Agent-Based Modeling of Urban Traffic Scenarios for Improved Priority Vehicle Mobility

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***Abstract*—This study is oriented to analyzing urban mobility challenges, with a focus on improving traffic flow conditions for priority vehicles in complex urban environments. Leveraging Agent-Based Models (ABM) in conjunction with Geographic Information Systems (GIS), the research aims to simulate various traffic scenarios to enhance the efficiency of urban mobility, with a particular emphasis on the movement of priority vehicles. The investigation explores the crucial role of priority vehicles, including but not limited to ambulances, within urban settings. It examines factors such as traffic congestion, infrastructure design, and the impact of traffic management strategies on the mobility of these essential services. A key component of this research involves conducting "What if?" analyses under different traffic conditions, such as mixed traffic flows, dedicated lanes, and emergency route prioritization. These simulations aim to evaluate the potential outcomes of various urban planning strategies on the efficiency of priority vehicle movement and overall traffic flow dynamics. This implementation serves as a foundational step towards understanding and simulating urban traffic scenarios. In the future, the project will integrate priority vehicles into the model and move to a High Performance Computing (HPC) environment. This article outlines the current state of the traffic model, focusing on the NetLogo implementation, and previews the upcoming integration of priority vehicles and the transition to HPC. While initially centered around Barcelona, the methodologies developed through this study are designed to be adaptable for application in other urban areas. The ultimate goal is to contribute to the development of effective traffic management strategies that prioritize the mobility of priority vehicles, thereby enhancing public safety and operational efficiency across densely populated urban environments.**

Keywords-Agent Based Modeling; traffic simulation; urban mobility simulation; real-world data; priority vehicles.

I. Introduction

Urban traffic management is a key focus in city planning. It covers a wide range of topics, including transportation planning, traffic control, and intelligent transportation systems. It also addresses congestion management, public transit, road safety, special event coordination, sustainability, and the use of data and analytics. Effective traffic management is crucial for ensuring efficient, secure, and sustainable mobility within urban areas and across broader transport networks.

Within the urban landscape, the occurrence of emergency situations demands a specialized approach to traffic management. It is essential to facilitate the rapid and safe navigation of emergency response vehicles—such as ambulances, fire trucks, and police cars—from their bases to the scene of an emergency. This necessitates the strategic planning of routes that not only minimize travel times but also prioritize safety and efficiency throughout the journey [1]. Particularly in the case of ambulances, route planning acquires added significance, covering both the journey to the emergency site and the subsequent transport of patients to medical facilities. Determining optimal routes under these conditions is vital, highlighting the necessity for flexible planning and management strategies that can adapt to various emergency situations.

Recent developments in emergency management, specifically regarding ambulances, have introduced a variety of approaches aimed at improving response times and maximizing coverage [2]. These innovations span from optimizing ambulance locations and creating platforms that combine route optimization with real-time patient monitoring to adopting Internet of Things (IoT)-based solutions. Furthermore, considerations extend beyond mere arrival times to include selecting safe routes that circumvent accident-prone areas, traffic lights, and adverse environmental conditions. There are also instances where the nearest hospital may lack the required capabilities to treat a patient, adding another layer of complexity to routing decisions.

The management of priority vehicles poses a complex challenge, involving aspects such as identifying alternative routes, collaborating with local authorities, signaling emergency routes, communicating with citizens, monitoring in real-time, ensuring adaptability and flexibility, coordinating with emergency services, training staff, evaluating infrastructure capabilities, and integrating technology. Effective planning of emergency routes is critical for guaranteeing quick and safe responses within complex systems, thereby aiding efficient traffic management during critical moments.

This ongoing research aims to address emergency situations through agent-based simulation, utilizing real-world data to analyze mobility flows and interactions among various vehicle types [3], as well as the conditions and outcomes of these interactions. By incorporating Geographic Information Systems (GIS) to tailor the simulation environment, the study aspires to create open simulations that are applicable beyond specific cities. The combination of Agent-Based Modeling (ABM), GIS environments, and real-world data will enable the analysis of different scenarios and strategies within urban or complex mobility environments, allowing for the examination of various episodes and strategies, whether real or hypothetical.

As this research progresses, the next steps will focus on the calibration and validation of the simulation model, enhancing its ability to integrate priority vehicles and generate different types of scenario simulations. This will pave the way for more accurate and insightful analyses of urban traffic management and emergency response strategies.

