université PARIS-SACLAY

TIME SERIES : NEW TRENDS IN DEEP-LEARNING

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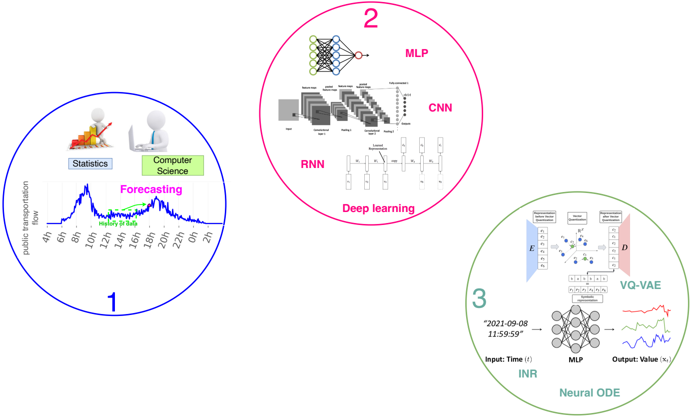
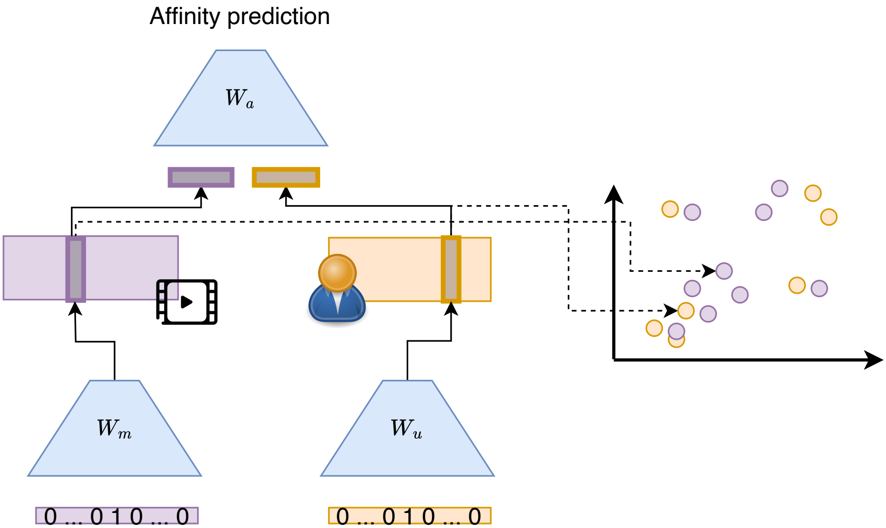
Introduction

- Mix sequence & representation learning
- (Try to) interpret machine learning models/predictions
- Exploiting transformer architecture (or not)
- Continuous representation for time-series



Representation learning & time series

Time series & representation learning



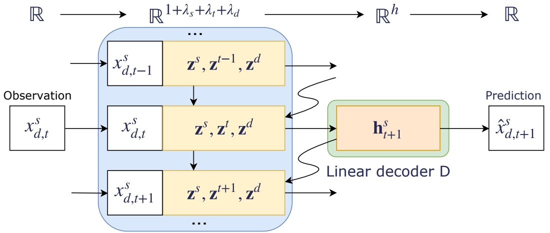
- How to use representation learning for time series?

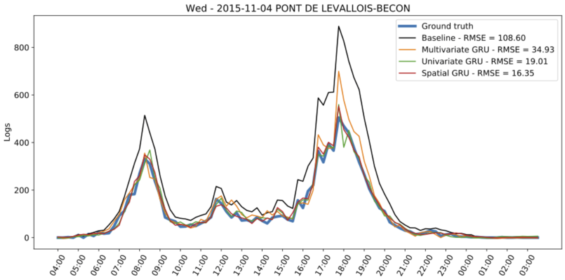
$\Rightarrow$ Exploiting the context

Modeling contextual information with RNN

Modeling a public transportation system:

- Station
- Day of the week
- Hour



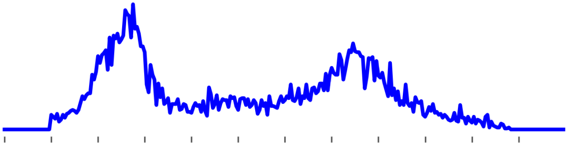


V. Guiguet et al., GRETSI 2019
Context aware forecasting for multivariate time series

RNN & latent factor disentanglement

Enforcing disentanglement:

Station 12
Wednesday



Target :
encoding independtly
the station and the day

Cribier-Delande et al., ESANN, 2020
Time Series Prediction from Multiple Factors

RNN & latent factor disentanglement

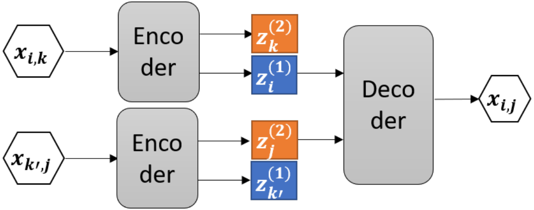
Proposed architecture:

Encoder :

- 2 independent RNN
- or 2 independent CNN / MLP ...

