Network Science Approaches to Improving Public Transportation

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1. Introduction

Public transportation in urban environments has long been the subject of scrutiny among the general public as well as across various disciplines, from urban planning to environmental science, economics, civil engineering, and sociology. The purported benefits of having an adequate public transportation system include a reduced environmental impact, a better usage of space in urban areas, a reduction (or possibly elimination) of traffic congestion and parking demand, improved public health, elevated economic welfare for the lower class, and a reduction in reliance on foreign industries (automobiles and energy). In order to achieve a good understanding of how to improve public transit systems, we must address certain questions:

- What factors contribute to the failure of transportation systems?
- What are the characteristics of a successful transportation system?
- What are the barriers to improving public transportation systems?
- How can these barriers be overcome?

The answers to these questions are not entirely objective however, since the system's users may have different priorities from each other, and its planners may have different priorities from its users. These various priorities will often conflict, resulting in the task of designing a good system being a rather complex as well as nuanced optimization problem. Some people may necessitate that the system is cheap while others may care more for comfort, and some may prefer routes with minimal transfers while others may prioritize a shorter total travel time. Likewise, an urban planner may design a system that prioritizes public transportation over privately-owned vehicles, but if the citizens oppose this change, then the plans might never come to fruition. These competing priorities as well as the inherent complexity of large networks creates a problem to which a perfect solution is effectively impossible to find.

While there are countless of potential factors which may improve or detract from the success of public transportation, such as politics, economics, or even psychology and sociology, this paper will explore network science-based contributions to solving this problem. Network science is an interdisciplinary field grounded in mathematics which explores the relationships and flows within complex systems. By modeling a transportation system as a network of nodes (stations and stops) and edges (routes) researchers can apply mathematical and algorithmic techniques to gain deeper insights of its structure and dynamics and how these might be manipulated in order to improve efficiency and robustness. Since the problem of public transit incorporates so many more aspects than just poorly planned routes and stops, there's a demand not for the discovery of an optimal urban design or transit system, but rather for an adaptable framework which can be adjusted based on the various possible constraints such as budget, existing infrastructure, geography, land laws and policies, and the desires of the local population. The necessary functions of this framework would include analyzing, simulating, and optimizing transit systems. The aim of this paper is to review various researchers work on this problem, and highlight their contributions towards analyzing and improving the design of public transportation systems.

2. Objective analysis

While sophisticated techniques including network analysis may be used to detect inefficiencies in public transportation systems, there are plenty of flaws which can be recognized through simple observation by a typical user. Some easily identifiable flaws are:

- Pick-up or drop-off locations are too far from the start or end points or are otherwise inconvenient to get to
- Pick-up times are not frequent enough
- Routes are too indirect
- Transport vehicles are unreliable (late, early, no-show)
- Transport vehicles are dirty, uncomfortable, or unsafe

In the book “Better Buses, Better Cities,” the author Steven Higashide explains how poor rider experience creates a negative-feedback cycle. The cycle typically works like this: When bus service is unreliable, with infrequent routes and long, unpredictable wait times, potential riders become frustrated. This frustration leads people to prefer other types of transportation, such as personal vehicles. As ridership declines, transit agencies often respond by further reducing service, which makes the bus system even less attractive. As the use of personal vehicles increases, traffic congestion also increases, further reducing the speed and attractiveness of buses. One method to combat this cycle is to create or designate bus-only lanes. A general-purpose lane in a city transports only 1,000-2,000 people per hour, while a bus-only lane transports 4,000-8,000 per hour (Higashide 2019). According to Higashide, travelling in cities where public transit is prioritized (such as London which has plenty of bus-only lanes) is often fastest by bus.

One necessary aspect for public transport to be appealing is that it must go where people want to go. This isn’t the case for some public transit systems which remained static while the cities and markets around them transformed. According to Higashide, this is partially due to indifference from decision-makers as well as their unwillingness to do anything which may cause controversy. This leads them to only making changes such as improving facilities and equipment, but not making any changes to the stops or routes, which would have the most impact on improving the system’s effectiveness. This problem can be better understood by applying accessibility analyses using network science which is discussed later in this paper.

