RT2text: Making Trajectory Summarization More Accessible through Text Generation

Lucas da Silva Menegol[1], **Vanessa Lago Machado**[1]
Élder Francisco Fontana Bernardi[1], **Tarlis Tortelli Portela**[2]

[1]Instituto Federal Sul-Rio-Grandense (IFSUL), Passo Fundo, RS – Brazil.

[2]Instituto Federal do Paraná (IFPR), Palmas, PR – Brazil

{lucasmenegol,vanessalagomachado}@gmail.com

elderbernardi@ifsul.edu.br, tarlis@tarlis.com.br

Abstract. *Trajectory summarization is vital for mobility analysis, extracting key movement patterns from large trajectory datasets. RT2text is a rule-based method that converts summarized trajectory into readable text. It uses regular expressions for data extraction, rule-based analysis, and Jinja2 templating for dynamic text generation, ensuring coherent descriptions of movement patterns. By incorporating Natural Language Generation (NLG), RT2text facilitates intuitive insights into mobility trends. We demonstrate RT2text's effectiveness in turning structured summarized trajectory into meaningful narrative, enhancing data accessibility for analysis and decision-making. The code for this work is available at* `https://github.com/RepresentantativeMAT/RT2text`.

1. Introduction

The increasing availability of trajectory data from GPS devices, mobile applications, and IoT sensors has enabled advanced mobility analysis in various domains, including urban planning, transportation management, and behavioral analytics. However, trajectory data often consists of complex spatial-temporal sequences that require significant effort to interpret. Trajectory summarization techniques aim to extract the most relevant movement patterns, preserving key mobility trends while reducing data complexity. Despite their effectiveness, most summarization approaches produce structured datasets that remain difficult for non-experts to interpret, necessitating a transformation from data-driven representations to human-readable formats.

We propose RT2text - *Representative Trajectory to text*, which converts summarized trajectories into textual descriptions. Using pattern recognition and template-based generation, RT2text creates concise mobility summaries to help users understand mobility trends. Through a running example, we demonstrate how RT2text transforms a summarized trajectory into a readable description, offering insights into movement behavior.

2. Basic Concepts and Related Works

The increasing prevalence of tracking technologies has led to a surge in trajectory data, which captures the movement patterns of objects over time and space. The Internet of Things (IoT) and social media have expanded this to multiple aspect trajectories (MATs), integrating spatial, temporal, and various heterogeneous semantic aspects [Mello et al. 2019], such as the transportation mode or purpose of the travel.

Given the enormous volume of GPS-generated data, trajectory summarization has become essential for data reduction, pattern recognition, and human interpretation [Machado et al. 2024]. Representative Trajectories (RTs) provide a compact abstraction of mobility patterns, enhancing storage, visualization, and analytical efficiency [Machado et al. 2025]. However, RTs often remain challenging to interpret, requiring further transformation into human-readable summaries.

To address this, Natural Language Generation (NLG), a subfield of Natural Language Processing (NLP), enables the automatic generation of coherent textual descriptions from structured data [Gatt and Krahmer 2018]. NLG techniques can be categorized into template-based, rule-based, and data-driven approaches. Template-based summarization utilizes predefined structures to populate data placeholders, transforming structured data into readable narratives. Rule-based methods rely on linguistic rules to produce direct output. In contrast, data-driven approaches, including machine learning and deep learning models, learn from extensive datasets to generate more context-aware text.

In this context, the increasing demand for human-interpretable insights has driven research toward automated textual descriptions of mobility data [Pugliese 2024]. Recent studies have explored Large Language Models (LLM) and automated text generation engines to convert raw movement data into coherent and human-readable descriptions. For example, [Rocchietti et al. 2024] employs LLMs to analyze geolocated images for urban region identification and description, using a data-driven method.

3. Methodology

This work presents a novel method for generating a textual description of a summarized trajectory (RT) using a rule-based dynamic text generation approach called RT2text. Implemented in Python, it leverages libraries for text processing and automation. Regular expressions (Regex) are used for data extraction and parsing, while Jinja2 facilitates template-based text generation, and rule-based summarization automates movement pattern descriptions. This approach makes summarized trajectory data human-readable, enhancing insights.

The RT2text takes an RT as input. Its methodology consists of two key components: (i) pre-processing and (ii) textual descriptor. RT2text outputs a summarized trajectory description in human-readable text, as illustrated in Figure 1.