Decoder:

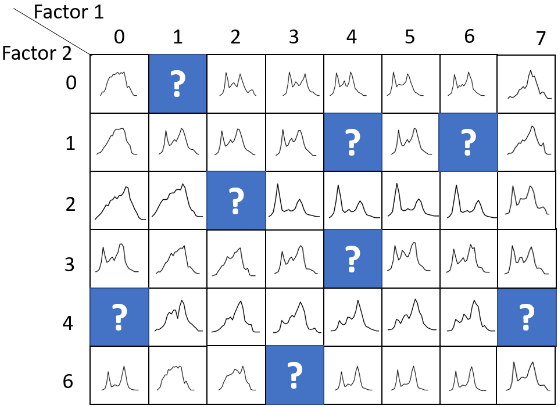
- Contextual CNN / RNN / MLP

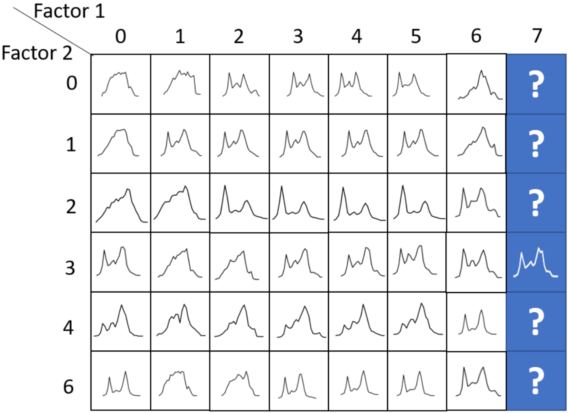


Cribier-Delande et al., ESANN, 2020
Time Series Prediction from Multiple Factors

RNN & latent factor disentanglement

Results:

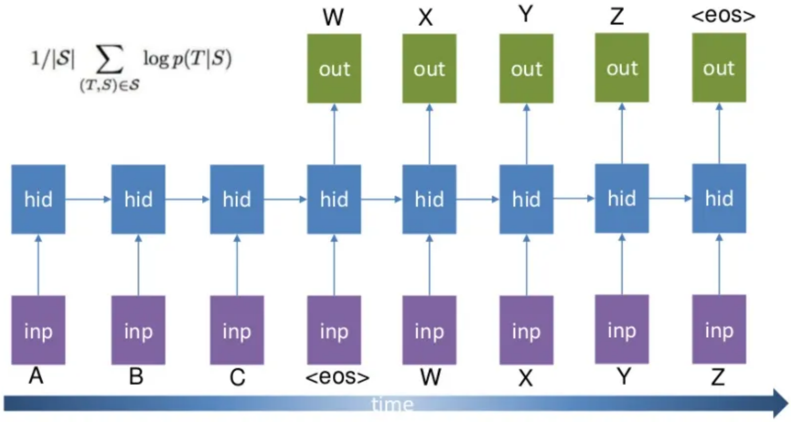




Cribier-Delande et al., ESANN, 2020
Time Series Prediction from Multiple Factors

Vector Quantization & Explainability

Encoder-decoder architecture

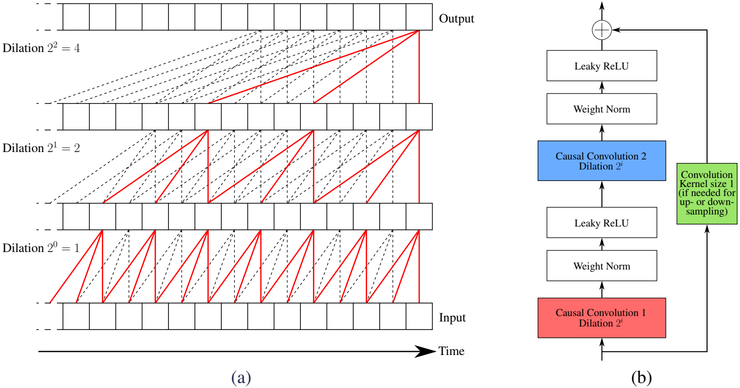


- Exploiting seq-2-seq paradigm in time series
- Encoding the time-series (& being able to decode it)