In the book “The Lost Subways of North America,” Jake Berman delves into the history of transit systems in specific U.S. cities. He mentions the popular theory that the current dismal state of transit is due to sabotage by corporate actors within the automobile and oil industries, but dismisses this as an oversimplification. One factor which Berman emphasizes is the general public's preference to automobiles and freeway construction and their unwillingness to vote for public transit development. Another is the impact of land use regulation on transit policy. In Los Angeles for example, the city implemented zoning regulations intentionally decentralization the population for the purpose of "preventing undue concentration of traffic." This is an indication that a major hindrance to the efficiency of public transit is a tendency among city planners as well as citizens to prioritize private vehicle transportation. Though this issue bleeds far into the domain of politics, network science analyses may contribute to solving this problem through influencing the change of such policies by providing empirical evidence of the inefficiencies they may produce.

3. Network science approaches

The optimization of public transportation systems is a multi-objective, combinatorial optimization problem with significant computational complexity. Mathematically, the challenge can be characterized as an NP-hard problem, which means that solving it requires computational resources that grow exponentially with the size of the input. NP-hard problems are those for which no known algorithm can guarantee a solution in polynomial time. Instead, these problems often require testing a vast number of possible combinations to find the best one—a task that quickly becomes infeasible as the scale increases.

For public transportation, the problem aims to minimize multiple, often conflicting objectives, including:

- Transportation cost
- Travel time
- Energy consumption
- Passenger convenience
- Network coverage
- Number of transfers
- Walking distance required

Given the computational complexity of this problem, the optimal solution isn't realistically attainable at any useful scale. For this reason, the development of heuristic-based algorithms which provide "good" solutions is an on-going subject of research, and likely will be long into the future, unless a major breakthrough in mathematics (or perhaps quantum computing) results in the ability to solve NP-hard problems.

3.1 Static Network Analysis

While static network analysis does not capture the dynamic nature of transit systems, it can provide an understanding of their overall structure. In static network analysis, the transit system is treated as an unchanging graph, with its stations and stops represented by nodes and its routes as connecting edges. This approach is useful for understanding the topological properties of the network. For example, static analysis can be used to identify key hubs or transfer points based on node centrality measures (e.g., degree centrality, betweenness centrality). These hubs represent the busiest stops where many routes converge, making them important for connectivity and passenger flow. Static analysis can also reveal structural vulnerabilities by identifying bridges or cut vertices – nodes or edges whose removal would disconnect parts of the network. This information is helpful for planning service disruptions (e.g. for maintenance) or planning a resilient design for infrastructure. While limited in its ability to capture temporal dynamics like changing schedules and passenger flows, static network analysis offers a baseline understanding of the system's inherent connectivity and structure, providing a starting point for more complex analyses.

Kurant and Thiran (2018) draw attention to the fundamental flaw in applying static network analysis to any transportation network (including the power grid, railways, roads, and pipelines). This flaw is that a static network captures only the topology of such a system, while carrying traffic is its ultimate goal. While *betweenness* can be used as a load estimator, this metric doesn't account for the varying amounts of traffic that crosses each edge. In their research, they show that the correlation between the real load across an edge and its betweenness is typically low in transportation networks. They construct three different static networks using timetable data from trains, buses, trams, metros, and other means of public transit. The nodes are all stations and stops, but each of their three networks differ in how they construct edges. One method is to connect all stops on the same route to each other, ignoring distance. This network can model distance in terms of transfers and represents what the authors refer to as the "space-of-changes." The second network they construct connect sets of adjacent stops on a route. This network can be used to measure distances in terms of stops and represents the "space-of-stops." The third network is constructed by placing an edge between each station connected by a route. This network can measure distance in terms of stations representing the "space-of-stations," and is a subgraph of the first network (space-of-changes.) The authors modify these networks using custom algorithms, and in so doing are able to extract the actual physical topology of the transit network as well as the network of traffic flows.

