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Mobility Networked Time-Series Forecasting Benchmark Datasets

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Abstract

Human mobility is crucial for urban planning (e.g., public transportation) and epidemic response strategies. However, existing research often neglects integrating comprehensive perspectives on spatial dynamics, temporal trends, and other contextual views due to the limitations of existing mobility datasets. To bridge this gap, we introduce **MOBINS** (**MOBI**lity **N**etworked time **S**eries), a novel dataset collection designed for networked time-series forecasting of dynamic human movements. **MOBINS** features diverse and explainable datasets that capture various mobility patterns across different transportation modes in four cities and two countries and cover both transportation and epidemic domains at the administrative area level. Our experiments with nine baseline methods reveal the significant impact of different model backbones on the proposed six datasets. We provide a valuable resource for advancing urban mobility research.

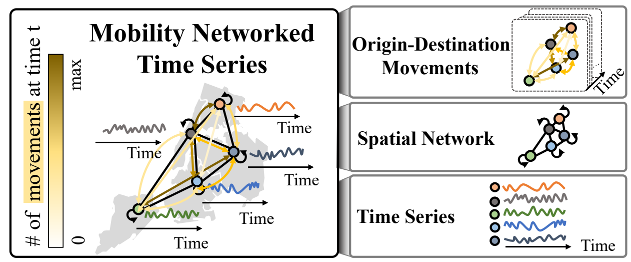

Figure 1: A structure of mobility networked time series in New York. **MOBINS** contains three components: (1) human movements from an origin to a destination over time, (2) spatial structure based on geographic proximity or a road network, and (3) time-varying features (e.g., numbers of taxi pick-ups and drop-offs) of each region. The first and third components cover the same period.

1 Introduction

Diverse and explainable human mobility datasets are crucial for advancing urban planning, affecting public transportation demand (Han et al. 2022), crowd congestion (Singh et al. 2020), traffic management (Liu et al. 2024), and infection prediction (Panagopoulos, Nikolentzos, and Vazirgiannis 2021). Previous research focused on forecasting traffic and crowd congestion in specific areas using various transportation modes, such as subway systems (TianChi 2019), ride-hailing services (Fivethirtyeight 2015), and taxis (TLC 2009). Additionally, there have been several attempts to predict COVID-19 infection by analyzing human mobility across different regions (Katragadda et al. 2022).

However, the datasets used in prior studies often fail to capture the diverse nature of human mobility from multiple perspectives. To comprehensively represent diverse mobility patterns, it is imperative to observe the movements of many individuals over an extended period, taking into account various transportation modes. Unfortunately, many studies estimate demand using data either in a single transportation mode or a short time frame (TianChi 2019; Panagopoulos, Nikolentzos, and Vazirgiannis 2021). Some efforts to understand human mobility rely on sparse movement data collected from a limited number of individuals. Despite the importance of understanding human mobility's impact on various aspects, such as transportation and epidemics, there is a lack of research that integrates additional information beyond transportation to enhance the diversity of mobility datasets.

Subway datasets (TianChi 2019), a networked mobility dataset consisting of stations with high human traffic volumes, meet many of the specified criteria. Nevertheless, the subway datasets themselves do not offer multiple perspectives—i.e., diversity. Although there have been several studies to broaden a single data perspective (Shi et al. 2020), they only integrate mobility data from a *single* source with other contextual information that shares the same static topology. It is insufficient, for example, to simply add weather information as an additional variable to the time series. Instead, it is critical to use mobility-effected information at specific points of interest (PoIs) to *create synergy* between dynamic movements and networked time series. This approach not only enhances performance but also aids in understanding social phenomena that are difficult to discern from a single data source.

To improve the diversity of human mobility datasets, it is essential to collect data from different transportation modes across diverse regions over an extended period, capturing numerous daily movements. Moreover, incorporating addi-

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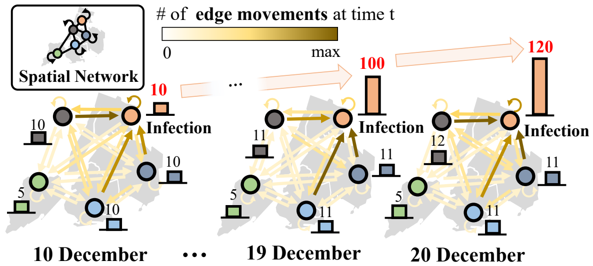


Figure 2: Dynamic edge movements and time-varying infection cases on a static spatial network. On top of the spatial network, node features represent the number of confirmed cases in each city or district over time, and edge features represent population movement flows between cities or districts over time. The increasing number of infection cases at the upper-right node is influenced by the increasing population flows to that node from other nodes.

tional contextual information, such as disease outbreaks, can aid in capturing various contextual patterns associated with spatio-temporal information. Meanwhile, for explainability purposes, the instances in the dataset should be organized on a network based on the spatial connectivity of each explainable area unit, such as an administrative area.

Towards diverse and explainable human mobility datasets, we propose **MOBINS**, **MOBI**lity **N**etworked time-**S**eries forecasting benchmark. **MOBINS** offers a unique combination of origin-destination movements, a spatial network, and multiple time series, as illustrated in Figure 1. It involves multiple transportation modes including buses, subways, express buses, and taxis, providing a rich representation of human mobility patterns. With observations spanning at least two years and numerous daily movements, **MOBINS** enables the development and evaluation of advanced forecasting models. To ensure broad applicability, we include the benchmark datasets for transportation and infection prediction across four cities and two countries. By representing the networked mobility datasets at the administrative area level and treating each node as a distinct entity, **MOBINS** helps the model interpretation of the underlying mobility patterns.

