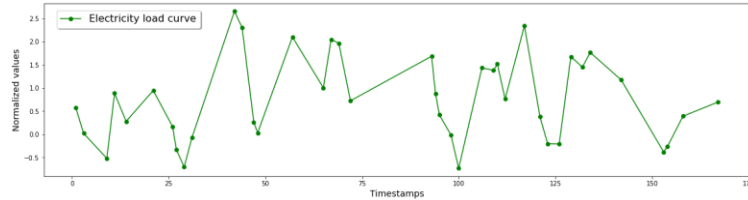


Time Series Continuous Modeling for Imputation and Forecasting with Implicit Neural Representations

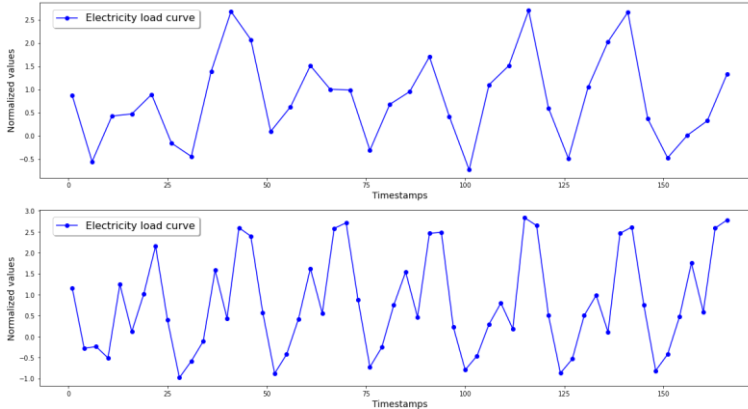
Vincent Guigue - AgroParisTech

Time Series : continuous phenomena / observed partially

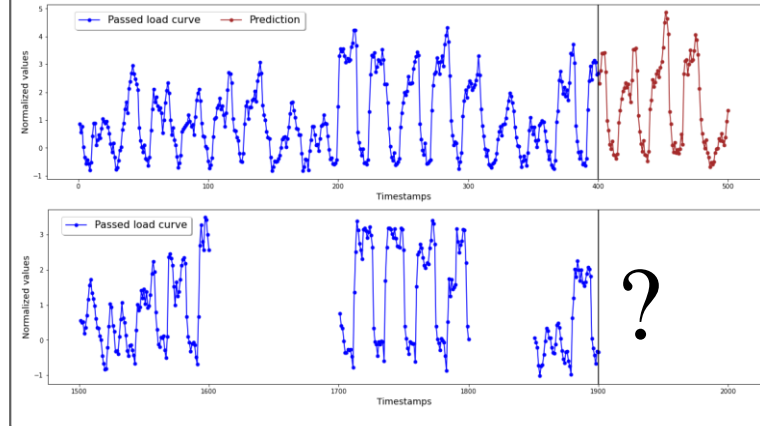
Irregular
samples



Unaligned
