1: Two different trajectories with the same source and destination (a) and the underlying road network (b) in Xian.

(Zhenyu Mao and Zhao, 2022) introduced a jointly contrastive learning framework that learns road network and trajectory representations simultaneously. However, they overlooked temporal dynamics, which are crucial for representation learning.

To address the limitations, we propose Time-Aware Road Network and Trajectory Contrastive Representation Learning (TCRLRT). Our model is an end-to-end approach that jointly learns representations of road networks and trajectories while incorporating temporal information through a learnable temporal encoding module. This enables the model to capture not only the spatial structure but also the time-sensitive nature of vehicle movements. Additionally, we enhance the training process through the synthesis of hard negative examples (Joshua Robinson and Jegelka, 2020), which helps the model learn more discriminative representations and improves its overall performance.

In summary, our key contributions include:

1. An integrated model that jointly learns road and trajectory representations, enriched with temporal information to capture dynamic traffic behavior.
2. Incorporating a hard negative sampling strategy to optimize the training process and enhance model robustness.
3. Comprehensive experimental validation on real-world datasets across multiple downstream tasks demonstrates the effectiveness and versatility of the proposed approach.

2 RELATED WORKS

Representation learning in road networks and trajectories has attracted substantial attention in recent years due to its importance in various traffic-related applications. Existing research can be broadly categorized into road network representation learning, trajectory representation learning, and joint approaches that integrate both types of data.

The study of road network representation learning typically aims to capture road segments' structural and functional properties. Traditional graph embedding methods, such as Node2Vec (Grover and Leskovec, 2016), employ biased random walks and skip-gram models to learn node embeddings, making them general-purpose but often insufficient for road-specific tasks. Similarly, DGI (Deep Graph Infomax) (Velickovic et al., 2019) leverages unsupervised learning to maximize mutual information between local and global graph representations but lacks explicit traffic and road-specific adaptations. More specialized methods have been developed to address these limitations. For example, RFN (Relational Fusion Networks) (Tobias Skovgaard Jepsen and Nielsen, 2019) introduces a more targeted approach, modeling interactions among nodes and edges through relational views and message passing. IRN2Vec (Mengxiang Wang and Yu, 2019) focuses on capturing the relationships between road segment pairs using samples from the shortest paths, enhancing the embedding process by incorporating task-related information through multi-objective learning. HRNR (Hierarchical Road Network Representation) (Ning Wu and Pan, 2020) advances these efforts by employing a hierarchical GNN (Scarselli et al., 2009) architecture to embed functional and structural properties at multiple levels—from road segments to larger structural regions. Despite these advancements, many of these methods either neglect trajectory data or only utilize it in isolated post-processing steps, missing out on potentially mutually beneficial learning between road segments and traffic movement

Trajectory representation learning methods primarily focus on modeling sequential movement data for downstream tasks such as travel time prediction and similar trajectory search. T2Vec (Xiucheng Li and Wei, 2018) takes an approach employing an encoder-decoder structure with LSTM (Hochreiter and Schmidhuber, 1997) units to handle noisy trajectory sequences and reconstruct trajectories to enhance representation learning. Advanced methods such as Toast (Yile Chen and Ellison, 2021) go further by integrating road network context with trajectory data, applying a Transformer-based module to incorporate auxiliary traffic information. This multi-step approach has demonstrated success in improving trajectory-based task performance. Similarly, GTS (Graph Trajectory Similarity) (Peng Han and Zhang, 2021) combines POI embeddings and GNN-LSTM networks to represent trajectories by learn-

ing both point-wise and sequence-level dependencies. Although these approaches address trajectory representation to varying degrees, they often do so without a unified approach that fully integrates road network data, which can lead to suboptimal performance in downstream applications.

Recently there have been efforts to create integrated models that leverage both road and trajectory data to embed interconnected elements simultaneously. Joint Contrastive Learning of Road Network and Trajectories (JCLRNT) (Zhenyu Mao and Zhao, 2022) presents a significant step forward by employing a contrastive learning framework to maximize mutual information between road and trajectory representations. However, it ignores modeling the temporal information in the learning phase. START (Jiawei Jiang and Wang, 2023) also proposes a framework for utilizing the road network and trajectories simultaneously, including temporal embeddings with minutes index and day-of-week index. However, it focuses only on trajectory representation learning.