Our dataset collection contains not only network-based interactions between nodes and edges but also temporal dynamics from time-varying features. Also, all datasets have a spatial network, where nodes represent locations such as stations, districts, and cities and edges represent connectivity between nodes based on subway lines, roads, and geographical adjacency. In Figure 2 visualizing part of a dataset in **MOBINS**, a spatial network created based on road network information is given as static data, and dynamic human mobility is represented through dynamic edge movements. In this case, the positive correlation between human movements and time-varying infection cases is captured. This kind of insight is difficult to uncover from a straightforward collection of multiple datasets, because their regions, spatial and temporal resolutions, and collection intervals may not be aligned. Therefore, this *new opportunity* clearly demonstrates the innovation and significance of **MOBINS**.

Our sophisticated and diverse dataset collection is publicly available together with forecasting methods at https://zenodo.org/records/14590709. A substantial amount of time and effort has been dedicated to gathering comprehensive datasets from various data sources, as well as merging and preprocessing them in preparation for their release. We aspire to contribute to the progress of the community that studies human mobility. Our contributions are as follows:

- **Datasets:** To the best of our knowledge, this is the first comprehensive dataset collection characterized by diversity and explainability for mobility networked time-series forecasting. Also, we provide code to use our datasets.
- **Experiments:** We conduct experiments to predict both time series and origin-destination movements. These experiments are based on various baselines with different backbones, applied to our dataset collection: transportation and epidemic datasets in four cities and two countries.
- **Takeaways:** Our experiments highlight the need for an integrated framework that simultaneously considers the three components—origin-destination movements, a spatial network, and multiple time series. These insights guide future research directions in developing advanced frameworks for mobility networked time-series forecasting.

2 Preliminaries

2.1 Forecasting with Mobility Time-Series Data

Human mobility prediction aims to predict each location's various attributes such as speed, demand, and congestion. In the context of traffic forecasting, studies employ traffic speed sensor datasets (Liu et al. 2024; Li et al. 2017) collected from PeMS (Performance Measurement System). Similarly, studies on demand or congestion prediction use modified in-/outflow datasets derived from various transportation modes, such as subway (TianChi 2019) or taxi (TLC 2009) datasets. Unlike conventional time-series forecasting, mobility time-series forecasting emphasizes both temporal and spatial modules. Spatial axes are represented using $N \times N$ grids based on given coordinates, while an adjacency graph captures spatial connectivity derived from PoIs or a correlation generated from the sensor proximity (Jiang et al. 2021). Alternatively, station-based spatial connectivity is employed to model the patterns of movements within a given graph (Ou et al. 2020).

2.2 Forecasting with Origin-Destination Data

Origin-destination (OD) forecasting focuses on predicting the number of movements between the regions, capturing the interaction patterns within a mobility network. Datasets from ride-hailing services (Fivethirtyeight 2015), taxi (TLC 2009), and subway (TianChi 2019) provide valuable information for deriving origins and destinations. OD movements between candidate origins and destinations, such as grids, stations, and PoIs, are forecasted using spatial and temporal modules (Han et al. 2022; Wang et al. 2019; Rong, Ding, and Li 2023). Meanwhile, several studies have attempted to enhance time-series forecasting performance by incorporating OD movements. For example, research on COVID-19 prediction in England (Panagopoulos, Nikolentzos, and Vazirgiannis 2021) and USA (Wang et al. 2023) has used the interaction between nodes, represented by the number of COVID-19 cases, and human mobility between regions. These studies leverage the relationship between inter-regional movement and the spread of infections to predict the number of cases in each region (Katragadda et al. 2022).

3 Mobility Networked Time Series

3.1 Problem Definitions

Mobility is represented along both spatial and temporal dimensions. The spatial component is structured through a graph, denoted as $G = (V, E)$. The node set $V = \{v_1, v_2, \ldots, v_N\}$ captures locational data, while the edge set E illustrates the connectivity between these nodes. Each node temporally aggregates *node time-series features* X_t, encompassing metrics such as transportation in/out-flow, ridership, infection rates, and additional time-sensitive data, where $X_t \in \mathbb{R}^{N\times d}$, d is the number of feature variables, and t is the index of the time. In scenarios where the graph G remains static, its *spatial network* $A \in \mathbb{R}^{N\times N}$ is defined through a fixed adjacency matrix. Conversely, in dynamic settings, G evolves with *OD movements* $M_t \in \mathbb{R}^{N\times N}$, where M_t^{ij} accurately measures the volume of movements from node v_i to node v_j at each time point t.

Definition 3.1 (MOBILITY NETWORKED TIME-SERIES FORECASTING)**.** Given a spatial network A and a corresponding historical dataset $D = \{D_1, D_2, \ldots D_T\}$, where $D_t = (X_t, M_t)$ includes node time-series features X_t and OD movements M_t, the objective of *mobility networked time-series forecasting* is to learn a function f that forecasts both the future node times-series features $\{X_{T+1}, X_{T+2}, \ldots, X_{T+H}\}$ and the future OD movements $\{M_{T+1}, M_{T+2}, \ldots, M_{T+H}\}$ over a forecast horizon H.

3.2 Limitations of Existing Mobility Datasets

Existing mobility datasets, as used in human mobility forecasting, are compared with the characteristics of our **MOBINS** in Table 1. We categorize existing human mobility datasets into three types. In the first type, the Hangzhou Subway dataset (TianChi 2019) offers deep analysis through individual unit data but is limited by its specific region and short collection period, sharing the limitation also observed in datasets like the NYC Uber dataset (Fivethirtyeight 2015). This dataset's collection from a single source makes it challenging to capture the diverse nature of human mobility. In the second type, LargeST (Liu et al. 2024) provides extensive data over a long collection period but lacks detailed human mobility information, such as OD movements. This limitation is also present in other PeMS-based datasets. In the third type, (Panagopoulos, Nikolentzos, and Vazirgiannis 2021) shared human mobility datasets that link movements with other factors. However, its short collection period makes it challenging to observe long-term trends, and the absence of a spatial network reduces its utility for spatial analysis.

For urban planning purposes (e.g., public transportation) and epidemic response strategies, human mobility datasets should provide multiple views of spatial and temporal dimensions, as well as exhibit qualities such as diversity and explainability. However, many datasets currently available do not meet these criteria. In Table 2, we highlight the specific shortcomings of existing human mobility datasets, emphasizing their deficiencies in capturing essential qualities.

