Trajectory Similarity Measures: A Comprehensive Survey, Benchmark and Evaluation [Experiment, Analysis & Benchmark]

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ABSTRACT

Trajectory data analytics has aroused a broad range of real-life applications across different fields. Trajectory similarity measure, which aims to evaluate the distance between two trajectories, is a fundamental functionality of trajectory analytics. In this paper, we conduct a comprehensive survey of almost all the representative trajectory measures in terms of three hierarchical perspectives (i.e., Non-learning vs. Learning, Free Space vs. Road Network, and Standalone vs. Distributed). Moreover, we provide an evaluation benchmark (publicly available at https://github.com/ZJU-DAILY/TSM) in real-world settings by introducing five transformation scenarios. Based on this benchmark, extensive experiments are conducted to evaluate the effectiveness, robustness, efficiency, and scalability of each trajectory distance measure, which provides a reference for similarity measure selection among traditional similarity measures, deep learning models, and distributed processing technologies.

PVLDB Reference Format:
Danlei Hu, Lu Chen, Hanxi Fang, Ziquan Fang, Yunjun Gao. Trajectory Similarity Measures: A Comprehensive Survey, Benchmark and Evaluation [Experiment, Analysis & Benchmark]. PVLDB, 16(X): XXX-XXX, 2023.
doi:XX.XX/XXX.XX

1 INTRODUCTION

With the proliferation of GPS-equipped devices and mobile computing services, massive trajectory data of moving objects such as people, vehicles, and vessels are being captured [25, 61]. For example, people tend to share visited places (e.g., POIs) on social networks by their smartphones to generate "check-in" trajectories; according to the AIS project [30], millions of vessels connected with the AIS services continuously report locations to ensure the sailing safety; the world's largest ridesharing company Uber collects up to 17 million vehicle trips daily [42]. An original trajectory T of a moving object is typically denoted as a time-ordered sequence of continuously observed spatio-temporal locations.

Trajectory data with its analytics benefit a broad range of real-life applications across different fields such as urban computing [24], transportation [62], behavior study [23], and public security [20], to name but a few. A fundamental functionality of most trajectory analyses is to evaluate the relationship/distance between two trajectories, i.e., trajectory similarity/distance measurement. With an accurate and efficient trajectory similarity measure, downstream trajectory analytics involving retrieval [33, 38], clustering [7, 18], classification [11, 17], and mobility pattern mining [14, 27] tasks can be well-supported to serve upper applications. For instance, Xie et al. [48] propose two distance measures to support similarity queries and joins in a large-scale trajectory dataset. Wang et al. [45] design a road network oriented distance measure for vehicle trajectory similarity computation, based on which, they [47] proceed to study k-means clustering to detect representative traveling paths in a city. In both cases, the trajectory similarity measure plays a fundamental role, and a different measure selection may result in totally different query results and clustering quality. More trajectory similarity based analyses tasks can refer to [25, 44].

Unlike isolated spatial points or one-dimensional time series where the distance definition is straightforward, it is non-trivial to define the distance between continuous and two-dimensional trajectories while considering trajectory characteristics: (i) Different data sources, i.e., free space vs. road network space. In the latter case, a proper trajectory measure should take the road topology into account, as people and vehicles cannot travel like vessels without spatial constraints [35]; (ii) Various sampling rates and lengths. Unlike time series that generally feature constant and high sampling rates [22], trajectory data shows varying samplings, resulting in variable trajectory lengths; (iii) The effect of noise. The noise points commonly exist, especially due to strength attenuation and interference in urban cities [57]; (iv) Complex geometrics. Compared to private-car trajectories that are usually inaccessible caused by privacy principles, taxi trajectories are widely studied in the community [6, 40, 46]. However, taxi trajectories exhibit much more diverse, complex, and flexible geometric, because of various pick-pop demands. To deal with these spatio-temporal characteristics, there are tremendous amounts of research efforts in designing dozens of trajectory similarity measures in the literature.

But being faced with a huge amount of trajectory measures, researchers are often too exhausted to select a proper one. On the one hand, there are too many trajectory measures, which were proposed under different scenarios, e.g., learning based and non-learning based, free-space oriented and road network oriented, as well as standalone and distributed processing. In each scenario, various measures also exist. Consequently, users need to spend tons of time and efforts to explore the specific details of each measure and

Proceedings of the VLDB Endowment, Vol. 16, No. 8 ISSN 2150-8097.
doi:XX.XX/XXX.XX

Table 1: Trajectory Similarity Measures (m and n denote the lengths of two trajectories, and d denotes the dimension of vector)