Research by John et al. (2014) highlights the importance of computational approaches in addressing urban transit network design. While traditional route planning has often relied heavily on local knowledge and simple guidelines, modern computational techniques offer more sophisticated solutions. The authors refer to research from 1984 by Ceder and Wilson where they identified five main stages for the planning of bus service:

1. Network design
2. Frequency setting
3. Timetable development
4. Bus scheduling
5. Driver scheduling

Since each of these planning stages are NP-hard, John et al. consider the attempt to solve all of them simultaneously an impractical endeavor and aim to address the network design element by determining an efficient set of routes on a predefined network of roads, rails, stops, and stations. The authors do this by employing a genetic algorithm based on the non-dominated sorting genetic algorithm II (NSGA-II). Their network design has a fixed transfer penalty (5 minutes), reflecting an assumption of extremely frequent transport at every stop. This assumption of a constant transfer penalty reflects the limitations of static network analysis, and has severe impact on the practicality of this research. While such frequent transit service would be ideal (per the recommendations of Higashide and Berman discussed earlier), many cities do not allocate such resources to public transit, and planners need a better way to create more realistic models in order to conduct analysis.

In contrast, Feng et al. (2019) uses a different approach to optimizing transit networks. Rather than assuming constant transfer times, their approach emphasizes the impact of transfer time composition on total trip time. They propose a genetic algorithm that optimizes transit routes based on dynamic transfer time compositions, aiming to reduce the number of trips with excessive transfer times. While this method better addresses the impact of transfer times in areas with infrequent service, it falls short of accurately modeling transit systems.

3.2 Temporal Network Analysis

While static network analysis can be used to better understand transit networks, it fails to capture the temporal nature of commuting. Real networks, including transit networks, change, with parts of the graph appearing or disappearing as time progresses. This characteristic of real networks can be modeled using temporal networks. This type of network may be more suited for analyzing public transit because transit systems are dynamic, with schedules, routes, and passenger flow changing throughout the day. A temporal network can be represented as a series of graphs, with each graph corresponding to a specific time interval. This technique models how connectivity and accessibility changes over time.

3.2.1. An efficient path finding algorithm

A fundamental requirement for the analysis of temporal networks is the ability to efficiently find shortest paths between pairs of nodes. Routing shortest paths by time across temporal networks is necessary in order to analyze a transit network's efficiency and how it compares to other modes of transportation. In a 2021 paper by Wang, Yishu et al., researchers address the need for constrained route planning on time-dependent and multi-modal representations of transportation networks. They construct multi-modal temporal networks using real datasets of transit schedules, stations, and roads for the cities of New York and San Francisco and the state of California. Below is their figure depicting the design they use in constructing this network.

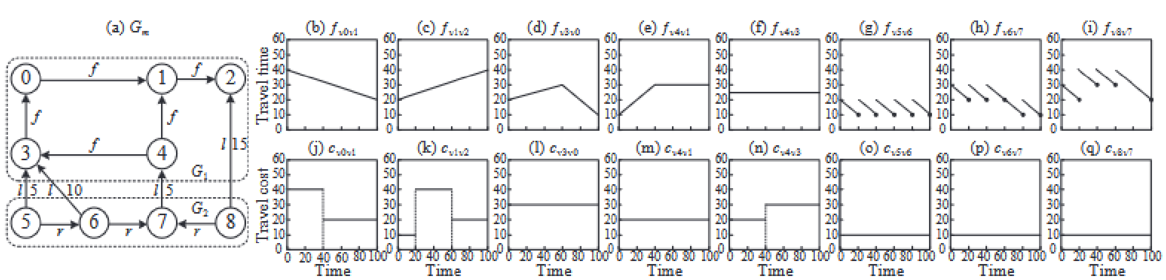

Fig. 1. An example multi-modal time-dependent network. (a): The network G_m. (b)-(i): The time functions for each edge. (j)-(q): The cost functions for each edge.

These networks are used to test three different path-finding algorithms they developed with varying objectives and optimization strategies including a pruning strategy and a local optimization strategy. One algorithm they develop aims to minimize a function of travel duration and travel cost. In their results, they analyze the time efficiency and computer memory efficiency of each algorithm on their constructed temporal networks. While such research contributes to the development of digital map technology (e.g. Google Maps), it can also be instrumental in enabling further research regarding transit systems.