sensors

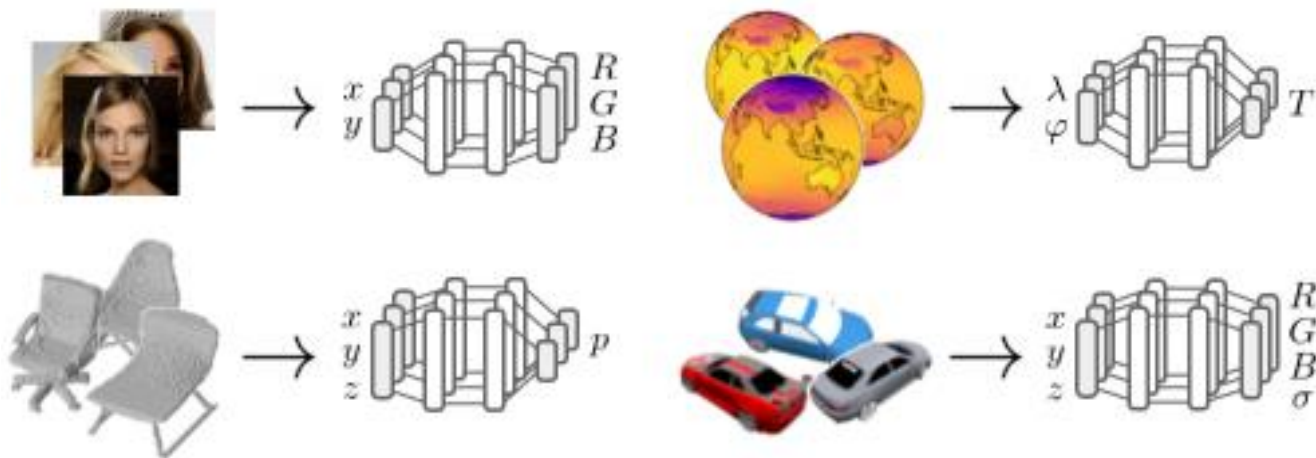


Unaligned train
and test setting



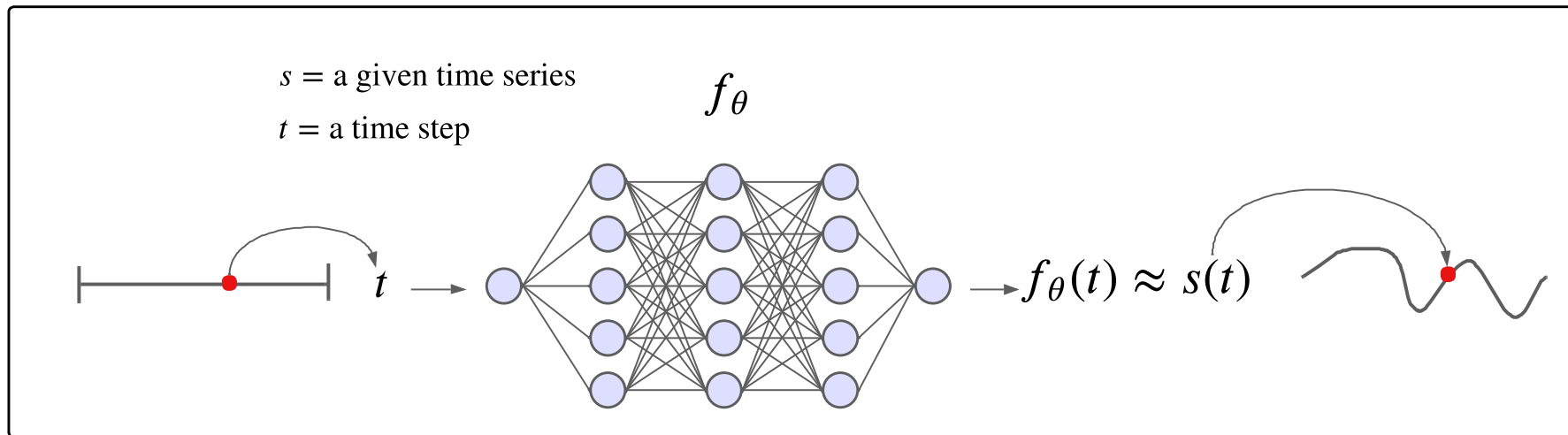
Technical options for continuous modeling

- Gaussian Processes [Williams & Rasmussen, 2006] / Neural Processes [Kim et al. 2019]
- Diffusion Model [Ho et al. 2020]
- Implicit Neural Representation (INR) [Dupont et al. 2022]