Our proposed model builds on these existing approaches by addressing their limitations and further enhancing the learning process. Specifically, we model an end-to-end contrastive learning framework with within-scale and cross-scale mutual information maximization, incorporating temporal information through a separate temporal encoder. The temporal information is modeled as a time-ordered sequence in replacement of the ordinary positional encoding. We also provide the model with synthesized harder negative samples. This allows for a more comprehensive and robust representation, leading to improved performance across various road and trajectory-based tasks compared to the baseline methods.

3 PRELIMINARIES

In this section, we introduce the notation and preliminaries, followed by the formal problem definition. Scalars are represented in italics (e.g., n), vectors in lowercase boldface (e.g., $\mathbf{h}$), matrices in uppercase boldface (e.g., $\mathbf{A}$), and sets in script capitals (e.g., $\mathcal{G}$).

3.1 Notations and Definitions

Road Network: A road network is modeled as a directed graph $\mathcal{G} = \langle S, \mathbf{A}_s \rangle$, where S is the set of vertices representing road segments, with $|S|$ as the number of segments. The adjacency matrix $\mathbf{A}_s \in \mathbb{R}^{|S|\times|S|}$ has entries $\mathbf{A}_s[s_i, s_j]$ that are binary, indicating whether there is a common intersection between the end of segment s_i and the start of segment s_j.

Trajectory: A trajectory $\mathcal{T}$ is a time-ordered sequence of pairs of consecutive road segments and timestamps, represented as $\mathcal{T} = [\langle s_i, t_i \rangle]_{i=1}^{m}$, where $s_i \in S$ denotes the i-th road segment in the trajectory, and t_i is the visit timestamp for s_i. Trajectories capture the movement of an object within the road network $\mathcal{G}$.

Representation Learning for Road Networks and Trajectories: Given a road network $\mathcal{G} = \langle S, \mathbf{A}_s \rangle$ and a set of historical trajectories $\mathcal{D}$, the objective is to learn a representation matrix $\mathbf{H}_s \in \mathbb{R}^{|S|\times d}$, where the i-th row, $\mathbf{h}_{s_i}$, represents the embedding for road segment s_i. Additionally, for each trajectory $\mathcal{T} \in \mathcal{D}$, we aim to learn a representation vector $\mathbf{h}_{\mathcal{T}} \in \mathbb{R}^d$.

4 PROPOSED TCRLRT METHOD

This section introduces a novel road and trajectory representation learning model called Time-Aware Contrastive Representation Learning for Road Network and Trajectory (TCRLRT). Figure 2 overviews our proposed model. The proposed TCRLRT takes the road network and trajectory sequence as input. These inputs are processed through an encoding module which consists of a graph encoder (GAT) for road network representation learning, a sequence encoder for trajectory encoding, and a temporal encoder. Then we calculate the loss function with its three components which estimate mutual information (MI) for road-road, trajectory-trajectory, and road-trajectory pairs. Finally, we jointly maximized these three MI estimators to obtain the representations.

4.1 Encoding Module

The encoding module includes a graph encoder for road network representation and a sequence encoder for trajectory representation. We also use a temporal encoder to encode temporal information in trajectory representations. We use Graph Attention Networks (GATs) (Petar Velickovic and Bengio, 2017) and a Transformer Encoder (Ashish Vaswani and Polosukhin, 2017) for graph and sequence encoding, respectively.

4.1.1 Graph Encoder for Road Segment Representations

Since road networks are directed graphs, spectral methods are not suitable. We represent road segments using GAT:

$$\mathbf{H}_s = \mathrm{GAT}(\mathbf{V}_s, \mathbf{A}_s) \tag{1}$$

Here, V_s is the initial embedding matrix for road segments, A_s is the adjacency matrix, and H_s is the out-