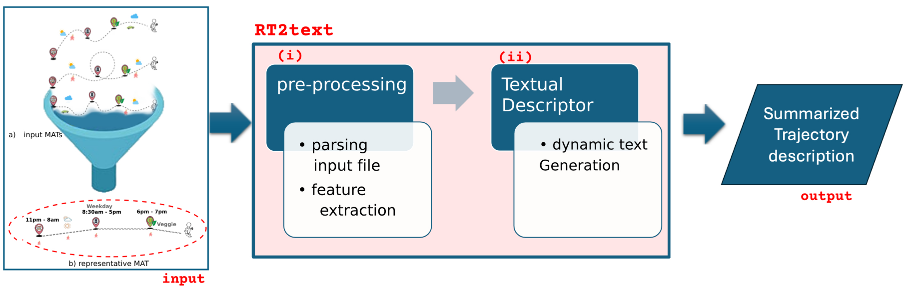

Figure 1. RT2text methodology

3.1. Pre-processing

The pre-processing component is responsible for loading, structuring, and extracting relevant information from the input summarized trajectory. This step ensures the RT is appropriately formatted and ready for textual description. This stage consists of two main phases: *parsing the input file* and *feature extraction*. In the first stage, RT2text parses the input file. RT2text utilizes the re module (regex) to extract and organize the summarized trajectory, facilitating efficient pattern matching and data extraction from the structured trajectory description. During this stage, the RT is segmented into three key parts: (i) $metadata$, containing general dataset information; (ii) $settings$, with summarization parameters; and (iii) $trajectory\_description$, detailing movement events. Since the goal of RT2text is to generate a human-readable description, the focus is primarily on the third part, which captures the most relevant movement patterns.

After parsing the RT ($trajectory\_description$), RT2text performs *feature extraction* to identify key aspects of mobility behavior, such as frequent locations (POI) and movement transitions. Additionally, RT2text classifies periods into morning, afternoon, evening, or night based on predefined intervals, ensuring the final description maintains a structured narrative according to the time of day. This structured data representation ensures RT patterns are efficiently extracted and prepared for automated text generation in the next component.

3.2. Textual Descriptor

Once the RT is structured and analyzed, RT2text generates a natural-language summary of movement patterns, transforming the structured RT into human-readable text.

To ensure fluency, RT2text applies formatting rules that enhance readability. Initially, PoIs are analyzed to determine whether a location should be described as a frequent or occasional visit. The system then captures transitions between locations to maintain a sequential narrative. If multiple destinations are available, the most frequent is selected.

Dynamic sentence structures are used to convert structured movement data into natural-sounding text with the Jinja2 templating engine. This method ensures a smooth flow while detailing when and where movement occurs and how often locations are visited. RT2text then refines the output by eliminating redundancy and enhancing consistency for a well-structured text description.

4. Running Example

To demonstrate how RT2text operates, we can refer to the example presented in [Machado et al. 2025], as shown in Figure 2. In this scenario, we have a collection of input MATs $\mathbf{T} = \langle q, r, s \rangle$, which are summarized using the MAT-SGT method. This results in $rt = \langle p_{rt_1}, p_{rt_2}, p_{rt_3}, p_{rt_4} \rangle$ (red line) in both a spatial (a) and a spatiotemporal (b) perspective, illustrating the progression of the input MATs alongside the calculated RT.

RT2text converts RT into a human-readable summary. It provides insights into the progression of events over time, detailing movement patterns and producing the output shown in Figure 2 as a complete or simplified version. The temporal movement over the PoI was analyzed here, capturing key transitions and common locations.

5. Conclusion

This paper presents RT2text, a rule-based method for generating human-readable textual descriptions from RTs. Using regular expressions for structured data extraction, template-based text generation, and rule-based summarization, RT2text converts RTs into a textual

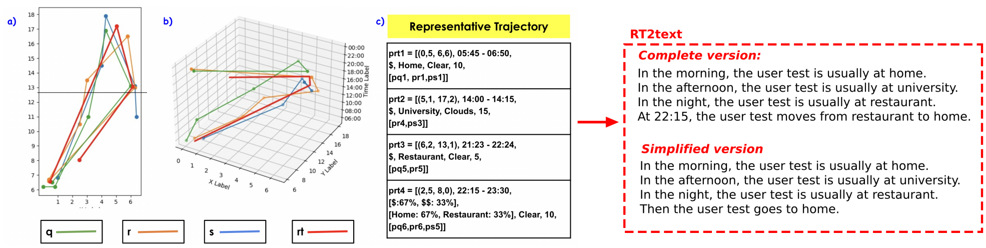

Figure 2. Representative trajectory (RT) visualization from multiple perspectives and its description by RT2text (Adapted from [Machado et al. 2025])

format, facilitating a more intuitive understanding of movement patterns without necessitating complex visualizations or domain expertise. The running example illustrates how RT2text effectively transforms MAT summaries into meaningful descriptions.

Rule-based methods, such as RT2text, provide transparency and control but have limitations, including difficulty with ambiguous input and a lack of learning from data. Their scalability may be affected by complex rule management, leading to maintenance challenges.

Future efforts will aim to enhance methods for addressing complex aspects of MATs, like activity recognition and transportation mode identification. Additionally, RT2text plans to integrate machine learning-based NLG for improved contextual adaptation and linguistic diversity, along with IA for insights into textual descriptions.

Acknowledgments

IFSUL supported this work according to EDITAL PROPESP – N° 06/2024.

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