3.2.2 Measuring time-dependent accessibility

In his 2015 research article titled *Time dependent accessibility*, Kaza also laments the limited nature of static networks in assessing the accessibility provided by a transit system. He critiques the traditional reliance on distance-based measures for accessibility analysis and advocates for person-based approaches which incorporate individual temporal constraints, drawing on Hägerstrand's (1970) time-geography framework. The reasons accessibility analyses are typically reliant on place-based models are: “(1) place is an important aggregative mechanism that summarizes the experiences of persons, (2) planners and decision makers have abilities to affect places through infrastructure improvements, in more direct ways than they could affect persons and (3) data to compute personal accessibility because of individual scheduling constraints are hard to come by” (Kaza, 2015). Kaza emphasizes the importance of capturing temporal variability in models, since the same trip may have drastically different durations depending on the time of day or day of the week. In his research, Kaza proposes a method to bridge place-based accessibility and space-time-based measures by constructing a temporal network with the following publicly accessible data:

- General Transit Feed Specification (GTFS) data, which is a standardized format developed by Google for public transportation schedules and relevant geographic information
- OpenStreetMap (OSM) data for computing the walking distances between stops

The walking travel times in this network are computed with an assumed walking speed constant of 4.8 km/h. Travel times between origin and destination pairs are calculated using Dijkstra’s algorithm as it is built into the ArcGIS™ Network Analyst software.

Kaza demonstrates how his methods capture travel-time variability by taking into account transit schedules, which are typically ignored in accessibility studies. He concludes that any measure of accessibility is limited in its capacity to reflect the experiences of real people, but ignoring the key aspect of volatility is a significant oversight which can mislead infrastructure investments and programs.

3.2.3 Optimizing for multiple objectives

In research published in 2018, Kujala et al. create a decision-support framework for public transit planners to generate Pareto-optimal journeys with temporal network analysis. A Pareto-optimal journey is one in which no criterion can be improved upon without worsening another. In the case of public transit, these criteria include total travel times, pre-journey waiting times, and the number of required transfers. By generating Pareto-optimal solutions, any of these tradeoffs can be variably prioritized. For example, solutions which require over a mile of total walking may be disqualified, as well as any route requiring a transfer. The authors construct a temporal network representing the metropolitan transit system of Helsiniki, Finland. Similarly to Kaza discussed in the previous section, Kujala et al. construct their model from publicly available GTFS and OSM data. Rather than assuming a constant walking speed of 4.8 km/h, Kujala et al. assume a walking speed of 70 m per minute (4.2 km/h) with an additional 3 min safety margin for transfers.

The authors implement a modification of the multi-criteria profile connection scan algorithm (mcpCSA). This algorithm computes Pareto-optimal public transit journeys by representing transit schedules as a series of connections, each defined by its departure stop, arrival stop, departure and arrival times, and the vehicle used. Transfer connections are precomputed to account for walking between stops, with considerations for walking distance, speed, and a safety margin to ensure realistic transitions.

The algorithm operates by scanning connections in reverse chronological order, starting with the latest departure times and progressing backwards. During this process, it updates the set of Pareto-optimal journey alternatives for each stop based on the journey options available from downstream stops. This ensures that the most efficient combinations of time, transfers, and routes are maintained. Transfer connections enable walking between stops within a predefined distance, but restrictions are applied to prevent excessive sequential walking transfers.