The next section of this article will explore the current state of the art, focusing on existing solutions and their applications. Section 3 will detail the simulation infrastructure and environment, including the architecture, implementation of the vehicle model, data acquisition methods, GIS system integration, and preliminary simulation results related to a roadway in Barcelona. Finally, Section 4 will present conclusions drawn from the findings thus far and outline future directions for research and development.

II. Related work | Methods

As urban traffic management evolves, the demand for accurate traffic simulations is increasing. In 2022, the market for traffic simulation systems was valued at around USD 4.10 billion. It is projected to grow significantly, reaching USD 7.83 trillion by 2030 [4]. Among the various approaches to traffic simulation, microscopic simulation stands out, holding a 40.97% market share in 2022 [4]. These models are increasingly essential for testing connected and automated driving technologies under real-world conditions, providing transportation managers and engineers with critical tools for improving traffic flow and reducing congestion globally.

Geographically, North America leads the global transportation simulation and predictive analytics market, largely due to its advanced infrastructure and early adoption of technology in the transportation sector. Europe follows closely, driven by the EU's emphasis on sustainable transport and smart cities initiatives, as well as emissions restrictions and traffic management regulations that encourage the adoption of predictive analytics and simulation tools [5].

A variety of traffic simulation software supports different simulation approaches. For microscopic simulations, notable examples include A/B Testing, Paramics Discovery, MATSim OS, OpenTrafficSim, CityFlow, VSim RTI, SIDRA, and Micromac. Macroscopic analyses are facilitated by software such as PTV Balance & Epics, Cube Voyager, and Quadstone Paramics Discovery, while mesoscopic approaches utilize software like TransModeler, Aimsun Next, AnyLogic, and SimWalk. Commercial offerings such as PTV Visum for macroscopic analysis, INRO for microscopic and mesoscopic levels, and open-source solutions like Eclipse SUMO and MATSim are also highlighted. Additionally, NetLogo, Repast, and MASON cater to broader simulation needs, including urban traffic simulation [6][7].

Strategies for traffic control, particularly concerning priority vehicles, focus on minimizing response times. These strategies encompass route optimization, traffic signal prioritization, and lane reservation. However, employing a single strategy is insufficient, underscoring the importance of integrating multiple solutions for a robust outcome [8]. Efforts towards optimization aim to reduce total response times, with implementations varying from genetic algorithms to Dijkstra algorithm applications integrated with GIS [1][5][9][10].

Agent-Based Modeling presents a unique opportunity to model complex urban systems, capturing human behavior and its evolution over space and time. Despite its advantages, challenges remain in calibration and validation due to computational demands and the complexity of evaluating interactions across multiple scales within ABM models. Moreover, the integration of real-world data and, more specifically, real-time data into ABM is an emerging field, with dynamic recalibration and state updates posing significant hurdles [11][12]. As this research progresses, future steps will address these challenges by focusing on the calibration and validation of the simulation model. Enhancing the model's ability to integrate priority vehicles and generate varied scenario simulations will be pivotal. These advancements will enable more accurate and insightful analyses of urban traffic dynamics and emergency response strategies, contributing to the ongoing development of effective traffic management solutions.

III. Simulation infrastructure & environment representation

The primary goal of this research is to develop and validate urban mobility maps using agent-based simulation models. This includes integrating GIS-based infrastructure models that handle both mixed and priority traffic. We aim to ensure robust validation with real-world data, focus on decision support systems (DSS), and design an agent-based model that can transition to High Performance Computing (HPC) environments for enhanced performance.

The study goes beyond traditional analyzes by taking an approach to obtaining answers to questions such as: "What if?" (What if we have one less lane on the road? What if we have a part of the road not operational and traffic must be diverted to other roads? What if a bus lane replaces a lane of the road, limiting traffic?, etc.) covering a spectrum of factors, including mixed traffic dynamics, the introduction of dedicated cycle lanes and the reduction of lanes for private vehicles. In particular, we expanded our approach to prioritizing routes for emergency vehicles, recognizing the critical role they play in urban safety and response times.