Diversity To accurately represent human mobility, datasets should encompass a wide array of contexts. Human movement can occur through various modes of transportation, such as subways, buses, high-speed trains, and taxis. A dataset that covers only a single mode of transportation, like the subway dataset (TianChi 2019), fails to provide a comprehensive view of mobility. Datasets incorporating *various modes* are essential for depicting the diverse nature of human mobility. From a spatial perspective, the mobility datasets should encompass *various regions* to capture the different spatial and contextual patterns, such as commercial, residential, and tourist patterns, emerging from diverse administrative areas. For instance, COVID datasets (Panagopoulos, Nikolentzos, and Vazirgiannis 2021) cover four EU countries, and LargeST (Liu et al. 2024) includes datasets from across California, including Los Angeles, the Bay Area, and San Diego. From a temporal perspective, datasets should also include *long periods* to offer insights into both short-term and long-term mobility patterns. However, except for LargeST (Liu et al. 2024), many datasets cover periods of less than one year, with some training models over periods even shorter than one month (TianChi 2019; Li et al. 2017). Moreover, mobility datasets must be collected with *many daily movements*. Unfortunately, several datasets are employed with only an insufficient number of daily movements (Wang et al. 2023), which fail to capture representative human mobility. Understanding human movements is not only about comprehending the movements themselves but also about linking information strongly correlated with these movements to get insights into social phenomena, which allows for the exploration of many aspects of human mobility. Therefore, *bi-modality* is helpful in comprehending human movements and their strongly correlated phenomena. For example, the COVID datasets consist of two types of data: OD movements from human mobility between regions based on mobile device data, and node time-series features from the number of infected individuals.

Explainability Decision-makers in urban planning require models with high explainability, which necessitates datasets with inherent explainability. Training models using grid or sensor identifiers (Li et al. 2017; Liu et al. 2024) is insufficient. *Explainable units* for locational information, e.g., administrative areas, are vital. In the spatial dimension of mobility, each dataset should realistically represent spatial connectivity. For instance, the subway dataset (TianChi 2019) records connectivity at the station level. Administrative areas can create a *spatial network* based on actual spatial adjacency and connectivity, indirectly helping to understand how the impact of an event spreads out.

4 Dataset Documentation

Our **MOBINS** dataset collection encompasses two domains: *transportation* and *epidemic*. For FAIR data guiding principles, **MOBINS** provides data elements, metadata, and an identifier at https://zenodo.org/records/14590709.

Datasets		Spatial Nodes	Spatial Network		OD Movements		Node Time-Series Features		Time Period
			Edges	Domain	Daily Movements	Modes	Daily Amounts	Domain	
Hangzhou Subway (TianChi 2019)		81	85	Station	2.9M	Subway	2.9M	Subway In/Out-flow	01/01/2019 – 01/25/2019
LargeST (CA) (Liu et al. 2024)		8600	201363	Distance	-	-	187.77M	Traffic Flow	01/01/2017 – 12/31/2021
COVID (England) (Panagopoulos, Nikolentzos, and Vazirgiannis 2021)		129	-	-	11.86M	Mobile Device	1975	Infection	03/01/2020 – 04/30/2020
MOBINS (Transporation)	Seoul	128	290	Station-based Administrative Area	2.68M	Smart Cards	4.02M	Subway In/Out-flow	01/01/2022 – 12/31/2023
	Busan	60	121		0.63M		0.75M		01/01/2021 – 12/31/2023
	Daegu	61	123		0.25M		0.34M		01/01/2021 – 12/31/2023
	NYC	5	12	Borough	0.10 M	Taxi	3.03M	Ridership	02/01/2022 – 03/31/2024
MOBINS (Epidemic)	Korea	16	45	City & Province	13.41M	Smart Cards	25834	Infection	01/20/2020 – 08/31/2023
	NYC	5	12	Borough	2418	Taxi	2038	Infection	03/01/2020 – 12/31/2023

Table 1: Comparisons based on the components of mobility networked time series (M: million).

Datasets	Diversity					Explainability	
	Various Modes	Various Regions	Long Period	Many Daily Movements	Bi-Modal Dataset	Explainable Units	Spatial Network
Hangzhou Subway (TianChi 2019)	X	X	X	O	O	O	O
LargeST (Liu et al. 2024)	O	O	O	-	X	X	O
COVID (Panagopoulos, Nikolentzos, and Vazirgiannis 2021)	O	O	X	O	O	O	X
MOBINS	O	O	O	O	O	O	O

Table 2: Comparisons based on crucial criteria for mobility datasets.

4.1 Dataset Construction

Transportation datasets The **MOBINS** dataset collection comprises transportation data from three South Korea cities (Seoul, Busan, and Daegu) and one U.S. city (New York City). The *Transportation-[Seoul, Busan, Daegu]* datasets include node time-series features from subway inflow/outflow data and OD movements from smart card usage across various public transportation modes. These datasets use subway maps to represent spatial connectivity, leveraging the commonalities between node time-series features and OD movements. However, pre-processing is required to align the data to a consistent spatial and hourly resolution, as node time-series features are generated for each station and OD movements are based on administrative areas. Figure 3 illustrates that stations within the same administrative area are consolidated into a single node in the spatial network, resulting in nodes represented by station-based administrative areas. The *Transportation-NYC* dataset includes OD movements from the NYC yellow and green taxi datasets (TLC 2009) and node time-series features from NYC subway, tram, and railway ridership data. The spatial network is built at the borough level to alleviate sparsity from the many nodes. Consequently, NYC taxi records from 263 zones and NYC ridership data from 428 stations are represented consistently.