Kujala et al. also introduce boarding-count-augmented temporal distance profiles to evaluate the relationship between travel times and the number of required transfers. Their analysis demonstrates that while some routes minimize travel duration, they may require additional transfers, highlighting a trade-off that is often overlooked in static analyses. By visualizing these metrics on maps (included below), Kujala et al. are able to depict transit

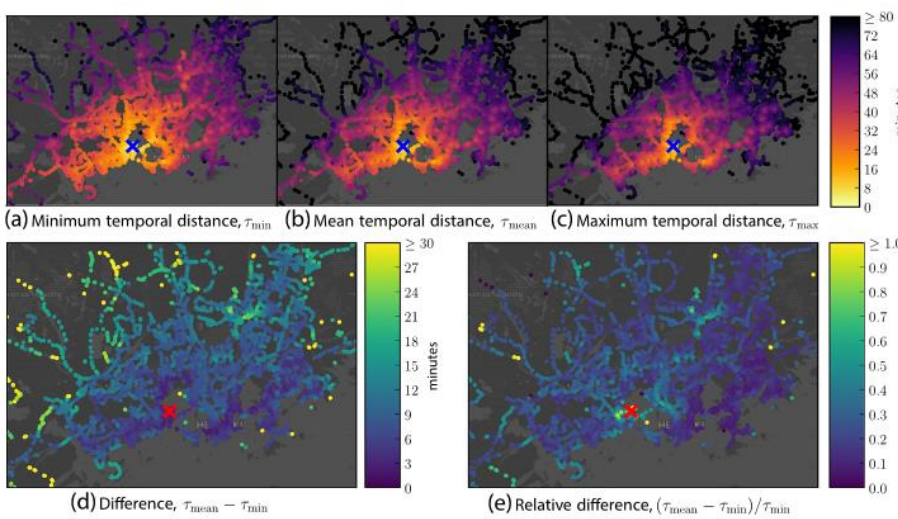

Fig. 9. Access times to Aalto University's main campus: differences in the minimum, mean and maximum temporal distance. In all maps, the campus is marked with a cross. In general, the map for the minimum temporal distance (a) shows that the campus is easily accessible from most PT stops, while the maps for the mean (b) and maximum (c) temporal distances indicate that there are areas with worse access. The differences between the mean and the minimum temporal distance (d) indicate that typically the longer one needs to travel the larger is the difference. When this difference is normalized by the minimum temporal distance (e), areas where the waiting time constitutes a major part of the mean temporal distance become highlighted, especially close to the destination. The area covered in each map is the same as in Fig. 7.
Source: Background map: © OpenStreetMap contributors, © CartoDB

accessibility which shows the effects that long transfers have on areas which are relatively close to the selected destination.

This approach allows for a more nuanced understanding of transit networks compared to static methods. It captures the dynamic nature of public transportation systems, offering insights into service gaps, frequency variations, and the impact of transfers on accessibility. The framework proposed by Kujala et al. provides public transport planners with a powerful tool which could be used in the optimization of networks and the improvement of rider experience.

3.2.4 Temporal Networks with GPS data

In the 2022 research paper "Optimizing travel routes using temporal networks constructed from global positioning system data in Kyoto tourism," Mukai et al. use GPS data to construct a temporal network for the purpose of analyzing public transit. Their approach is to divide urban maps into 50-meter square grids and create timetables of transitions between these grids. The GPS data is also used to estimate time weights for edges between grid squares using probability density functions rather than specific values. This approach allows for more nuanced analysis of urban transportation than static network analysis by capturing the phenomenon of variable congestion and transit delays as well as the impacts of non-public-transit related events. The authors use this network to construct the time-dependent traveling salesman problem (TDTSP) and solve it using ant colony optimization. The resulting route-finding algorithm is more dynamic and responsive to real-time urban mobility patterns. While this system can be used for planning individual routes, it can also be applied to solving other issues within the public transit domain such as vehicle routing problems, crowd avoidance, and the formulation and evaluation of transportation plans.

3.3 Spatial-Temporal Network Analysis

This type of analysis incorporates spatial information as well as temporal information into a network. While temporal networks focus primarily on time-based connections, spatial-temporal networks incorporate location information and may reveal more information about the network, such as physical constraints or spatial relationships and dependencies (Srikanth 2023).