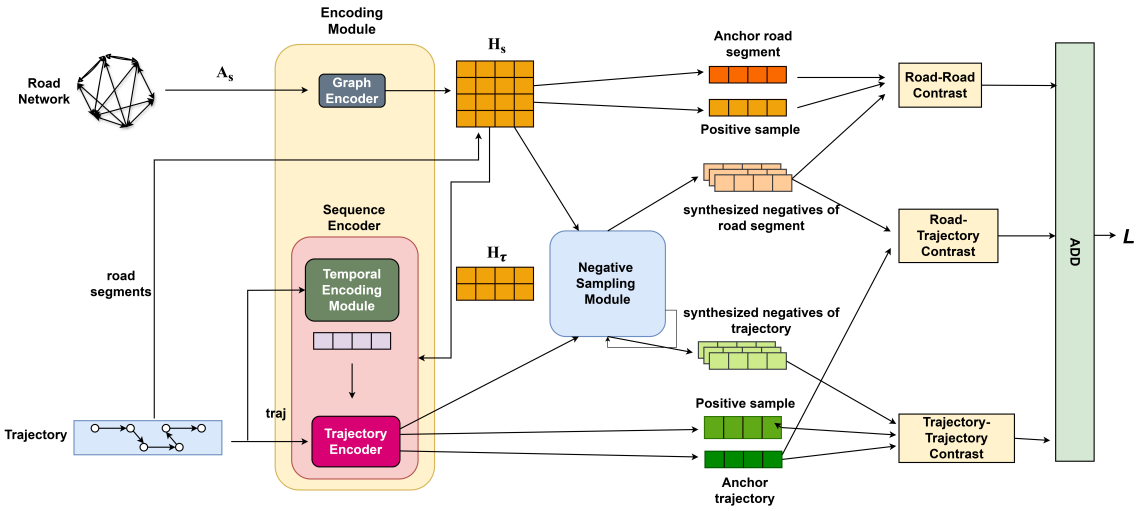


Figure 2: Proposed Time-Aware Contrastive Representation Learning for Road Network and Trajectory Model.

put of the graph encoder, the representation matrix of the graph with s road segments. The ith row of H_s is the representation vector for the road segment in the road segment set S. GAT enables effective handling of directed graphs and has demonstrated superior performance.

4.1.2 Sequence Encoder for Trajectory Representation

Trajectories are encoded as sequences, using road segment representations to generate a trajectory representation. Given a trajectory $\tau = \{(s_1,t_1),(s_2,t_2),\ldots,(s_n,t_n)\}$, we represent the input to the sequence encoder as:

$$\mathbf{H}_\tau = \{\mathbf{h}_{s_1},\mathbf{h}_{s_2},\ldots,\mathbf{h}_{s_n}\} \tag{2}$$

where $\mathbf{h}_{s_i} \in \mathbb{R}^d$ is the ith row of $\mathbf{H}_s$, representing the embedding of the road segment s_i in the trajectory. The input to the sequence encoder, $\mathbf{H}_\tau$, is combined with TE, the temporal encoding of the time sequence of the trajectory, in place of traditional positional encoding. The sequence encoder processes $\mathbf{H}_\tau$ to produce the final trajectory embedding $\mathbf{h}_\tau$, incorporating both the structural information from road segments and the temporal encoding TE to capture the timing of the trajectory data effectively.

4.1.3 Temporal Encoding

Traditional positional encoding can only represent basic sequential orders. However, trajectory data involves visit records distributed unevenly across the temporal axis. Inspired by the work of (Huaiyu Wan and Lin, 2022), we replace the positional encoding by creating an encoding with making two significant modifications: (1) replacing the position indexes with the prefix sum of time differences of consecutive pairs in trajectories, and (2) using trainable parameters.

Formally, traditional positional encoding in transformers is defined as:

$$\mathrm{PE}(o) = [\cos(\omega_1 o),\sin(\omega_1 o),\ldots,\cos(\omega_d o),\sin(\omega_d o)] \tag{3}$$

where $\omega_k = \frac{1}{10000^{2k/d}}$, PE represents the positional encoding function, o is the position index, ω_k are the positional parameters, and $2d$ is the dimension of the encoding vector. The limitation of using positional encoding in trajectory representation is that it does not accurately capture the temporal sequence of the trajectory. Positional encoding assumes a uniform distribution of positions, which may work well in NLP and vision tasks where words or image pixels are evenly spaced. However, the temporal distance between consecutive road segments in a trajectory is often non-uniform. To address this, we use a temporal encoding defined as:

$$\mathrm{TE}(t) = [\cos(\omega_1 t),\sin(\omega_1 t),\ldots,\cos(\omega_d t),\sin(\omega_d t)] \tag{4}$$