Category			Measure	Venue	Complexity	Metric	Unequal Length	Parameter Free	Noise Sensitive	Representation
Non-learning	Free Space	Standalone	ED	/	$O(n)$	✓	×	×	×	Point
			DTW	ICDE98	$O(mn)$	×	✓	✓	×	Point
			LCSS	ICDE02	$O(mn)$	×	✓	×	✓	Point
			EDR	SIGMOD05	$O(mn)$	×	✓	×	✓	Point
			EDwP	ICDE15	$O(mn)$	×	✓	✓	✓	Segment
			ERP	VLDB04	$O(mn)$	✓	✓	×	×	Point
			Hausdorff	TITS10	$O(mn)$	✓	✓	✓	×	Point
			Frechet	CGA95	$O(mn)$	×	✓	✓	×	Point
			LIP	STRR07	$O((m+n)log(m+n))$	×	✓	✓	×	Point
			OWD	GIS05	$O(mn)$	×	✓	×	×	Point
			Seg-Frechet	VLDB17	$O(mn)$	×	✓	✓	×	Segment
		Distributed	DFT	VLDB17	$O(mn)$	×	✓	✓	×	Segment
			DITA	SIGMOD18	$O(mn)$	×	✓	✓	×	Point
			REPOSE	ICDE21	$O(mn)$	×	✓	✓	×	Point
	Road Network	Standalone	NetDTW	ITSC14	$O(mn)$	×	✓	✓	×	Point
			NetLCSS	SIGKDD22	$O(mn)$	×	✓	×	✓	Point
			LORS	SIGIR18	$O(mn)$	×	✓	✓	×	Segment
			TP	VLDB17	$O(mn)$	×	✓	×	×	Point
			NetERP	VLDB19	$O(mn)$	✓	✓	×	×	Point
			NetEDR	VLDB19	$O(mn)$	×	✓	×	✓	Point
			LCRS	ICDE19	$O(mn)$	×	✓	✓	×	Segment
		Distributed	DISON	ICDE19	$O(mn)$	×	✓	×	×	Segment
Learning	Free Space	Standalone	NEUTRAJ	ICDE19	$O(m+n)$	/	✓	×	✓	Vector
			Traj2SimVec	IJCAI21	$O(m+n)$	/	✓	×	✓	Vector
	Road Network	Standalone	GTS	SIGKDD21	$O(d)$	/	✓	×	×	Vector
			ST2Vec	SIGKDD22	$O(d)$	/	✓	×	×	Vector

the relations/differences among them. On the other hand, the evaluations on various trajectory measures are still not well organized. For instance, some measures only focus on efficiency, while others may put more attention on effectiveness and robustness. To address the problems mentioned above, a comprehensive survey, benchmark, and evaluation will be a great help for researchers involved in this important topic. Specifically, considering three-dimensional aspects, we classify the existing representative trajectory measures proposed from 1995 to 2022 year in a hierarchical way, i.e., **Non-learning** vs. **Learning** (first hierarchy), **Free Space** vs. **Road Network** (second hierarchy), and **Standalone** vs. **Distributed** (third hierarchy). Table 1 summarizes trajectory similarity measures.

Although previous systematic surveys have made some efforts, they mainly focus on non-learning, free-space, or standalone based measures and thus significantly narrow the studied scope of trajectory similarity community. For example, Gudmundsson and Toohey et al. [41] only review four most basic trajectory distance measures including Euclidean distance (ED), DTW [53], LCSS [43], and Fréchet [1]. Based on it, Sousa et al. [6] append partial vehicle trajectory similarity measures, e.g., LORS [45], LCRS [54], and Net-EDR [16]. Note that, experimental evaluation of these measures are not studied in these surveys. Su et al. [37] conduct the state-of-the-art survey and experimental evaluation for trajectory similarity measures under the non-learning, free-space, and standalone contexts. The studied scope in [37] is highlighted by the dark backdrop in Table 1. In contrast, we conduct a much more systematic review and evaluation of almost all representative trajectory measures involving non-learning vs. learning, free-space vs. road-network, as well as standalone vs. distributed. We conduct a three-dimensional survey due to three following motivations:

i) As deep learning has made great success in AI community, many researchers [8, 13, 22, 51, 58] start leveraging the powerful approximation capabilities of neural networks to attempt to replace the traditional handcrafted trajectory measures with learning-based deep models. Besides, increasing efforts have been devoted to embracing learning-based techniques as an integral part of trajectory data management and analytics, such as deep clustering [9], deep mobility pattern mining [39], and deep path recommendation [55], to name but a few. As such, we believe that we have reached an imperative point to systematically study the contribution and explore the relations, differences, and pros/cons among the emerging learning-based and classic non-learning based trajectory measures.

ii) In the early stage, most of the trajectory measures [37] are proposed for objects that move freely in the Euclidean space, e.g., bird or vessel trajectories. Recently, the proliferation of vehicle navigation systems and location based services (LBSs) enable the massive collection of vehicle and people trajectories in road networks. In that case, the free-space oriented trajectory measures cannot reflect the true distance between moving objects in a moving-constrained road network. In view of this, many network-aware trajectory measures [16, 35, 45, 54] are designed for respective scenarios and applications. To the best of our knowledge, there is no previous work has given a systematic review and experimental evaluation of these network-based trajectory measures.

iii) Since the amount of trajectory data can easily exceed the storage capacity and processing ability of a single machine, another popular line of trajectory similarity study is designing efficient and scalable frameworks upon distributed processing platforms (e.g., Spark) for large-scale trajectory similarity analytics. Towards this direction, several system-level frameworks are also developed.