Sutskever et al., 2014,
Sequence to Sequence Learning with Neural Networks

Unsupervised learning framework

Step 1: Encoding



$+$ max pooling

Franceschi et al., NeurIPS 2019,
Unsupervised Scalable Representation Learning for Multivariate Time Series

Unsupervised learning framework

Step 2: Unsupervised learning

- Given subseq x^{pos} and local contexts x^{ref}:

  Idea Skip Gram: $\arg\max_{\theta} \prod_{x^{ref}} \prod_{x^{pos} \in x^{ref}} p(x^{ref} | x^{pos}; \theta)$

- $p(D = 1 | x^{ref}, x^{pos}; \theta) \Rightarrow$ proba. that x^{pos} occur in the context x^{ref}
- Triplet loss

$$\arg\max_{\theta} \prod_{ref,pos} p(D = 1 | x^{ref}, x^{pos}; \theta) + \underbrace{\prod_{ref,neg} p(D = 0 | x^{ref}, x^{neg}; \theta)}_{\text{Negative Sampling}}$$

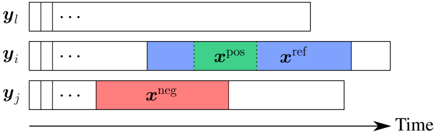
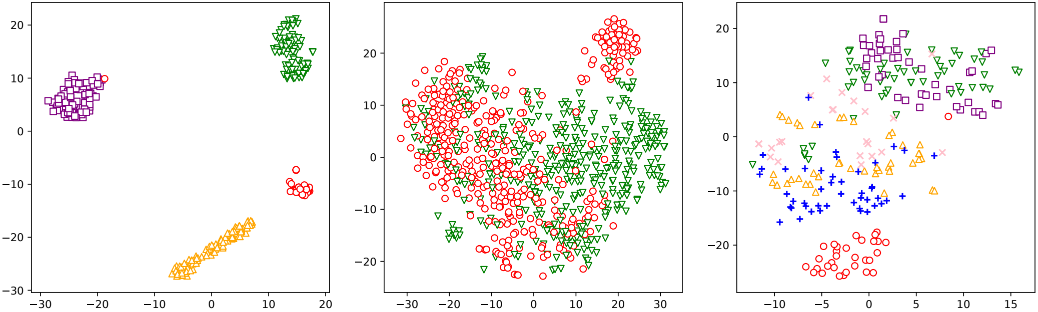


Figure 1: Choices of $\boldsymbol{x}^{\text{ref}}$, $\boldsymbol{x}^{\text{pos}}$ and $\boldsymbol{x}^{\text{neg}}$.

Franceschi et al., NeurIPS 2019,
Unsupervised Scalable Representation Learning for Multivariate Time Series

Unsupervised learning framework

Interesting latent space for time-series:



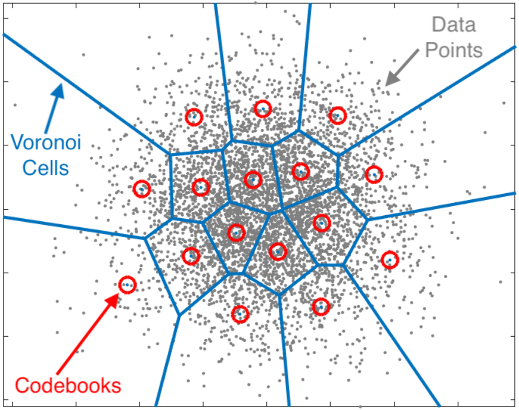
(a) DiatomSizeReduction. (b) FordB. (c) OSULeaf.

- Very good classification results with simple Logistic Regression

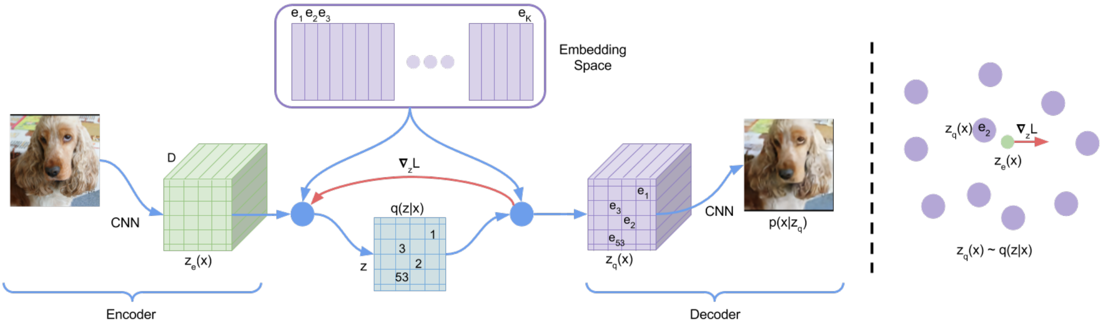
Franceschi et al., NeurIPS 2019,
Unsupervised Scalable Representation Learning for Multivariate Time Series