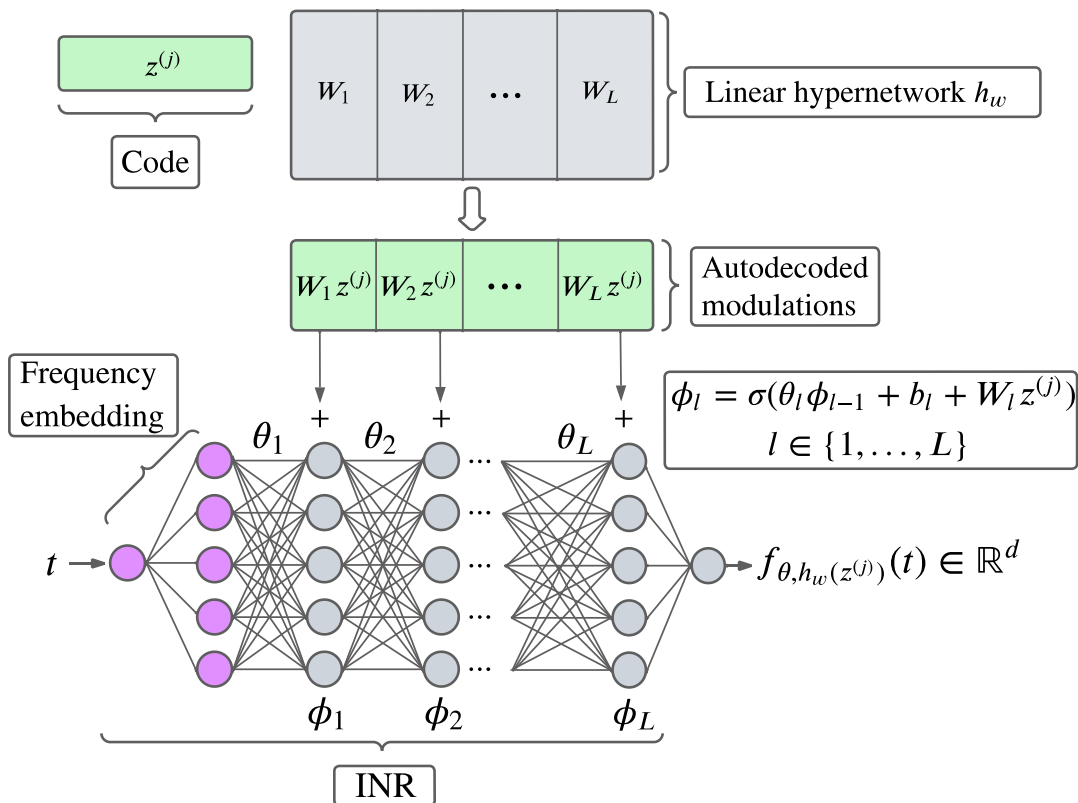


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Dealing with Multiple Time Series : HyperNetwork architecture



HyperNet

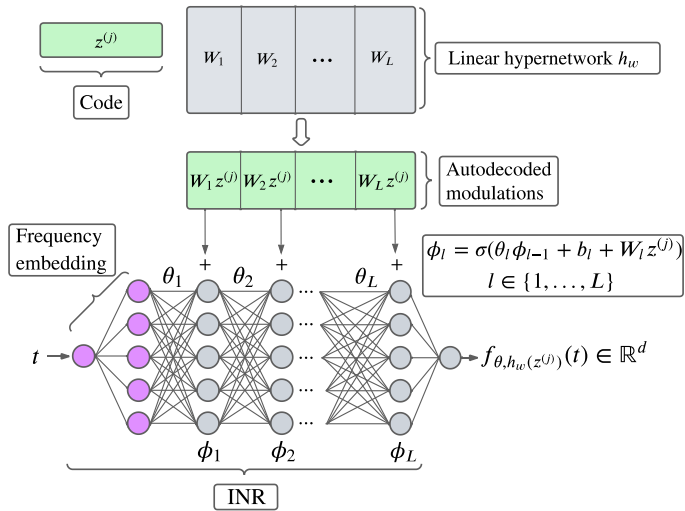
- 1 TS = 1 code z
- Linear mapping
- Generate specific b

INR = 1 time series

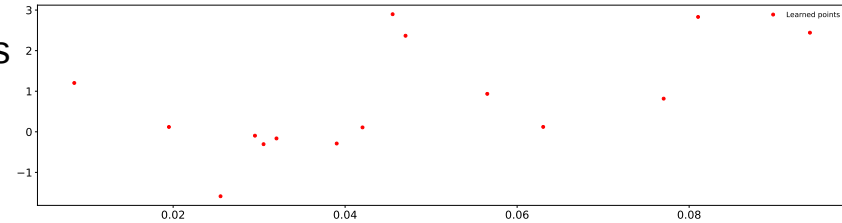
- Fixed 1st layer (Fourier)
- MLP : shared θ / specific b

Dealing with Multiple Time Series : Hypernetwork architecture

Inference:

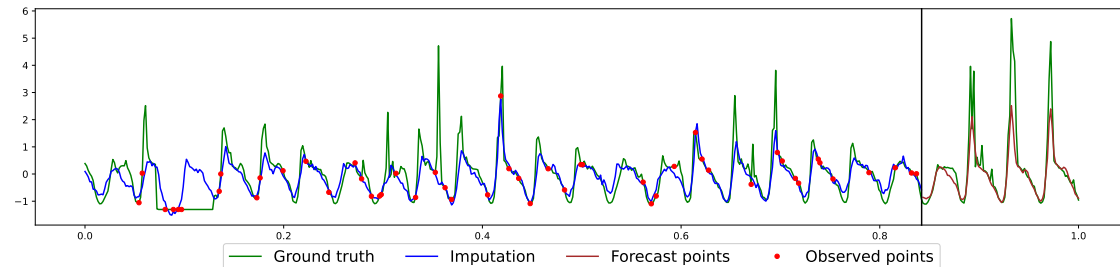


1. Observations



2. Determining code z

3. Inputation + Forecasting



Results: it works in a very diverse range of situations

- Imputation
- Long range forecasting
- Forecasting from incomplete data

- Imputation
- Long range forecasting
- Forecasting from incomplete data

		Continuous methods						Discrete methods			
		ΔT	TimeFlow	DeepTime	mTAN	Neural Process	CSDI	SAITS	BRTS	TIDER	
Electricity	0.05	0.324 $\pm$ 0.013	0.379 $\pm$ 0.037	0.575 $\pm$ 0.089	0.357 $\pm$ 0.015	0.462 $\pm$ 0.021	0.394 $\pm$ 0.019	0.329 $\pm$ 0.015	0.427 $\pm$ 0.010		
	0.10	0.250 $\pm$ 0.010	0.333 $\pm$ 0.034	0.412 $\pm$ 0.047	0.417 $\pm$ 0.057	0.368 $\pm$ 0.072	0.308 $\pm$ 0.011	0.287 $\pm$ 0.015	0.396 $\pm$ 0.009		
	0.20	0.225 $\pm$ 0.008	0.244 $\pm$ 0.013	0.342 $\pm$ 0.014	0.320 $\pm$ 0.017	0.341 $\pm$ 0.068	0.261 $\pm$ 0.008	0.285 $\pm$ 0.011	0.391 $\pm$ 0.010		
	0.30	0.212 $\pm$ 0.007	0.240 $\pm$ 0.014	0.335 $\pm$ 0.015	0.300 $\pm$ 0.022	0.277 $\pm$ 0.059	0.236 $\pm$ 0.008	0.221 $\pm$ 0.008	0.384 $\pm$ 0.009		
	0.50	0.194 $\pm$ 0.007	0.227 $\pm$ 0.012	0.340 $\pm$ 0.022	0.297 $\pm$ 0.016	0.168 $\pm$ 0.003	0.209 $\pm$ 0.008	0.193 $\pm$ 0.008	0.386 $\pm$ 0.009		
Solar	0.05	0.095 $\pm$ 0.015	0.190 $\pm$ 0.020	0.241 $\pm$ 0.102	0.115 $\pm$ 0.015	0.374 $\pm$ 0.033	0.142 $\pm$ 0.016	0.165 $\pm$ 0.014	0.291 $\pm$ 0.009		
	0.10	0.083 $\pm$ 0.015	0.159 $\pm$ 0.013	0.251 $\pm$ 0.081	0.114 $\pm$ 0.014	0.375 $\pm$ 0.038	0.124 $\pm$ 0.018	0.137 $\pm$ 0.015	0.276 $\pm$ 0.010		
	0.20	0.072 $\pm$ 0.015	0.149 $\pm$ 0.020	0.314 $\pm$ 0.085	0.109 $\pm$ 0.016	0.217 $\pm$ 0.023	0.108 $\pm$ 0.014	0.109 $\pm$ 0.012	0.270 $\pm$ 0.010		