Here, TE replaces the position index o with an absolute timestamp t, and the parameters $\{\omega_1,\omega_2,\ldots,\omega_d\}$ are set to be trainable. This approach enables the transformer to capture meaningful temporal distances between records directly within its encoder. We incorporate this temporal encoding into our model by combining it with the trajectory encoding as follows:

$$\mathbf{h}_\tau = \mathrm{Pool}(\mathrm{TransEnc}(\mathbf{H}_\tau + \mathrm{TE})) \tag{5}$$

where $\mathrm{TransEnc}(\cdot) : \mathbb{R}^{|\tau|\times d} \to \mathbb{R}^{|\tau|\times d}$ is the transformer encoder applied to the input sequences, followed by a mean-pooling operation $\mathrm{Pool}(\cdot) : \mathbb{R}^{|\tau|\times d} \to$

$\mathbb{R}^d$. The outputs $\mathbf{H}_s$ and $\mathbf{h}_\tau$, generated by the GAT and transformer encoder, respectively, are used as the final representations of the road network and trajectory.

4.2 Negative Sampling

In contrastive learning, we need an anchor, positive samples, and negative samples that contribute to learning the contrast in representations. Positive samples are typically taken as an augmented or denoised version of the original anchor. For negative sampling, methods such as random index-based sampling and minibatch sampling are commonly used. We adopt a synthesized negative sampling approach like MOCHI (Yannis Kalantidis and Larlus, 2020) to create hard negatives for an effective and optimized representation learning process. This approach combines positive samples with some negatives to generate synthetic hard negatives, which helps the model learn more challenging examples. Given embeddings of a sample x, we generate synthetic hard negatives by combining a positive sample x^+ with negative samples x^- using a weighted average:

$$x_{\text{mixed}} = \alpha \cdot x^- + (1-\alpha) \cdot x^+ \tag{6}$$

where α is chosen to be between 0.3 and 0.7 to balance the contribution of positive and negative samples.

5 CONTRASTIVE LOSS FUNCTION

The contrastive loss function is designed to optimize latent space representations by maximizing the mutual information (MI) for positive pairs (related samples) and minimizing it for negative pairs. We use the loss function defined by (Zhenyu Mao and Zhao, 2022) as consisting of three components:

Road-Road Contrastive Loss: The road-road contrastive loss (L_{SS}) measures the MI between each road segment and its contextual neighbors. The context of a road segment includes structural neighbors, recorded in adjacency matrices A_s with a direct connection. Formally, the road-road loss L_{SS} is defined as:

$$L_{SS} = -\frac{1}{|S|} \sum_{s_i \in S} \left(\frac{1}{|C(s_i)|} \sum_{s_j \in C(s_i)} I(\mathbf{h}_{s_i}, \mathbf{h}_{s_j}) \right) \tag{7}$$

Trajectory-Trajectory Contrastive Loss: The trajectory-trajectory loss L_{TT} is formulated using the contrastive objective:

$$L_{TT} = -\frac{1}{|T|} \sum_{\tau_i \in T} I(\mathbf{h}_{\tau_i'}, \mathbf{h}_{\tau_i}) \tag{8}$$

where τ_i' is a noisy version of trajectory τ_i. Noisy trajectories are generated using techniques such as random masking and replacements, along with a "detour" strategy that replaces part of the trajectory with an alternative path sharing the same start and endpoints.

Road-Trajectory Contrastive Loss: The road-trajectory contrastive loss L_{ST} is defined as:

$$L_{ST} = -\frac{1}{|\mathcal{T}|} \sum_{\tau_j \in \mathcal{T}} \left(\frac{1}{|\mathcal{S}|} \sum_{s_i \in \mathcal{S}} w_{\tau_j}[s_i] \cdot I(\mathbf{h}_{s_i}, \mathbf{h}_{\tau_j}) \right) \tag{9}$$

where $w_\tau[s_i]$, representing the RS-T distance, combines the original trajectory length and the length of an alternative route, providing a flexible "soft" weighting for potential positive samples:

$$w_\tau[s_i] = \frac{|\tau|}{|\tau'| + \delta(s_i, \tau)} \tag{10}$$

Here, $\delta(s_i, \tau)$ represents the minimum number of segments from s_i to any segment in τ.