Vector Quantization (VQ)

- Machine Learning = mainly suitable for continuous values
- Quantization = continuous ⇒ discrete values
- Assumption: categorical values are more interpretable
  - Pattern identification



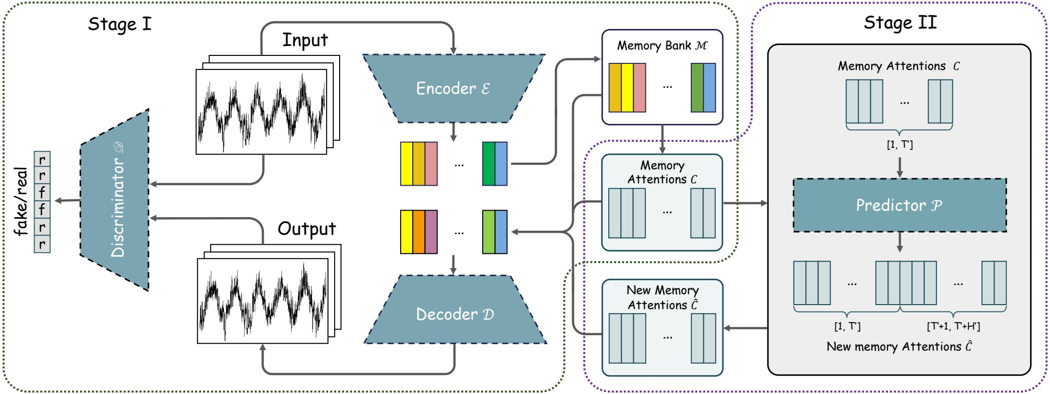
VQ-Variational Auto-Encoder



- Interpretability = discrete representation $\Rightarrow$ object decomposition
- … & limited codebook

A. van den Oord et al., NeurIPS 2017,
Neural Discrete Representation Learning

VQ-VAE Implementation for time-series



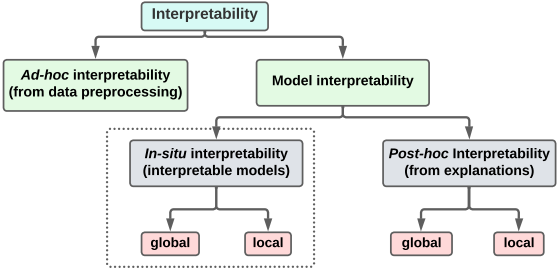
- Discrete decomposition, signal reconstruction
- $+$ Aversarial discriminator ($\Rightarrow$ noise reconstruction ?)

J. Yu et al., ICLR 2023,
MATS: Memory Attention for Time-Series forecasting

Decoding strategies & explainability

Hypothese:

Enforcing constraints on the decoder to preserve interpretability

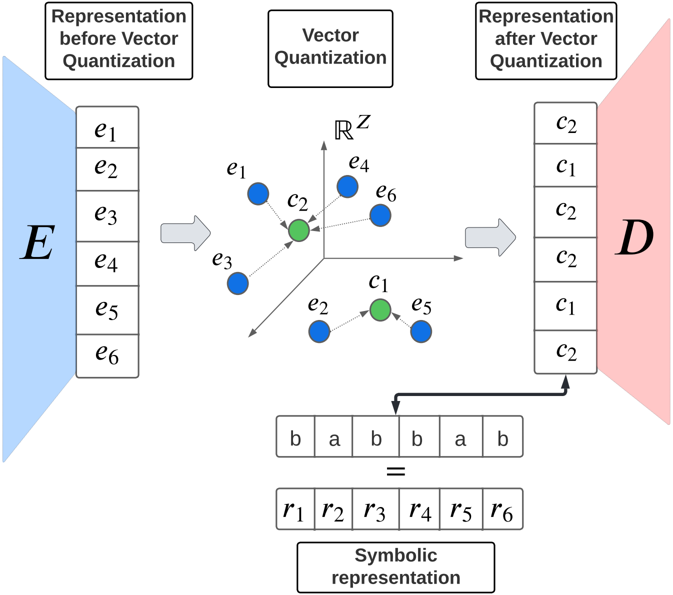


- Limited number of discrete patterns
- Ability to decode a pattern
- Time Consistency
- Shift-invariance
- On classification downstream task: interpret the decision