		TimeFlow		DeepTime		Neural Process		Discrete methods			
H	ΔT	Imputation error	Forecast error	Imputation error	Forecast error	Imputation error	Forecast error	Process	Patch-TST	DLinear	AutoFormer
Electricity	96	0.5	0.151 $\pm$ 0.003	0.239 $\pm$ 0.013	0.209 $\pm$ 0.004	0.270 $\pm$ 0.019	0.460 $\pm$ 0.048	0.496 $\pm$ 0.078			
		0.2	0.208 $\pm$ 0.006	0.260 $\pm$ 0.015	0.249 $\pm$ 0.006	0.296 $\pm$ 0.023	0.644 $\pm$ 0.079	0.650 $\pm$ 0.095			
		0.1	0.272 $\pm$ 0.006	0.295 $\pm$ 0.016	0.284 $\pm$ 0.007	0.324 $\pm$ 0.026	0.740 $\pm$ 0.083	0.737 $\pm$ 0.106			
	192	0.5	0.149 $\pm$ 0.004	0.235 $\pm$ 0.011	0.204 $\pm$ 0.004	0.265 $\pm$ 0.018	0.461 $\pm$ 0.045	0.498 $\pm$ 0.070			
		0.2	0.209 $\pm$ 0.006	0.257 $\pm$ 0.013	0.244 $\pm$ 0.007	0.290 $\pm$ 0.023	0.601 $\pm$ 0.075	0.626 $\pm$ 0.101			
		0.1	0.274 $\pm$ 0.010	0.289 $\pm$ 0.016	0.282 $\pm$ 0.007	0.315 $\pm$ 0.025	0.461 $\pm$ 0.045	0.724 $\pm$ 0.090			
Traffic	96	0.5	0.180 $\pm$ 0.016	0.219 $\pm$ 0.026	0.272 $\pm$ 0.028	0.243 $\pm$ 0.030	0.436 $\pm$ 0.025	0.444 $\pm$ 0.047			
		0.2	0.239 $\pm$ 0.019	0.243 $\pm$ 0.027	0.335 $\pm$ 0.026	0.293 $\pm$ 0.027	0.596 $\pm$ 0.049	0.597 $\pm$ 0.075			
		0.1	0.312 $\pm$ 0.020	0.290 $\pm$ 0.027	0.385 $\pm$ 0.025	0.344 $\pm$ 0.027	0.734 $\pm$ 0.102	0.731 $\pm$ 0.132			
	192	0.5	0.176 $\pm$ 0.014	0.217 $\pm$ 0.017	0.241 $\pm$ 0.027	0.234 $\pm$ 0.021	0.477 $\pm$ 0.042	0.476 $\pm$ 0.043			
		0.2	0.233 $\pm$ 0.017	0.236 $\pm$ 0.021	0.296 $\pm$ 0.027	0.276 $\pm$ 0.020	0.685 $\pm$ 0.109	0.678 $\pm$ 0.108			
		0.1	0.304 $\pm$ 0.019	0.277 $\pm$ 0.021	0.331 $\pm$ 0.025	0.324 $\pm$ 0.021	0.888 $\pm$ 0.178	0.877 $\pm$ 0.174			
TimeFlow improvement		/	/	18.97 %	11.87 %	61.88 %	58.41 %				

336	0.257 $\pm$ 0.040	0.247 $\pm$ 0.033	0.306 $\pm$ 0.039	0.220 $\pm$ 0.038	0.244 $\pm$ 0.035	0.450 $\pm$ 0.127	0.394 $\pm$ 0.096
720	0.266 $\pm$ 0.048	0.250 $\pm$ 0.045	0.339 $\pm$ 0.037	0.288 $\pm$ 0.060	0.250 $\pm$ 0.067	0.830 $\pm$ 0.043	0.441 $\pm$ 0.056
TimeFlow improvement		/	6.56 %	30.75 %	2.64 %	7.30 %	35.43 %

Conclusion: A path towards foundation models for time series

A way to learn semantic representations

Connections with diffusion models

Data generation/augmentation

Time Series Continuous Modeling for Imputation and Forecasting with Implicit Neural Representations

Etienne Le Naour^{*1,2}, Louis Serrano^{*1}, Léon Migus^{*1,3}, Yuan Yin¹, Ghislain Agoua²
Nicolas Baskiotis¹, Patrick Gallinari^{1,4}, Vincent Guigue⁵

¹ Sorbonne Université, CNRS, ISIR, 75005 Paris, France

² EDF R&D, Palaiseau, France

³ Sorbonne Université, CNRS, Laboratoire Jacques-Louis Lions, 75005 Paris, France

⁴ Criteo AI Lab, Paris, France

⁵ AgroParisTech, Palaiseau, France

{louis.serrano, leon.migus, yuan.yin, nicolas.baskiotis, vincent.guigue}@sorbonne-universite.fr
{etienne.le-naour, ghislain.agoua}@edf.fr