Tribby and Zandbergen (2012) claim to have created a high-resolution multimodal spatial-temporal model incorporating a walking network and a transit network in order to analyze the changes to accessibility brought about by new bus routes in Albuquerque, New Mexico. The advantage they were looking to gain with this model was to factor in walk times and wait times in their measurement of accessibility by introducing a temporal aspect to spatial networks. With these time calculations taken into consideration, their findings indicated that the new bus routes introduced in Albuquerque did significantly increase travel time savings. However, while they did incorporate temporal information by calculating walk times between transit stops (assuming a walking speed of 3 km/h), average route durations, and average wait times, their model is not technically a temporal network since there is no temporal dimension along which the graph changes.

3.3.1 Disparities in travel times between car and transit

In their study, Liao et al. (2020) highlight the significant disparities in travel times between car use and public transit across four major cities: São Paulo, Stockholm, Sydney, and Amsterdam. They address the issue of static network analysis relying on simplistic assumptions, such as constant vehicle speeds, and how this makes them unsuitable for addressing the challenges faced by public transportation systems. By employing a data fusion framework that integrates real-time traffic data, transit schedules, and travel demand derived from social media, the authors reveal how travel times fluctuate based on temporal and spatial variables.

In their analysis, the authors used a hexagonal grid system with high spatial and temporal resolutions in order to analyze travel times. Their analysis indicates that public transit can take 1.4 to 2.6 times longer than car travel, with this difference varying significantly throughout the day. This increased travel time as well as large variability is a discouraging factor for travelers to opt for public transit options. These findings highlight the necessity for planners to more accurately model transit systems in order to simulate real-world travel experiences rather than relying on static models based on naïve assumptions. Liao et al. emphasize that planners of successful transportation systems must take this into account, and suggest that they use open data standards such as GTFS data for public transit schedules and HERE Traffic data for real-time road speeds in order to do so.

3.3.2 Measuring accessibility of selected locations

In a similar fashion to previously discussed authors, Zhou et al. emphasizes the inadequacy of static models in accounting for the multi-faceted and temporal nature of urban travel. In an alternative approach to network analysis, the authors account for the multi-modality and temporal aspects of the transit system by conducting spatial-temporal analysis without the construction of a graph. They construct a spatial-temporal grid for the city of Nanjing China in order to assess the accessibility to healthcare services based on location. Their model utilizes spatial distribution data of the population, pediatric clinic services data, and data from the 2021Q1 Traffic Analysis report of Major Cities in China. The traffic analysis data is used to compute the average impedance of travel through the area during four separate time slots depending on location.

While these techniques don't draw directly from network science, there is a correlation. The temporal grid can be thought of as a temporal network, but one in which the nodes are grid squares linked to each of its neighbors with an edge weighted by that location's current traffic congestion. A similar technique was discussed earlier in 4.2.4 when it was employed by Mukai et al., however Zhou et al. forego this type of conversion in their analysis.

Their findings reveal patterns which were not captured by preceding research based on analysis of single-mode transportation services. These patterns show a high concentration of people with low accessibility to healthcare services. The authors recommend that the framework they developed be used by policymakers and planners in order to optimize the relocation of hospitals to reduce urban traffic congestion.

3.4 Graph Neural Networks

Another network science-based tool which can be used to analyze public transit is Graph Neural Networks (GNNs). GNNs are used to learn complex patterns and relationships within network data. This machine learning technique can efficiently capture spatial dependencies and interactions between different parts of the transit system. GNNs can operate directly on the graph structure of the transit network in order to learn representations of nodes (stations, stops) and edges (routes) that capture both their individual properties and their relationships to other nodes. This type of analysis can be applied in the forecasting of passenger demand, optimization of routes, identification of critical infrastructure, and detecting anomalies. Such analysis conducted with GNNs has potential to capture patterns which other temporal-spatial network analysis techniques may miss, and can improve the computational efficiency of assessing complex networks.

3.4.1 Demand forecasting

In 2009, Tsai et al. introduce two neural network architectures for predicting railway passenger demand: Multiple Temporal Units Neural Network (MTUNN) and Parallel Ensemble Neural Network (PENN). Both architectures process daily and monthly temporal features separately, in contrast to conventional Multi-Layer Perceptron (MLP) approaches which combine all features at input.