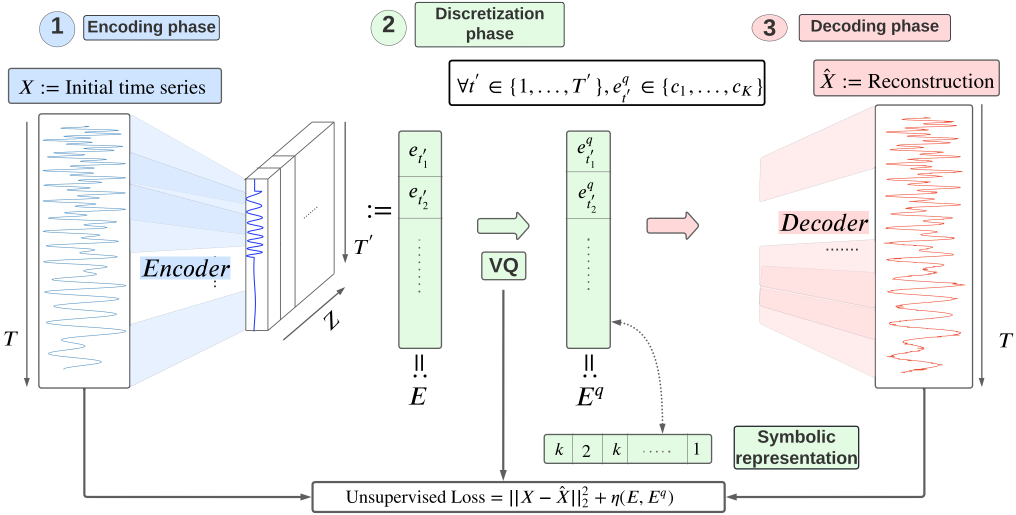
Transfer between task:
first attempts

LeNaour et al., DSAA 2023,
Interpretable time series neural representation for classification purposes

Architecture & Enforced properties [LeNaour 23]

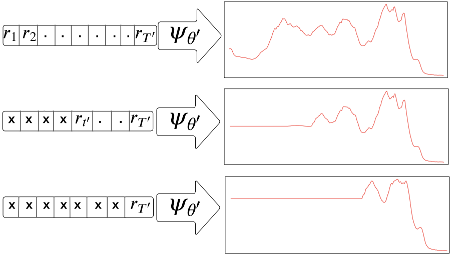


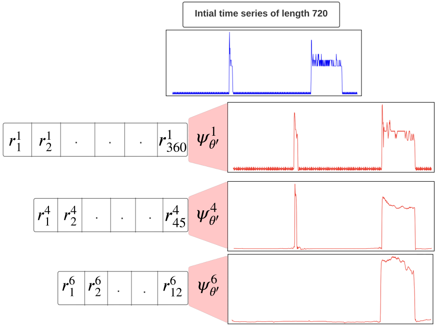
Architecture & Enforced properties [LeNaour 23]



Architecture & Enforced properties [LeNaour 23]

