Lequan LIN, Zhengkun LI, Ruikun LI, Xuliang LI, Junbin GAO, 2024. Diffusion models for time-series applications: a survey. *Frontiers of Information Technology & Electronic Engineering*, 25(1):19-41.
https://doi.org/10.1631/FITEE.2300310

Diffusion models for time-series applications: a survey

Key words: Diffusion models; Time-series forecasting; Time-series imputation; Denoising diffusion probabilistic models; Score-based generative models; Stochastic differential equations

Corresponding author: Lequan LIN
E-mail: lequan.lin@sydney.edu.au
ORCID: https://orcid.org/0009-0006-4677-7327

Motivation

- In recent years, diffusion models, a family of deep learning based generative models, have been extended to time-series applications, and many powerful models have been developed.
- Considering the deficiency of a methodical summary and discourse on these models, we provide this survey as an elementary resource for new researchers in this area and to provide inspiration to motivate future research.
- The survey primarily focuses on diffusion models for time-series forecasting, imputation, and generation. It also compares existing methods with in-depth discussion, while presenting their real-world applications, relevant data resources, and future research directions.

Summary of literature

- The survey reviews on diffusion models for time-series forecasting, imputation, and generation, and presents them, separately, in three individual sections. A summary of literature is listed as follows.

Application	Data type	Method	Source
Time-series forecasting	Multivariate time series	TimeGrad	Rasul et al., 2021
		ScoreGrad	Yan et al., 2021
		D^3VAE	Li Y et al., 2022
		DSPD/CSPD	Biloš et al., 2023
		TimeDiff	Shen and Kwok, 2023
	Spatio-temporal graphs	DiffSTG	Wen et al., 2023
		GCRDD	Li RK et al., 2023
Time-series imputation	Multivariate time series	CSDI	Tashiro et al., 2021
		DSPD/CSPD	Biloš et al., 2023
		SSSD	Alcaraz and Strodthoff, 2023
	Spatio-temporal graphs	PriSTI	Liu MZ et al., 2023
Time-series generation	Multivariate time series	TSGM	Lim et al., 2023
		DiffTime	Coletta et al., 2023
		Loss-DiffTime	Coletta et al., 2023
		Guided-DiffTime	Coletta et al., 2023

Model comparison

- The comparison of methods includes an assessment of their capabilities in handling various tasks and data types, along with an examination of their diffusion and sampling processes.

Method	Forecasting	Imputation	Generation	Data	Diffusion	Sampling
TimeGrad	✓			MTS/STG	Discrete	Autoregressive
ScoreGrad	✓			MTS/STG	Continuous	Autoregressive
D^3VAE	✓			MTS/STG	Discrete	One-shot
DSPD	✓	✓		MTS/STG	Discrete	One-shot
CSPD	✓	✓		MTS/STG	Continuous	One-shot
TimeDiff	✓			MTS/STG	Discrete	One-shot
DiffSTG	✓			STG	Discrete	One-shot
GCRDD	✓			STG	Discrete	Autoregressive
CSDI	✓	✓		MTS/STG	Discrete	One-shot
SSSD	✓	✓		MTS/STG	Discrete	One-shot
PriSTI	✓	✓		STG	Discrete	One-shot
TSGM			✓	MTS/STG	Continuous	Autoregressive
DiffTime			✓	MTS/STG	Discrete	One-shot
Loss-DiffTime			✓	MTS/STG	Discrete	One-shot
Guided-DiffTime			✓	MTS/STG	Discrete	One-shot

Applications and datasets

- The survey showcases relevant application in real-world domains such as energy control and transportation.
- Additionally, we share valuable resources of frequently used public datasets to support researchers and practitioners in testing and understanding diffusion models for time series. Below is a fraction of resources presented in the survey.

Domain	Dataset	Source
Energy	SOLAR	https://github.com/laiguokun/multivariate-time-series-data
	ELECTRICITY	https://archive.ics.uci.edu/ml/datasets/ElectricityLoadDiagrams20112014
	NORPOOL	https://www.nordpoolgroup.com/Market-data1/Power-system-data
	CAISO	http://www.energyonline.com/Data
	ETTm1	https://github.com/zhouhaoyi/ETDataset
	ETTh1	https://github.com/zhouhaoyi/ETDataset
Traffic	TRAFFIC	http://pems.dot.ca.gov
	TAXI	https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page
Climate	WEATHER	https://www.bgc-jena.mpg.de/wetter/
Finance	EXCHANGE	https://github.com/laiguokun/multivariate-time-series-data
Website	WIKIPEDIA	https://github.com/mbohlkeschneider/gluon-ts/tree/mv_release/datasets

Future research and conclusion

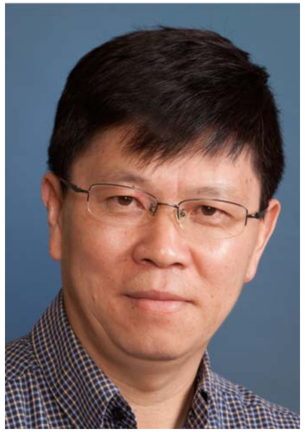
- Three future research directions of diffusion models for time series have been proposed in the end of the survey, including heavy model selection, insufficient research on noise injection, and unsatisfactory performance with spatio-temporal graphs.
- Although existing methods have shown good performance with empirical evidence, the survey concludes by emphasizing that they are usually associated with very high computational costs.
- Moreover, because most diffusion models are constructed with a high level of theoretical background, there is still a lack of deeper discussion and exploration of the rationale behind these models, i.e., why they could work and when they may not work.

Lequan LIN received her Bachelor of Commerce degree (Hons) in business analytics at the University of Sydney Business School, the University of Sydney, Australia, in 2022. She is currently a PhD student in the Discipline of Business Analytics, at the University of Sydney Business School. Her recent research interest involves machine learning, especially graph neural networks and generative models.

Zhengkun LI received his Bachelor of Commerce degree in finance and business analytics (with first-class honor) and his PhD degree in business analytics from the University of Sydney, Sydney, Australia, in 2018 and 2023, respectively. He is currently a postdoctoral researcher at the Postdoctoral Programme of Zhongtai Securities Co., Ltd, Jinan, China and the Postdoctoral Programme of PBC School of Finance, Tsinghua University, Bejing, China. His research interests include machine learning, financial econometrics, and factor investing.

Ruikun LI received his Master’s degree in financial mathematics from the University of California, San Diego, USA, in 2018. He is currently a PhD student in the Discipline of Business Analytics at the University of Sydney Business School, Australia. His research interest focuses on machine learning, graph neural networks, and graph-based time series learning, especially the spectral feature method for unevenly spaced time series forecasting.

Xuliang LI received his BS and Master degree from Tsinghua University, Beijing, China, in 2016 and 2020, respectively. He is currently a PhD student in the University of Sydney Business School, Australia. His research interests include speech processing and business data analysis.



Junbin GAO graduated from Huazhong University of Science and Technology (HUST), China, in 1982 with a BSc in computational mathematics and obtained his PhD from the Dalian University of Technology, China, in 1991. He is a professor of big data analytics in the University of Sydney Business School at the University of Sydney and was a professor in computer science in the School of Computing and Mathematics at Charles Sturt University, Australia. He was a senior lecturer, lecturer in computer science from 2001 to 2005 at the University of New England, Australia. From 1982 to 2001, he was an associate lecturer, lecturer, associate professor, and professor of mathematics at HUST. His main research interests include machine learning, data analytics, Bayesian learning and inference, and image analysis.