MTUNN uses partially connected weights to process daily and monthly features in separate network sections before integration, while PENN employs two independent networks that combine their outputs for final predictions. Testing on Taiwan Railway Administration data showed both architectures outperformed traditional MLPs, with MTUNN achieving 8.1% improvement in MSE and PENN achieving 10.5%. PENN emerged as the preferred model due to its simpler structure (66 parameters vs. 79 for MLP) and extensibility for incorporating additional variables.

The researchers demonstrate that separating temporal features in neural network architectures significantly improves railway demand forecasting accuracy compared to conventional approaches that mix all input features together. While their work focused on passenger rail specifically, these architectural principles could be applied to other transportation demand forecasting problems where multiple temporal patterns exist. The PENN architecture's modular design makes it particularly suitable for extension to new prediction tasks and integration of additional data sources.

3.4.2 Improving computational efficiency of analysis

In 2023, Cong, Weilin, et al. propose a machine-learning model they call "GraphMixer" for the purpose of predicting links within temporal networks. They demonstrate how GraphMixer outperforms several state-of-the-art models, such as JODIE, DySAT, TGAT, and TGN, in temporal network link prediction, despite requiring fewer parameters and simpler data preprocessing. While this research was not conducted on traffic or transit networks, temporal link prediction can be used to forecast transit demands (Tsai et al. 2009). This capability may be utilized to test a transit network model in events for which the travel data is unavailable, e.g. sports events, evacuations, adverse weather events, etc. The temporal network used in this link prediction model could be similar to the network created by Mukai et al. which is built with GPS data, or it could use railway ticket sales like the model by Tsai et al., or perhaps bus ticket sales and rideshare data.

4 Future Research

One idea for further research is to construct specific metrics which indicate the performance of a transit network. One metric might be calculated by comparing the average distance on a space-of-stops network (described by Kurant and Thiran) to the average distance on a network constructed with the same nodes but using the entire road system instead of transit routes. This would only require static network analysis and would be a meaningful indicator of the efficiency of the transit routes' paths in regards to distance compared to cars. This could similarly measure the efficiency of route's paths in regards to time if conducted on a temporal network utilizing an efficient distance measuring algorithm such as Wang, Yishu, et al.'s constrained route planning algorithm. This type of metric could also be expanded to help evaluate any aspect of a transit system by employing algorithms designed to optimize any specific factor, such as price or number of transfers.

Additionally, if spatial information is embedded in a temporal graph which is used to train a Graph Neural Network, the spatial information may help capture meaningful patterns created by geography, attractions, weather patterns, etc. in order to improve link prediction. Such a model may be capable of providing helpful simulations to evaluate a transit networks' performance in events from which we don't have the travel data (e.g., evacuations, natural disasters, sporting events).

These types of analyses would assist planners in evaluating proposed changes such as new bus routes, schedules, the addition or removal of stops and stations, or the introduction of new modes of transportation (e.g. hyperloops, monorails). Such analysis could aid in the prediction of the impact and efficiency of such changes without relying on speculation. This could help prevent the approval of costly projects which result in underwhelming impact on the communities they're intended to service, and also optimize the usage of already existing infrastructure.

5 Conclusion

Improving public transport is an extremely complex problem which spans across many disciplines since there are countless factors (e.g. zoning laws, public opinion, geography) which may contribute to their success or demise. Static network analysis can be used to analyze the topology of a transportation network, though the conclusions which can be drawn from such analysis are severely limited in their usefulness due to the importance of the temporal aspect of travel. Temporal network and spatial-temporal network analysis techniques are more capable in being able to measure the efficiency of a transit network and the amount of accessibility it provides. Graph neural networks may have useful applications as well, particularly in their potential for traffic forecasting. The widespread adoption of meaningful metrics developed from these techniques could result in a more systematic approach to addressing and improving public transportation. The establishment of such an approach may generate credibility resulting in the influence of public opinion and policy, enabling the implementation of meaningful changes. These changes may ultimately reduce negative environmental impact as well as improve the quality-of-life for the general public, by positively affecting their mobility, finances, and health.

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