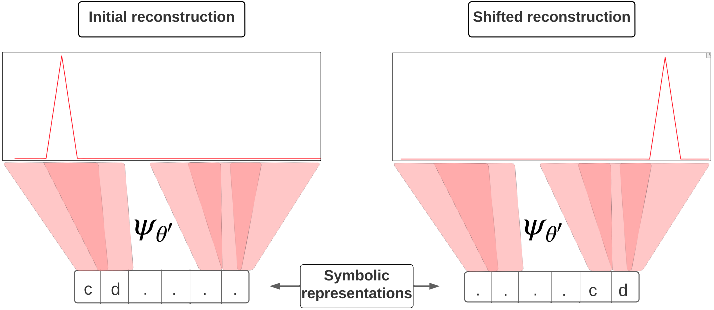
Decoding





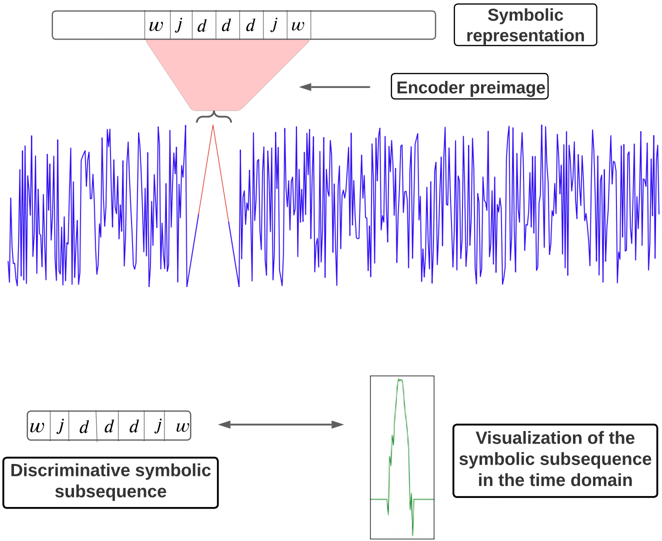
Architecture & Enforced properties [LeNaour 23]

Shift-equivariance



Architecture & Enforced properties [LeNaour 23]

Decision interpretability



Architecture & Enforced properties [LeNaour 23]

Best performances...
among interpretable framework

Not far from SOTA, but still a gap

Datasets	Ours	SAX SEQL	SAX VSM	FS	LTS	DTW CV
Coffee	0.964	**1.000**	0.929	0.929	**1.000**	**1.000**
Computers	**0.728**	0.676	0.620	0.500	0.584	0.620
DistalPhalanxOAG	0.755	0.818	**0.842**	0.655	0.779	0.626
DistalPhalanxOC	0.732	0.718	0.728	**0.750**	0.719	0.725
DistalPhalanxTW	0.640	**0.748**	0.604	0.626	0.626	0.633
Earthquakes	0.734	**0.789**	0.748	0.705	0.741	0.727
ECG5000	**0.932**	0.924	0.910	0.923	**0.932**	0.925
FordA	0.883	0.851	0.827	0.787	**0.957**	0.691
GunPoint	0.940	0.987	0.987	0.947	**1.000**	0.913
Ham	0.705	0.705	**0.810**	0.648	0.667	0.600
Herring	**0.656**	0.578	0.625	0.531	0.625	0.531
ItalyPowerDemand	0.906	0.734	0.816	0.917	**0.970**	0.955
LargeKitchenApp	0.864	0.760	**0.877**	0.560	0.701	0.795
PhalangesOC	0.748	0.717	0.710	0.744	**0.765**	0.761
ProximalPhalanxOC	0.818	0.818	0.828	0.804	**0.834**	0.790
ProximalPhalanxOAG	0.839	0.844	0.824	0.780	**0.849**	0.785
ProximalPhalanxTW	0.771	**0.792**	0.610	0.702	0.776	0.756
RefrigerationDevices	0.533	0.541	**0.653**	0.333	0.515	0.440
ScreenType	0.499	0.461	**0.512**	0.413	0.429	0.411
ShapeletSim	0.994	0.994	0.717	**1.000**	0.950	0.700
SmallKitchenApp	**0.795**	0.776	0.579	0.333	0.664	0.672
Strawberry	**0.962**	0.954	0.957	0.903	0.911	0.946
Wafer	0.975	0.993	**0.999**	0.997	0.996	0.995
Wine	0.759	0.556	**0.963**	0.759	0.500	0.611
Worms	**0.714**	0.536	0.558	0.649	0.610	0.532
Mean	**0.793**	0.770	0.769	0.715	0.764	0.725

(Even more) recent improvements

- Frequency decomposition (+temporal decomposition)