The marked layout seeks to use traffic control strategies related to priority vehicles, such as different techniques for lane reservation, route optimization and signal prioritization. Regarding the typology of existing priority vehicles, ambulances are of special interest due to their relevance in the route to the point of emergency as well as the route to take the injured to the hospital. In addition to the time needed to reach the incident, factors such as guaranteeing a safe route to the destination hospital (the closest hospital may not be the appropriate one), and the time at which the incident occurred, among others, are elements to highlight.

A. Architecture

The proposal aims to extract geographical areas for analysis using limiting coordinates and bounding boxes based on GIS. From these areas, it will extract various environmental layers such as terrain, rivers, roads, and buildings. These layers and their characteristics will then form the foundation for the model's representation. On this basis, the different types of agents are generated and distributed, representing the elements of the simulation and forming the global set, environment and agents, for the simulation.

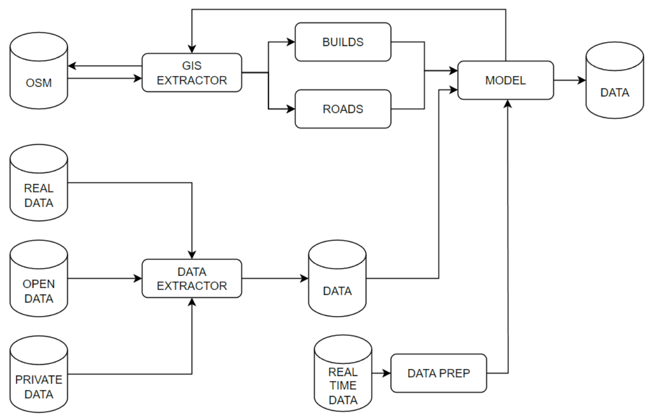

Figure 1. Block diagram for data ingestion.

The architecture of our proposal is illustrated in Figure 1. The model has as inputs, on the one hand, the elements that form the environment that, as shown, is now worked with buildings and roads. These elements of the environment are obtained from Open Street Maps (OSM) [13], using the GIS extraction block. In addition to the environment data, the model receives static data inputs from different Open Data sources, real data that can be available, and private data sources that can be accessed. This static information is complemented with real-time information that allows the model to adjust with data from direct sources of information. Using the environment information, along with the static and dynamic data provided to the model, we can configure and develop the simulation scenarios. Once the scenarios are prepared, we can proceed to execute the simulation. This will generate the results that will allow the evaluation of the effectiveness of the different configurations made on the agents' environment.

B. Vehicle model implementation

The model used for vehicles has a series of characteristics that allow its configuration where we have, as direct inputs (see Figure 2):

- Acceleration
- Deceleration
- Limit speed
- Probability of turning when reaching intersection
- "Patience" level
- Maximum speed
- Minimum speed
- Number of passengers
- Priority
- Type of vehicle

Acceleration and deceleration are key variables for analyzing traffic flow. They determine the speed limits that the model uses to assign different speeds to vehicles, always adhering to the established speed limit. The turning probability will be used to decide whether a vehicle will change lanes at an intersection or continue on its current path. The patience level is used for cases in which faster vehicles catch up with slower ones and have to reduce their speed, where they consume their patience level, reaching, in certain cases, exhausting it and, as a consequence, making a lane change on the road. The maximum and minimum speeds are calculated taking the limit speed as a reference. The type of vehicle and the number of passengers also influence the way a vehicle travels on the road. Finally, priority defines how vehicles will react in the way. Furthermore, for the execution of each simulation it is necessary to indicate the GIS coordinates that allow delimiting the work area and extracting the characteristics of the environment and the number of vehicles that determines the volume of mobile agents that will be in the simulation.

The environment model represents how static elements will influence traffic flow. Elements such as signals, traffic lights or pedestrian crossings that are elements that can regulate and coordinate the flow of traffic, minimize conflicts and reduce congestion.