Epidemic datasets The **MOBINS** dataset collection includes epidemic datasets that consist of node time-series features obtained from COVID-19 infection count and OD movements obtained from a smart card or taxi trip records in South Korea or New York City (NYC). The "Epidemic" section in Figure 3 illustrates the composition of the *Epidemic-Korea* dataset based on the spatial networks characterized by an adjacency matrix with diagonal ones representing the connectivity between cities and provinces. The OD movements from buses, urban rails, railways, and long-distance buses are used to represent inter-city or inter-provincial movements. However, islands are excluded due to their distinct transportation modes. Each node represents a city or a province, with COVID-19 infection cases recorded at each administrative area. Similarly, for the *Epidemic-NYC* dataset, node time-series features are based on daily infection cases from the five boroughs, while OD movements are comprehensively integrated from the yellow and green taxi datasets (TLC 2009).

4.2 Collection Process

All datasets in the **MOBINS** are collected from reliable sources. These sources provide publicly accessible data downloads based on their administrative systems. The source data from smart transit card information systems is accessed through API calls. Data from the Korea Public Data Portal is available under the CC BY license. For unlicensed sources, we obtained responses about the uses for research via phone or email. Additionally, data from the Korea Disease Control and Prevention Agency (KDCA) was used without numerical value modifications after obtaining permission.

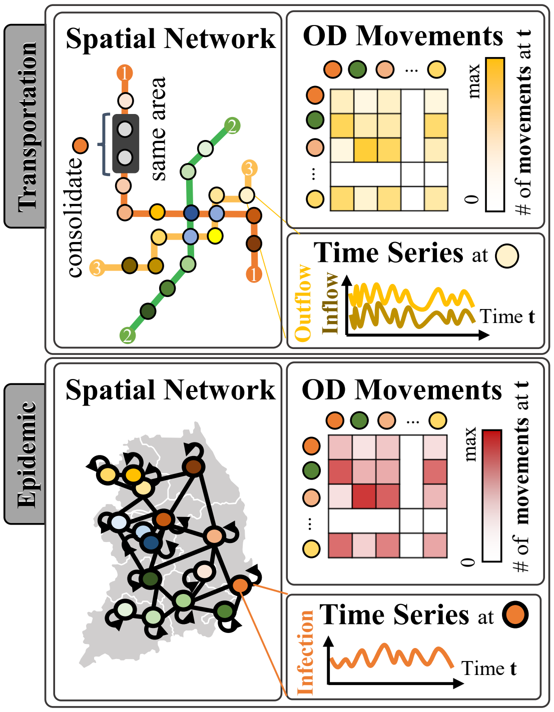


Figure 3: **MOBINS** Composition in South Korea.

The **MOBINS** comprises three main elements for each dataset: (1) OD movements, (2) a spatial network, and (3) time series. The OD movements and time series components are derived from various sources, which are detailed below.

References of Origin-Destination Movements

- **Transportation-[Seoul, Busan, Daegu]**: Korea Public Data Portal [1] and Smart transit card information system [2]
- **Transportation-NYC:** NYC TLC [3]
- **Epidemic-Korea:** Smart transit card information system [2]
- **Epidemic-NYC:** NYC TLC [3]

References of Time Series

- **Transportation-[Seoul, Busan, Daegu]:** Korea Public Data Portal (Seoul [4] [5], Busan [6] and Daegu [7])
- **Transportation-NYC:** NYC Data Portal [8]
- **Epidemic-Korea:** KDCA [9]
- **Epidemic-NYC:** NYC Health [10]

[1] https://www.data.go.kr/en/data/15081036/fileData.do
[2] https://stcis.go.kr/wps/main.do
[3] https://www.nyc.gov/site/tlc/about/tlc-trip-record-data.page
[4] https://www.data.go.kr/en/data/15048032/fileData.do
[5] https://www.data.go.kr/en/data/15060424/fileData.do
[6] https://www.data.go.kr/en/data/3057229/fileData.do
[7] https://www.data.go.kr/en/data/15002503/fileData.do
[8] https://data.ny.gov/Transportation/MTA-Subway-Hourly-Ridership-Beginning-February-202/wujg-7c2s
[9] https://ncv.kdca.go.kr/pot/cv/trend/dmstc/selectMntrgSttus.do
[10] https://github.com/nychealth/coronavirus-data/blob/master/trends/cases-by-day.csv

References of a Spatial Network We process these reliable source datasets to reconstruct datasets with consistent periods and spatial node units. The datasets cover extensive periods and maintain overlapping OD movements and time series within the periods. We generate spatial networks based on spatial connectivity. All datasets have OD movements and time series from different sources, which have different spatial areas. Therefore, we align the spatial areas as follows:

- **Transportation-[Seoul, Busan, Daegu]:** The spatial networks are constructed with 'station-based administrative area', as shown in transportation datasets of Figure 3. We align the administrative area based on the station-based network. In other words, we create a 'station-based administrative area' by connecting stations in the same administrative area with the same node.
- **Transportation-NYC and Epidemic-[Korea, NYC]:** The datasets are based on administrative areas such as city, province, and borough, and the network is organized based on the spatial connectivity between each area, as shown in Figure 1 and epidemic datasets of Figure 3.

To protect privacy, the source datasets and our processed data do not contain any personally identifiable information. The data were collected at aggregate levels, such as boroughs. Although **MOBINS** provides coarser spatial granularity compared to the source datasets, which capture fine-grained movements, our datasets effectively reduce the risk of individual identification. Also, with an average of over 4,000 daily movements per node, the datasets provide insights into overall human mobility patterns rather than individual movements.

4.3 Preprocessing/Cleaning/Labeling

Each dataset in the **MOBINS** collection is derived from different sources for OD movements and time series. To ensure consistent spatial and temporal resolution, we align these two sources. In the *Transportation-[Seoul, Busan, Daegu]* datasets, we use 'station-based administrative areas' as spatial node units, treating stations within the same administrative area as a single node. For the *Transportation-NYC* dataset, we use boroughs as spatial node units to align the spatial resolution between taxi zones and stations. In the *Epidemic-Korea* dataset, the source infection case data is collected at the city and province levels. Hence, we use OD movements based on the city and province levels to match spatial resolution. For the *Epidemic-NYC* dataset, we use the borough level to maintain consistent spatial node units. After the spatial resolutions are determined, we generate the spatial network based on these resolutions. Regarding the temporal aspect, although the source frequency of OD movements from *Transportation-[Busan, Daegu, NYC]* is less than 15 minutes, we set the frequency to 1 hour in the **MOBINS** to match the time-series data frequency. This integration of double sources with positive or negative correlations enables the interpretation and forecasting of data from various contextual perspectives.