Overall Loss Function: The overall loss L is computed as a weighted sum of L_{SS}, L_{TT}, and L_{ST}:

$$L = \lambda_{SS} \cdot L_{SS} + \lambda_{TT} \cdot L_{TT} + \lambda_{ST} \cdot L_{ST} \tag{11}$$

where the λs are some weight parameters such that $\lambda_{SS} + \lambda_{TT} + \lambda_{ST} = 1$. In all cases, the Jensen-Shannon mutual information estimator is used to enhance stability against variations in the number of negative samples.

6 EXPERIMENTS

We evaluate our proposed framework in two real-world datasets and four traffic-related tasks and compare it with the state-of-art methods.

6.1 Datasets and Preprocessing

The datasets used in this study are provided by the GAIA project in collaboration with Didi and consist of two months of car-hailing trip data from the cities of Xi'an and Chengdu, China. Each dataset includes GPS records for individual trips. Road network data for both cities was gathered from Open Street Map, and a map-matching algorithm was employed to align the GPS coordinates to specific road segments. Through this process, trajectories were converted into sequences of road segments. To ensure quality, we filtered out trajectories that included fewer than three road segments or had a duration shorter than one minute. The Xian dataset contains 6,161 road Segments with 15,779 edges, whereas the

same numbers for the Chengdu dataset are 6,632 and 17,038. Average Road Segments per Trip for the Xian and Chengdu dataset are 31.11 and 30.87 respectively.

6.2 Downstream Tasks and Benchmarks

We conduct four downstream traffic tasks, with two road segment-based tasks and the other two being trajectory-based tasks. We compare our method to several state-of-the-art road and trajectory representation learning methods, as well as graph representation learning methods. Methods designed solely for specific tasks are excluded from the comparison, as we aim to learn robust representations for various tasks. Task-specific methods often include tailored representations and components, resulting in an inconsistent and unfair comparison.

6.2.1 Road Segment-Based Tasks

To assess the representation of road networks, we focus on two main tasks: (1) road label classification and (2) traffic speed prediction.

Road Label Classification: This task is analogous to node classification in graphs. Road-type labels, such as motorways and living streets, are collected from the Open Street Map. The five most common label types are selected as prediction targets. A classifier composed of a fully connected layer followed by a softmax layer is applied to the road segment representations. The performance is evaluated using Micro-F1 (Mi-F1) and Macro-F1 (Ma-F1) scores.

Traffic Speed Prediction: This is a regression task where the objective is to predict the average speed on each road segment, calculated from trajectory data. A linear regression model is trained using the road representations, and the evaluation is conducted using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

6.2.2 Comparison with Existing Methods

We compare our approach to various advanced road and graph representation methods:

- **Node2Vec:** Learns node embeddings by exploring neighborhoods within w-hops through parameterized random walks.
- **DGI:** A contrastive learning approach that maximizes the mutual information between node and graph representations.
- **RFN:** Builds node and edge representations based on relational views, using message passing for interaction.
- **IRN2Vec:** Captures relationships between road segment pairs using shortest path samples and multi-objective learning.
- **HRNR:** Utilizes a hierarchical GNN-based architecture with three levels to capture structural and functional properties.
- **Toast:** Incorporates auxiliary traffic context to train a skip-gram model and uses a Transformer module to extract travel-related semantics.
- **JCLRNT:** JCLRNT applies a unified framework to learn road network representations by using within-scale road-road contrast and cross-scale road-trajectory contrast with an adaptive weighting strategy to optimize road-trajectory representation.

6.2.3 Trajectory-Based Tasks

To evaluate trajectory representations, we focus on two main tasks: (1) trajectory similarity search and (2) travel time prediction.

Trajectory Similarity Search: The objective is to identify the most similar trajectory to a given query trajectory from a database. Trajectory representations are used to calculate similarity scores and rank the results in descending order. Performance metrics include Hit Ratio@10 (HR@10) and Mean Rank (MR).

Travel Time Prediction: This task involves predicting the travel time for a given trajectory.

6.2.4 Benchmarks for Trajectory Representation

The following methods are used as benchmarks for trajectory representation:

- **ParaVec:** Learns paragraph embeddings by treating each trajectory as a paragraph.
- **T2Vec:** An encoder-decoder model that reconstructs trajectories from noisy sequences of road segments using LSTM units.
- **Toast:** Description already provided in 6.2.1
- **GTS:** Learns embeddings for points of interest (POIs) followed by trajectory encoding using a GNN-LSTM network.
- **JCLRNT:** Description already provided in 6.2.1

6.3 Simulation Settings

The training dataset comprises 500,000 trajectories, and we train the model using the Adam optimizer (Kingma and Ba, 2015) with a batch size of 64 over 10 epochs. First, the representation vectors for

Table 1: Performance Comparison for Road Label Classification and Traffic Speed Inference.