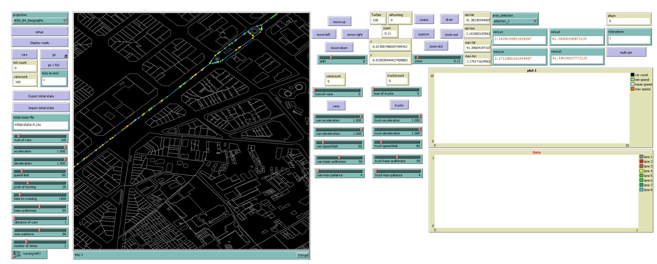

Figure 2. A screenshot showing the interface of the model using the NetLogo platform

The methodology chosen for this work is a phased incremental development strategy, structured around four main tasks:

1) Use data collected and extracted from the real world
2) Integrate GIS data into agent-based simulation environments
3) Develop mobility models based on real data within the GIS infrastructure
4) Formulate multi-lane traffic models, with a specific focus on an urban road characterized by high-density controlled traffic and its immediate surroundings.

Each aspect of the methodology has been developed to facilitate data collection from the real world. Software has been created to recognize various types of vehicles, working directly with videos captured on-site. This software analyzes the footage to extract data on vehicle type, lane occupancy, direction, speed, and distance. The initial version has been based on an improved version of DeepSORT and YOLOv5 libraries [14] to gather information from the most representative streets in Barcelona, analyzing various traffic types. This approach allowed us to obtain speed distributions and measure the distances between vehicles.

Integrating geographic data into an agent-based simulation environment enables us to visualize the roads used in the simulation. It also allows us to incorporate environmental data into the model. NetLogo [15] has be ssen selected as the simulation environment, which supports GIS extensions. NetLogo has been selected because it is designed for agent-based modeling solutions, without limiting access to its functions and features, flexibility, cost and research focus. Customization and modification to specific needs may not be possible with proprietary software due to restrictions on source code access. This development has been designed as a first functional simulation infrastructure in order to verify the main concepts and transfer it to HPC infrastructure (based on Repast [16]) for large simulations. Figure 3, on the left, shows the simulation environment with the representation of the environment in white and the traffic routes, active elements in the simulation, in blue. Currently, the road characteristics includes various data points, name, geographic coordinates (longitude and latitude), direction, angle, road type, number of lanes, maximum speed, and interconnection points with other roads, among others.

The right side of Figure 3 shows a screenshot of the analysis area acquired directly from the Open Street Maps [13]. Comparing the left part with the right part of Figure 3 and taking into account that the analysis environment reflects only the road of interest and the existing buildings, we can see the accuracy and veracity of the data represented.

The development of the model integrates the information, presented above, about the roads in the GIS representation (see Figure 3) and works directly on this rich representation in NetLogo. The model integrates data on each road's characteristics and sections. This provides direct information on coordinates, distances between points, and angles of road elements. It also includes details such as road type, number of lanes, maximum speed, road name, and whether it is paved. These attributes are available to each agent during the simulation. Regarding the agents, they have been implemented with the variables reflected above where we can see their representation in Figure 3.

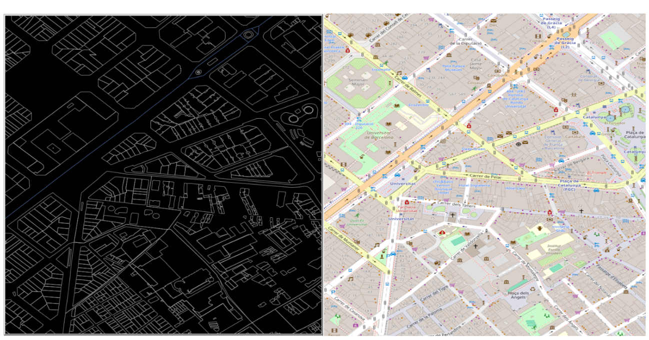

Figure 3. Analysis area.

The current model already represents a multilane system, of a specific high-density road in Barcelona, Gran Via de les Corts Catalanes, as well as its surroundings, representing the different options through the data obtained through GIS and the adjustment of the available parameters.

C. Data acquisition

As mentioned earlier, initially, we characterized Barcelona's street traffic by capturing its key features through video recordings. Using AI libraries, we detected vehicles and their attributes to model typical traffic flow. Additionally, we integrated GIS data into a NetLogo-based model created from this real-world data.