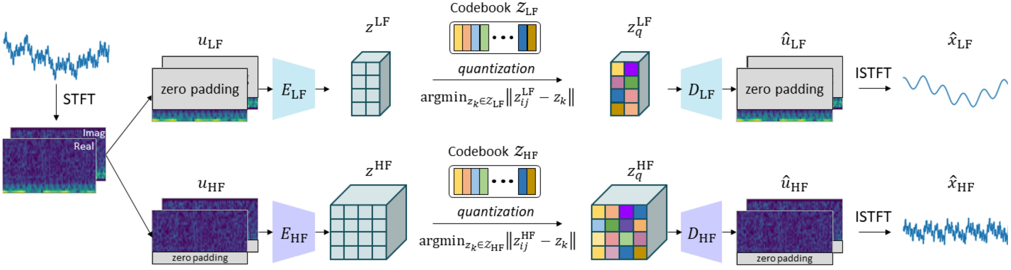


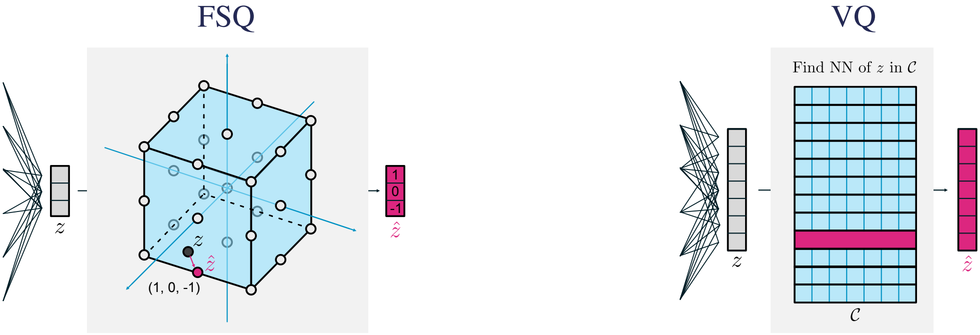
Figure 1: Overview of our proposed VQ (*i.e.*, tokenization) (stage 1).

- Towards new discretization techniques: finite scalar quantization

D. Lee et al., AISTATS 2023,
Vector Quantized Time Series Generation with a Bidirectional Prior Model

(Even more) recent improvements

- Frequency decomposition (+temporal decomposition)
- Towards new discretization techniques: finite scalar quantization



F. Mentzer et al., arXiv 2023,
FINITE SCALAR QUANTIZATION: VQ-VAE MADE SIMPLE

Conclusion

A *dynamic* field of research :-)

- Maybe transformer architectures are required to enable **transfer**

Transformer architecture

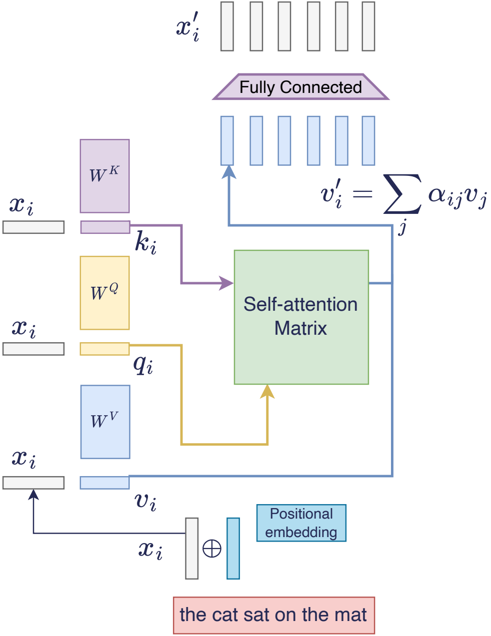
Transformer for time-series

Recent and abundant litterature:

- LogTrans (NeurIPS 2019)
- Informer (AAAI 2021 Best paper)
- Autoformer (NeurIPS 2021)
- Pyraformer (ICLR 2022 Oral)
- Triformer (IJCAI 2022)
- FED-former (ICML 2022)

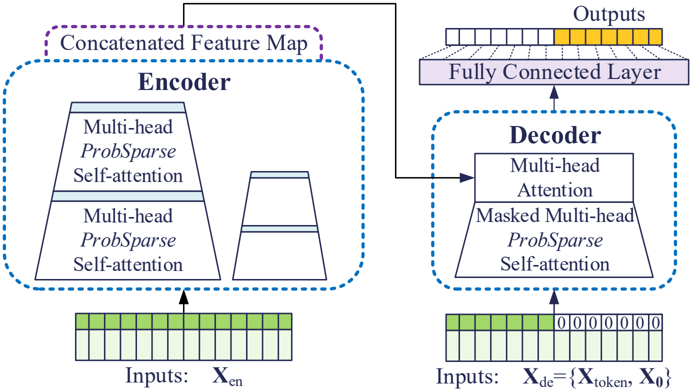
... And a great recent review

A. Zeng et al., AAAI 2023,
Are Transformers Effective for Time Series Forecasting?



Transformer & Long term prediction

Informer Architecture (AAAI 2021 Best paper)