Among our dataset collection, the source OD movements of the *Transportation-Seoul* dataset have 14 missing days in the Korea Public Data Portal. These missing days are filled with additional OD movement information from the smart transit card information system. Meanwhile, source OD movements from the NYC taxi dataset (TLC 2009) contain abnormal taxi records. To provide clean NYC OD movements, we remove abnormal taxi records if the difference between drop-off and pick-up timestamps is less than 0 seconds or more than 6 hours for each record. To facilitate future data updates, we maintain backups of the raw source data.

4.4 Uses

The **MOBINS** repository is publicly available for mobility networked time-series forecasting tasks, providing comprehensive views of spatial dynamics, temporal trends, and other contextual aspects. Since we have addressed the challenges of aligning spatial and temporal resolution, researchers who want to use mobility networked time-series datasets can easily develop their fusion methodologies. From a positive societal impacts perspective, the **MOBINS** can be used for urban planning and epidemic response strategies, helping administrators understand human mobility and social phenomena to formulate better policies. Researchers can leverage the dataset collection to apply their models in various ways by comprehensively viewing spatial dynamics, temporal trends, and other contexts. However, in terms of a negative societal impacts perspective, *Epidemic-[Korea, NYC]* datasets can cause problems if misinterpreted, potentially leading to regional biases. Researchers should be cautious not to confuse correlation with causation and recognize other factors like population density. Additionally, researchers should avoid over-interpreting infection data, considering the difference between 'confirmed' and 'infected' timestamps.

4.5 Distribution

We created the **MOBINS** to advance the human mobility community and distribute the dataset collection without cost.

MOBINS License The **MOBINS** consists of two categories. First, the *Transportation - [Seoul, Busan, Daegu, NYC]* and *Epidemic-NYC* datasets are available under a CC BY-NC 4.0 International License. Second, the *Epidemic-Korea* datasets are available under a CC BY-NC-ND 4.0 International License. The code implementations accompanying the datasets are released under the MIT License.

5 Dataset Strawman Analysis

5.1 Transportation-[Seoul, Busan, Daegu, NYC]

Temporal Aspects Figure 4 illustrates both the 'hours of the day' and 'months of the year' patterns in the *Transportation-Busan* dataset, using the long-term data collection spanning at least two years. The dataset exhibits a strong positive correlation between OD movements and node time-series features, as evident from the similar temporal distributions. Though these two modalities may show different values at a fine granularity, their aggregated trends coincide with each other, which confirms the validity of the dataset. Common temporal patterns include commuting patterns at 8 a.m. and 6 p.m., where both OD movements and inflow/outflow reach their peak values, as shown in Figure 4a. Also, these temporal patterns in Figures 4a and 4b highlight the importance of capturing both short-term and long-term dynamics in mobility networked time-series forecasting.

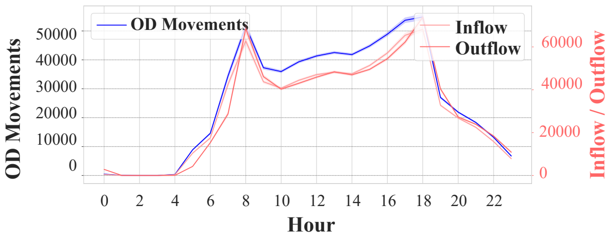
Spatial Aspects Figure 5a displays the total sum of OD movements between nodes, and Figure 5b is a matrix based on hops, indicating the number of nodes to be traversed from one node to another on the spatial network. Figure 5 reveals a negative correlation between OD movements and the hop matrix. In the hop matrix, darker colors represent a lower number of hops in the spatial network. Conversely, areas with higher (brighter) OD movements are associated with lower (darker) hops in the hop matrix. Therefore, a spatial network and OD movements are correlated, with higher mobility observed between nodes that have lower hops.

5.2 Epidemic-[Korea, NYC]

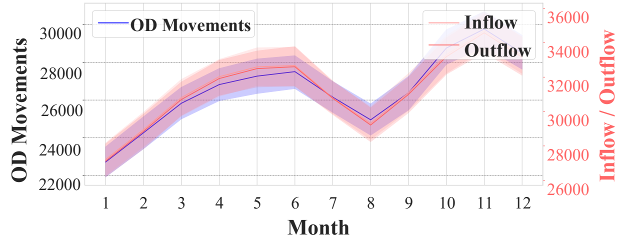
Temporal Aspects Figure 6 presents the daily infection cases and daily OD movements for the *Epidemic-[Korea, NYC]* datasets. Figures 6a and 6b reveal a negative correlation between infection cases and movements during the early stages of the COVID-19 pandemic. As infection cases increase, human movements decrease, indicating a change in mobility patterns in response to the outbreak. From a temporal perspective, the *Epidemic-[Korea, NYC]* datasets demonstrate a strong negative correlation between node time-series features (infection cases) and OD movements, providing comprehensive insights into the interplay between the spread of infection and human mobility. This temporal analysis emphasizes the importance of considering the dynamic relationship between human mobility and disease spread.

Spatial Aspects Figure 7 presents a comprehensive visualization of all three components of the mobility networked time series on the day when the infection cases peaked for each Epidemic dataset (Korea: 03/17/2022 and NYC: 01/03/2022). The analysis reveals that nodes in close spatial proximity do not necessarily guarantee similar values for OD movements and infection cases. Furthermore, the areas with the highest OD movements do not always correspond to those with the highest infection cases, as observed in both Korea and NYC. However, in the *Epidemic-Korea* dataset, high OD movements typically indicate significant population exchanges in specific regions, which tend to correlate with areas having a high number of infection cases. Conversely, the *Epidemic-NYC* dataset shows a different pattern, where Brooklyn has the highest number of infection cases despite Manhattan having high OD movements.