Task	Road Label Classification				Traffic Speed Inference			
	Xian		Chengdu		Xian		Chengdu	
	Mi-F1 ↑	Ma-F1 ↑	Mi-F1 ↑	Ma-F1 ↑	MAE ↓	RMSE ↓	MAE ↓	RMSE ↓
Node2Vec	0.524	0.495	0.586	0.559	7.12	9.00	6.41	8.22
DGI	0.463	0.337	0.475	0.358	6.43	8.41	6.12	7.98
RFN	0.516	0.484	0.577	0.570	6.89	8.77	6.57	8.43
IRN2Vec	0.497	0.458	0.531	0.506	6.52	8.52	6.60	8.59
HRNR	0.541	0.527	0.631	0.609	7.03	8.82	6.52	8.45
Toast	0.602	0.599	0.692	0.659	5.95	7.70	5.71	7.44
JCLRNT	0.637	0.629	0.729	0.701	4.69	6.85	5.02	7.08
Proposed TCRLRT	**0.645**	**0.634**	**0.742**	**0.713**	**4.57**	**6.78**	**4.96**	**7.01**

Table 2: Performance Comparison for Similar Trajectory Search and Travel Time Estimation.

Task	Similar Trajectory Search				Travel Time Estimation			
	Xian		Chengdu		Xian		Chengdu	
	MR ↓	HR@10 ↑	MR ↓	HR@10 ↑	MAE ↓	RMSE ↓	MAE ↓	RMSE ↓
Para2vec	216	0.251	279	0.205	220.5	302.7	244.7	345.4
T2Vec	46.1	0.781	38.6	0.806	165.2	240.7	207.5	311.0
Toast	10.1	0.885	13.7	0.905	127.8	190.8	175.6	265.0
GTS	11.0	0.889	12.9	0.896	126.3	186.7	176.1	267.9
JCLRNT	8.87	0.928	9.54	0.912	121.9	179.5	163.6	243.5
Proposed TCRLRT	**8.50**	**0.932**	**9.10**	**0.916**	**120.0**	**178.2**	**162.0**	**241.5**

the road segments and trajectories are extracted from both the benchmark models and our proposed model. These vectors, standardized to a dimension of 128, are used in various downstream tasks. The trajectory data set is split into training and evaluation sets based on the date, ensuring that there is no overlap. Temporal sequences are constructed as an absolute time-ordered sequence with a prefix sum starting at 0. The value of λ_{SS}, λ_{TT}, and λ_{ST} is found to be optimal at 0.1, 0.1, and 0.8 respectively. The parameter α for the generation of negative samples using mixing is set to 0.3, a lower value is chosen to produce harder samples.

6.4 Results and Analysis

The simulation results for the four tasks are presented in Tables 1 and 2, with the best results highlighted in bold. Higher values of Mi-F1, Ma-F1, and HR@10 indicate better performance (↑), while lower values of MAE, RMSE, and MR indicate better performance (↓). General methods such as Node2vec, DGI and Para2Vec perform poorly, as they do not capture the unique characteristics of road networks and trajectories. Methods like IRN2Vec and T2Vec perform better due to their richer contextual information. Toast and GTS show improvements in travel-time estimation and trajectory retrieval. JCLRNT employs contrastive learning but does not consider temporal modeling. Our approach incorporates temporal information and a hard negative sampling strategy to optimize training, outperforming JCLRNT and other baselines.

7 CONCLUSIONS

In this paper, we proposed a model of representation learning for road networks and trajectories. Our approach introduces an end-to-end framework that jointly learns road network and trajectory representations, incorporating a learnable temporal encoding and synthesizing harder negatives for optimized training. We conducted experiments on two real-world datasets, evaluating the model on four downstream tasks: two focused on road segments and two on trajectories. For future work, we plan to enhance hard negative sampling techniques specifically tailored for road network and trajectory-based tasks. We also plan to incorporate more modalities of features like text and images to model the representation learning with heterogeneous graphs.

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