To calculate the angular distance between two points on a sphere using latitude and longitude, we use the Haversine method (equation 1) [17]. Haversine is very popular and frequently used when a GIS implementation or analyzing path and fields are developed:

$$\begin{aligned} a &= sin^2(\Delta\varphi/2) + cos\varphi_1 * cos\varphi_2 * sin^2(\Delta\lambda/2) \\ c &= 2 * atan2(\sqrt{a}, \sqrt{(1-a)}) \\ d &= R * c \end{aligned} \tag{1}$$

In the Haversine equation where φ is latitude, λ is longitude, R is earth's radius (mean radius = 6,371km) is how we translate the above formula to include latitude and longitude coordinates. $\Delta\varphi$ is the difference in latitude and $\Delta\lambda$ is the difference in longitude.

To obtain the direction of the vehicle, its angle, aligned with the direction of the road, the formula shown is used [18]:

$$\begin{aligned} \theta = atan2(&sin\Delta\varphi * cos\varphi_2, cos\varphi_1 * sin\varphi_2 \\ &- sin\varphi_1 * cos\varphi_2 * cos\Delta\varphi) \end{aligned} \tag{2}$$

where φ_1,λ_1 is the start point, φ_2,λ_2 the end point ($\Delta\lambda$ is the difference in longitude). The Haversine Formula is used to calculate distances during the initial setup phase. This step involves importing all relevant data for the map area into NetLogo. All tasks are performed within the NetLogo graphical environment. If it's the first time working with the map, the global work area is used to execute all data generation steps. This process extracts all environmental characteristics from the global map, including the sequences of geographical points defining each road. It also involves calculating distances between points and angles of each road segment using the Haversine formula.

This information will be readily available during the simulation, allowing agents to access it without additional calculations. This setup enables us to concentrate on managing agents and their interactions. During the simulation, agents will calculate distances and direction angles as they move along the roads, based on their defined behavior.

D. GIS integration

At this point the solution has been evolved, enriching the information about the roads in the GIS representation and a model has been implemented that already works directly on this enriched representation in NetLogo. The current model integrates detailed road characteristics, including coordinates, distances between points, and angles of road elements. It also provides information on road type, number of lanes, maximum speed, road name, and paving status. Additionally, it includes links between routes and their connection points. This comprehensive integration has enabled the model to evolve into a multilane representation.

Figure 4. Simulation screenshot showing cars on different lanes.

Figure 4 illustrates the partial simulation area, showcasing the vehicles in various colors. The colors of each vehicle represent the lane in which they are located. For example, the yellow color represents the vehicles that are in lane 1, the leftmost one, the cyan color represents the vehicles that are in lane 2 of the road, and so on. This allows us to visually identify the vehicles on each lane and define how the vehicles behave when they are on the different lanes and the interaction between them when they move along the different lanes.

Based on the field analysis data -covering vehicle types, lane occupancy, direction, speed, distance, and their evolution over time- the validation criteria for the simulation results have been established.

Currently, the simulation provides information on the evolution of maximum, average, and minimum speeds, as well as the overall vehicle volume at each moment (see Figure 5). In addition to the speeds, the simulation provides us with information about the existing speeds in the different lanes and how they vary over time. In addition to speed lane data, the simulation also offers insights into the variations in speeds across different lanes and how these change over time. In the case of speeds, the results show how global speeds evolve (see Figure 5), where maximum speeds between 46.1 km/h and 63.9 km/h and minimum speeds of 12.2 km/h have been obtained due to congestion, and 34 km/h as the most stable value. The average speeds have been maintained between 32.6 km/h and 47.6 km/h for a volume of 20 vehicles on the road.

The analysis of the lanes, depicted in Figure 6, reveals that the fourth lane from the left (colored yellow) among the five lanes has the highest maximum speed. It also shows the second lowest minimum speed of 14 km/h, while the lowest minimum speed is 12 km/h, observed in the first lane (colored gray). Overall, the average speeds across sections range between 22 km/h and 47 km/h.

The conclusions drawn from the results reaffirm previous findings, which validated that traffic fluidity primarily depends on traffic intensity, and that acceleration and deceleration directly influence traffic flow. The next phase of our research focuses on improving the imported road characteristics, integrating them into the model, and incorporating traffic signals and various types of vehicles.

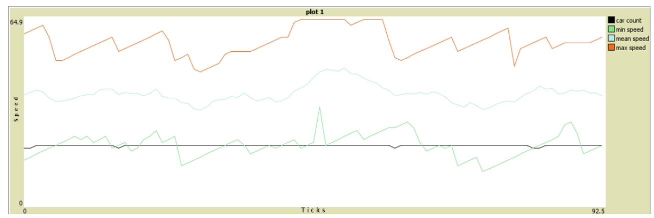

Figure 5. Simulation screenshot showing the number and speed of vehicles.