In summary, the analysis and interpretation of the temporal and spatial aspects of the transportation and epidemic datasets highlight the importance of mobility networked time-series forecasting and the need for fusion methodologies. Mobility networked time-series forecasting allows for the development of models that can effectively capture the intricate temporal and spatial dependencies in human mobility data, adapt to evolving patterns and relationships, and provide accurate predictions to support data-driven decision-making. in various domains. Moreover, fusion methodologies enable the integration of multiple data sources, providing a more comprehensive and holistic understanding of human mobility patterns and their complex relationships.

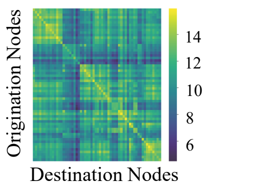


(a) [**Hours of the day**] Average and 95% confidence interval

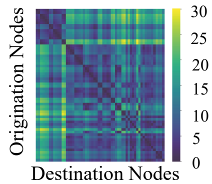


(b) [**Months of the year**] Average and 95% confidence interval

Figure 4: Temporal patterns with positive correlations between inflow/outflow and OD movements about different periods in the *Transportation-Busan* dataset. Inflow/outflow and OD movements on all nodes are aggregated hourly or monthly.

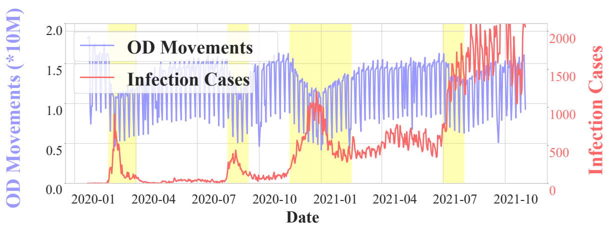


(a) OD Movements (log scale).

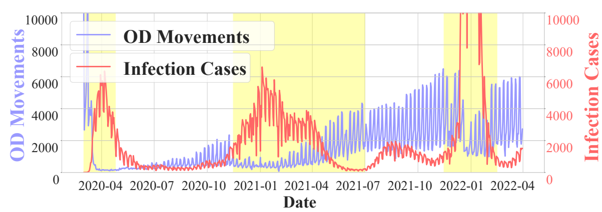


(b) Hop Matrix.

Figure 5: Spatial patterns of the OD movements and hop matrix in the *Transportation-Busan* dataset.



(a) [**Korea**] Period: 01/01/2020 – 10/31/2021.



(b) [**NYC**] Period: 03/01/2020 – 03/31/2022.

Figure 6: Temporal patterns show negative relationships between infection cases and OD movements in the *Epidemic-[Korea, NYC]* datasets. The negative correlation is prominent in the yellow background. Infection cases and OD movements about all nodes are summed daily (M: million).

6 Experiments

6.1 Experimental Settings

Table 3 summarizes the statistics of the datasets used in our experiments. To evaluate our dataset collection with a four-day look-back window and various prediction lengths, we use Mean Absolute Error (MAE) as an evaluation metric, as shown in Table 4. We assess model performance across three different prediction lengths: 7, 14, and 30 days, to capture both short-term and long-term forecasting capabilities. Previous studies have employed prediction lengths ranging from 96 to 720 steps for long-term forecasting and 6 to 48 steps for short-term forecasting (Wu et al. 2022). For *Transportation-[Seoul, Busan, Daegu, NYC]* datasets that have a 1-hour time interval, we evaluate long-term forecasts at horizons of 168, 336, and 720 hours (i.e., 7, 14, and 30 days). Since the 1-hour interval results in many time points, these horizons are considered long-term. Meanwhile, for the *Epidemic-[Korea, NYC]* datasets, which have a 1-day time interval, the same prediction periods of 7, 14, and 30 days represent short-term forecasts. Therefore, our dataset collection serves as a comprehensive benchmark for both long-term and short-term mobility networked time-series forecasting, depending on the datasets' time interval, with prediction lengths consistently set to 7, 14, and 30 days. For fair comparisons, all baselines are configured to follow the same experimental setup, running for 10 epochs with early stopping. All experiments are conducted on Ubuntu with an NVIDIA RTX 3090Ti GPU.

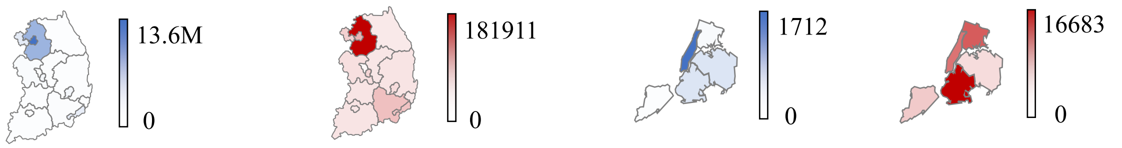
6.2 Baselines

In our evaluation with **MOBINS**, we choose prediction models as our benchmark, including (i) Linear-based models: DLinear, NLinear (Zeng et al. 2023); (ii) RNN-based model: SegRNN (Lin et al. 2023); (iii) Transformer-based models: Informer (Zhou et al. 2021), Reformer (Kitaev, Kaiser, and Levskaya 2020), PatchTST (Nie et al. 2022); (iv) CNN-based model: TimesNet (Wu et al. 2022); (v) GNN-based models: STGCN (Yu, Yin, and Zhu 2018), MPNNLSTM (Panagopoulos, Nikolentzos, and Vazirgiannis 2021).

6.3 Baseline Evaluation Results

In this section, we outline the key results from our experiments, detailing how each baseline performs across a range of datasets. The outcomes highlight the relative strengths and weaknesses of different forecasting models and offer insights into their applicability in diverse contexts.

- **Linear models:** DLinear was the best model for the *Transportation-Daegu* dataset across all prediction lengths and for the *Transportation-[Seoul, Busan]* datasets for 14-day and 30-day predictions. This result suggests that linear models can be highly effective in scenarios with simpler data patterns or lower degrees of complexity.



(a) [**Korea**] OD Movements (b) [**Korea**] Infection Cases (c) [**NYC**] OD Movements (d) [**NYC**] Infection Cases

Figure 7: Spatial visualizations of the OD movements and infections in the *Epidemic-[Korea, NYC]*. In terms of each node, (a) and (c) display the sum of both total origin movements that belong to the node as the destination and total destination movements that belong to the node as the origination. (b) and (d) are the sum of the infection cases in a maximum infection day (M: million).

Domain	Dataset	# Node	Target Dim.	Total Period	Train Days	Test Days	Time Interval
Transportation	Seoul	128	16640	01/01/2022 – 12/31/2023	548	182	1 hour
	Busan	60	3720	01/01/2021 – 12/31/2023	822	273	1 hour
	Daegu	61	3843				
	NYC	5	30	02/01/2022 – 03/31/2024	593	197	1 hour
Epidemic	Korea	16	272	01/30/2020 – 08/31/2023	990	330	1 day
	NYC	5	30	03/01/2020 – 12/31/2023	1051	350	1 day

Table 3: Dataset statistics '# Node' is the number of nodes which indicate regions (e.g., stations or PoIs). We newly define forecasting target attributes with node time-series features and OD movements. For every node, the 'Target Dim.' is defined by $N^2 + d \cdot N$, where N is the number of regions and d is the number of feature variables from each node.

- **RNN-based models:** SegRNN showed competitive performance but did not achieve the best scores on any dataset, indicating that RNNs may face challenges with the increased complexity and longer-range dependencies typically associated with time-series forecasting tasks.
- **Transformer-based models:** Recent approaches such as Informer, Reformer, and PatchTST were assessed. PatchTST excelled in the *Transportation-Seoul* dataset for the 7-day prediction length. This result emphasizes the adaptability and versatility of Transformer-based approaches, which are known for their ability to handle long-range dependencies effectively.
- **CNN-based models:** TimesNet achieved the lowest error rates in several datasets, including the *Transportation-[Seoul, NYC]* and *Epidemic-[Korea, NYC]* datasets across all prediction lengths. These findings suggest that CNN-based models can be highly effective in certain contexts, particularly when dealing with spatio-temporal patterns.
- **GNN-based models:** STGCN and MPNNLSTM were evaluated, but they did not outperform other baseline models in any of the datasets. However, their performance was competitive, indicating that GNN-based approaches have the potential to manage complex network relationships and scenarios involving spatio-temporal interactions.

6.4 Summary of Findings

Overall, the best model choice depends on the dataset's specific characteristics and underlying data patterns.

- While linear models such as DLinear and NLinear perform well in simpler scenarios, they struggle with more complex data patterns and non-linear relationships. These models are limited in their ability to capture intricate temporal dependencies and are not suitable for datasets with highly dynamic or irregular patterns. However, in our datasets, they are simple but powerful baselines.
- RNN-based models, such as SegRNN, face challenges in handling long-range dependencies and complex temporal patterns. As the sequence length increases, RNNs suffer from vanishing or exploding gradients (Pascanu, Mikolov, and Bengio 2013), limiting their effectiveness in capturing long-term dependencies. Therefore, SegRNN performs badly on our transportation datasets.
- While Transformer-based models demonstrate promising results in handling long-range dependencies, they struggle with capturing local patterns and short-term dynamics. The self-attention mechanism can be computationally intensive, especially for longer sequences (Wang et al. 2020), which can limit their scalability.
- GNN-based models are designed to handle complex network relationships but require careful design and fine-tuning to achieve optimal performance. The performance of GNN-based models heavily depends on the quality and representation of the graph structure, which can be challenging to construct for some datasets.

These findings provide a valuable reference for researchers when selecting appropriate forecasting models for their applications. The comprehensive evaluation reinforces the importance of experimentation and context-driven decision-making in the field of mobility networked time-series forecasting. However, the limitations of existing forecasting models highlight the need for innovative approaches that can address the challenges posed by complex and diverse datasets. That is, a novel approach is anticipated to outperform DLinear and TimesNet for this challenging problem.