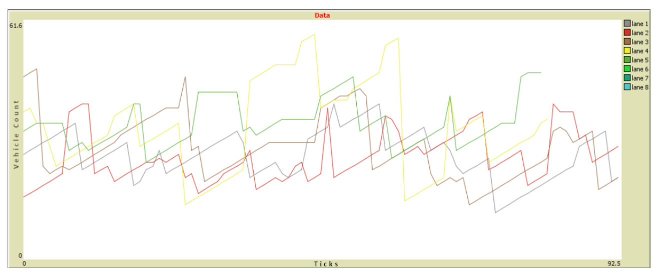

Figure 6. Simulation screenshot showing lane occupancy level.

Currently, the model integrates vehicles based on the characteristics of the represented roads. The approach will evolve to enhance both the environmental model and the vehicle types representation. Next, priority vehicles will be incorporated using techniques discussed earlier, such as implementing priority signals, reserving lanes, and optimizing routes. This will be analyzed to see how a mixed solution can improve the global system performance and results by affecting maximum, average, and minimum speeds.

IV. Conclusion and Future Work

In this work we present a model that is evolving to provide a way to represent traffic flow, with different types of vehicles, where we will have the ability to integrate priority vehicles and generate different types of scenario simulations.

Over the last years, there has been significant progress in four key areas: traffic management, route optimization for priority vehicles, agent-based models, and traffic simulation software. However, challenges remain. These include improving efficiency and computing capacity, adapting to the dynamic nature of mobility, and refining model validation and calibration. Calibration and validation techniques vary widely depending on the specific traffic issues and their complexity. Additionally, reproducibility is challenging, as previous models are often difficult to replicate. We must also address the capabilities of open-source solutions for integrating various modules or frameworks to manage transportation systems and control traffic behavior effectively.

The research presented herein has laid a solid foundation for the development of an agent-based model (ABM) focused on urban traffic scenarios, with a particular emphasis on improving mobility for priority vehicles. Through the integration of Geographic Information Systems (GIS) and real-world data, the study has demonstrated the potential of ABM to simulate complex urban traffic dynamics, offering insights into the efficiency of various traffic management strategies under different conditions. The implementation of the model in NetLogo, leveraging GIS data from Open Street Maps, has allowed for the creation of an urban environment that can be adapted for various cities beyond Barcelona. The model's ability to simulate multi-lane traffic systems and incorporate detailed road characteristics has been instrumental in analyzing traffic flow dynamics and will allow assessment of the impact of priority vehicles on overall traffic efficiency.

The preliminary simulation results have provided insights into traffic flow dynamics, highlighting the influence of vehicle acceleration, deceleration, and lane occupancy on traffic fluidity. These findings underscore the importance of considering these factors in urban planning and traffic management strategies, particularly in relation to improving conditions for priority vehicles such as ambulances.

Looking ahead, the next phase of this research will focus on several key areas:

- Enhancing Road Characteristics: Further refinement of the environmental model will involve integrating more detailed road characteristics and traffic signals into the simulation. This will allow for a more accurate representation of real-world conditions and facilitate the analysis of how these elements impact traffic flow and priority vehicle mobility.
- Incorporating Priority Vehicles: The integration of priority vehicles into the model will enable the exploration of various strategies aimed at improving their mobility. This includes the implementation of priority signals, lane reservation, and route optimization techniques. The impact of these strategies on overall traffic flow dynamics will be closely examined.
- Transition to High Performance Computing (HPC): To accommodate larger-scale simulations and more complex scenarios, the model will transition to an HPC environment. This will enhance computational efficiency and allow for the analysis of traffic dynamics across larger urban areas.
- Validation and Calibration: Ongoing efforts will focus on the calibration and validation of the simulation model against real-world data. This will ensure the accuracy of the model's predictions and its applicability to real-world traffic management challenges.

By addressing these areas, the research aims to contribute significantly to the development of effective traffic management strategies that prioritize the mobility of priority vehicles. Ultimately, this work seeks to enhance public safety and operational efficiency across densely populated urban environments, paving the way for smarter and more sustainable cities.

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