Pred. day	Domain	Dataset	Linear-based		RNN-based	Transformer-based			CNN-based	GNN-based	
			DLinear	**NLinear**	**SegRNN**	**Informer**	**Reformer**	**PatchTST**	**TimesNet**	**STGCN**	**MPNNLSTM**
7 days	Trans.	Seoul	0.3858 (±0.0068)	0.4021 (±0.0003)	0.7022 (±0.0363)	0.9204 (±0.0018)	0.5637 (±0.0315)	0.3995 (±0.0046)	**0.3822 (±0.0062)**	0.4053 (±0.0047)	0.6401 (±0.0009)
		Busan	**0.5743 (±0.0056)**	0.5898 (±0.0006)	0.9986 (±0.0087)	3.4773 (±0.0031)	0.7316 (±0.0075)	0.6411 (±0.0052)	0.6103 (±0.0642)	0.6945 (±0.0032)	0.9556 (±0.0035)
		Daegu	**0.4677 (±0.0004)**	0.4919 (±0.0003)	0.7876 (±0.0597)	1.3885 (±0.0038)	0.5338 (±0.0014)	0.4916 (±0.0011)	0.4902 (±0.0087)	0.4901 (±0.0032)	0.7337 (±0.0018)
		NYC	0.4491 (±0.0011)	0.4460 (±0.0005)	0.9226 (±0.0462)	0.9147 (±0.007)	0.5503 (±0.0036)	0.4687 (±0.0027)	**0.3984 (±0.0024)**	0.4601 (±0.0019)	0.6627 (±0.0015)
	Epic.	Korea	0.5767 (±0.0031)	0.5828 (±0.0015)	0.5936 (±0.0072)	1.7884 (±0.0013)	0.7137 (±0.0320)	0.6014 (±0.0392)	**0.4133 (±0.0058)**	0.7427 (±0.0199)	0.7827 (±0.0062)
		NYC	0.4830 (±0.0016)	0.4666 (±0.0022)	0.4896 (±0.0179)	1.0627 (±0.0015)	0.5945 (±0.0165)	0.5026 (±0.0044)	**0.3948 (±0.0033)**	0.5794 (±0.0038)	0.6934 (±0.0062)
14 days	Trans.	Seoul	**0.3878 (±0.0047)**	0.4072 (±0.0003)	0.7183 (±0.0071)	0.6453 (±0.0043)	0.6310 (±0.0105)	0.4006 (±0.0028)	0.4015 (±0.0312)	0.4182 (±0.0257)	0.6399 (±0.0013)
		Busan	**0.5830 (±0.0075)**	0.5934 (±0.0003)	0.9913 (±0.0243)	0.9482 (±0.0012)	0.7434 (±0.0045)	0.6324 (±0.0023)	0.6175 (±0.0611)	0.6862 (±0.0044)	0.9528 (±0.0040)
		Daegu	**0.4696 (±0.0004)**	0.4942 (±0.0004)	0.8154 (±0.0039)	0.7284 (±0.0004)	0.5486 (±0.0045)	0.4919 (±0.0007)	0.4826 (±0.0033)	0.4888 (±0.0021)	0.7323 (±0.0009)
		NYC	0.4579 (±0.0023)	0.4501 (±0.0004)	0.9027 (±0.0237)	0.7229 (±0.004)	0.5623 (±0.0071)	0.4680 (±0.0011)	**0.3988 (±0.0017)**	0.4629 (±0.0023)	0.6624 (±0.0008)
	Epic.	Korea	0.6258 (±0.0006)	0.6088 (±0.0010)	0.6484 (±0.0210)	1.0182 (±0.0116)	0.8025 (±0.0180)	0.6467 (±0.0196)	**0.4562 (±0.0063)**	0.7726 (±0.0269)	0.8003 (±0.0075)
		NYC	0.5008 (±0.0008)	0.4784 (±0.0016)	0.5341 (±0.0298)	0.7046 (±0.0402)	0.6012 (±0.0169)	0.5100 (±0.0048)	**0.4026 (±0.0033)**	0.5855 (±0.0069)	0.6970 (±0.0095)
30 days	Trans.	Seoul	**0.3924 (±0.0020)**	0.5949 (±0.0001)	0.7503 (±0.0708)	0.6425 (±0.0006)	0.6446 (±0.0059)	0.4082 (±0.0034)	0.4082 (±0.0095)	0.4215 (±0.0075)	0.6431 (±0.0016)
		Busan	0.5985 (±0.0023)	0.6038 (±0.0004)	0.9622 (±0.0453)	0.9365 (±0.0024)	0.7654 (±0.0241)	0.6424 (±0.0028)	**0.5969 (±0.0126)**	0.6759 (±0.0015)	0.9402 (±0.0001)
		Daegu	**0.4750 (±0.0004)**	0.5006 (±0.0004)	0.8132 (±0.0057)	0.7285 (±0.0021)	0.5849 (±0.0124)	0.4957 (±0.0017)	0.4846 (±0.0023)	0.4923 (±0.0017)	0.7315 (±0.0012)
		NYC	0.4747 (±0.0019)	0.4592 (±0.0004)	0.9075 (±0.0185)	0.723 (±0.0013)	0.5709 (±0.0122)	0.4811 (±0.0022)	**0.4054 (±0.0040)**	0.4627 (±0.0045)	0.6598 (±0.0005)
	Epic.	Korea	0.7035 (±0.0028)	0.6479 (±0.0012)	0.7318 (±0.0504)	1.0122 (±0.0077)	1.1443 (±0.0469)	0.7268 (±0.0197)	**0.5049 (±0.0118)**	0.8537 (±0.0500)	0.8247 (±0.0172)
		NYC	0.5304 (±0.0014)	0.4875 (±0.0010)	0.5272 (±0.0286)	0.7243 (±0.0138)	0.6370 (±0.0121)	0.5408 (±0.0068)	**0.4068 (±0.0044)**	0.6154 (±0.0189)	0.6932 (±0.0104)

Table 4: Prediction comparison between nine baselines in terms of average **MAE** and standard deviation (in parentheses) with all prediction lengths (7, 14, and 30 days) in all datasets. The best model across each dataset is highlighted in **bold**. Please note the following abbreviations: "Pred." means "Prediction", "Trans." refers to "Transportation" and "Epic." denotes "Epidemic".

7 Future Work and Limitations

The complexity of mobility patterns requires diverse and comprehensive analysis for mobility networked time-series forecasting. Therefore, every component of mobility datasets captures spatio-temporal variability across multiple transportation modes and organizes the datasets into a bi-modal form, facilitating a comprehensive understanding of mobility trends over time. Additionally, the structure of the datasets with explainable units under a spatial network increases explainability, aiding decision-makers in interpreting mobility trends and implications for urban planning (Li et al. 2012; Hoang, Zheng, and Singh 2016) and epidemic control (Ni and Weng 2009; Katragadda et al. 2022) and these insights can significantly impact policy-making and economic decisions.

While **MOBINS** dataset collection serves as a forecasting benchmark, the presence of distribution shifts due to the changes in the *Epidemic-[Korea, NYC]* datasets suggests that they can be utilized for time-series online learning, adapting models in real-time. Additionally, the benchmark can be extended for research on imputation, clustering of traveling behaviors, and hierarchical time-series forecasting. Despite the advantages of our datasets, there are a few constraints, such as the fact that **MOBINS** is limited to only two domains and its period of dataset collection is mostly only two to three years, which is not enough to support annual patterns.

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