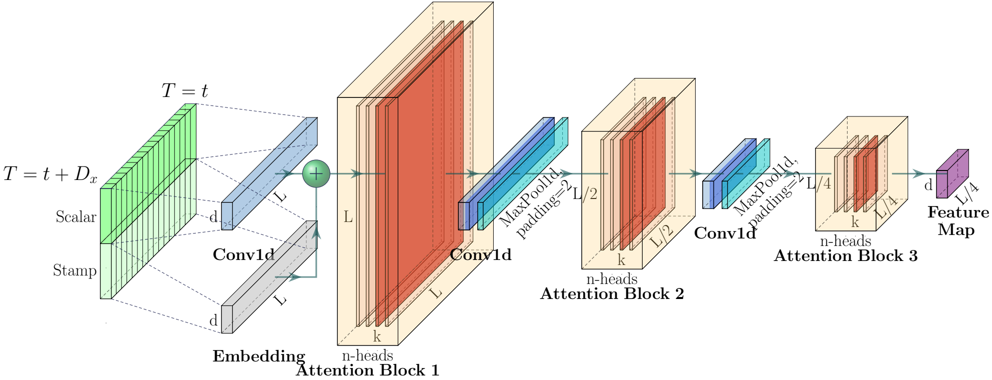


- Interactions on patterns $\Rightarrow$ a key to long term predictions

H. Zhou et al., AAAI 2021,
Informer: Beyond Efficient Transformer for Long Sequence Time-Series Forecasting

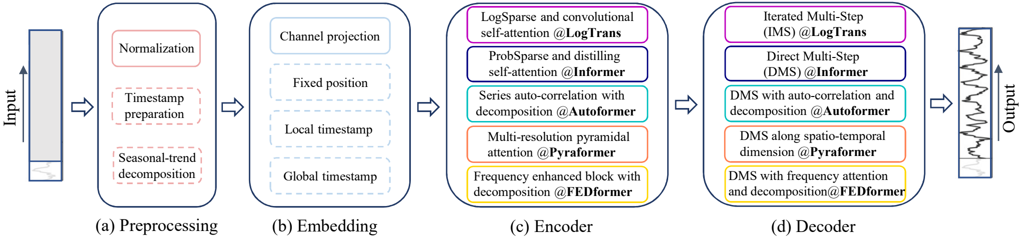
Transformer & Long term prediction

Informer Architecture (AAAI 2021 Best paper)

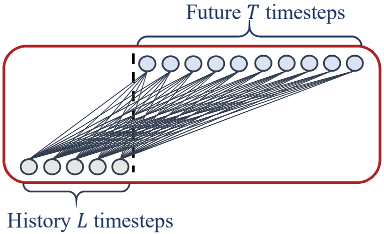


- Convolution = representation of continuous words
- Time stamps = position embeddings

Baseline importance



Very simple proposition



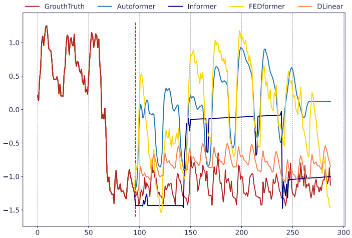
A. Zeng et al., AAAI 2023,
Are Transformers Effective for Time Series Forecasting?

Baseline importance

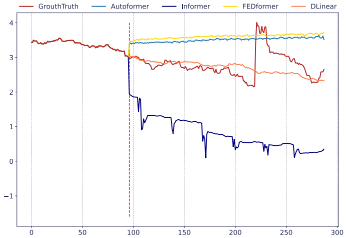
Methods		IMP.	Linear*		NLinear*		DLinear*		FEDformer		Autoformer		Informer		Pyraformer*		LogTrans		*Repeat**	
Metric		MSE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Electricity	96	27.40%	**0.140**	**0.237**	0.141	**0.237**	**0.140**	**0.237**	0.193	0.308	0.201	0.317	0.274	0.368	0.386	0.449	0.258	0.357	1.588	0.946
	192	23.88%	**0.153**	0.250	0.154	**0.248**	**0.153**	0.249	0.201	0.315	0.222	0.334	0.296	0.386	0.386	0.443	0.266	0.368	1.595	0.950
	336	21.02%	**0.169**	0.268	0.171	**0.265**	**0.169**	0.267	0.214	0.329	0.231	0.338	0.300	0.394	0.378	0.443	0.280	0.380	1.617	0.961
	720	17.47%	**0.203**	0.301	0.210	**0.297**	**0.203**	0.301	0.246	0.355	0.254	0.361	0.373	0.439	0.376	0.445	0.283	0.376	1.647	0.975
Exchange	96	45.27%	0.082	0.207	0.089	0.208	**0.081**	0.203	0.148	0.278	0.197	0.323	0.847	0.752	0.376	1.105	0.968	0.812	**0.081**	**0.196**
	192	42.06%	0.167	0.304	0.180	0.300	**0.157**	0.293	0.271	0.380	0.300	0.369	1.204	0.895	1.748	1.151	1.040	0.851	0.167	**0.289**
	336	33.69%	0.328	0.432	0.331	0.415	**0.305**	0.414	0.460	0.500	0.509	0.524	1.672	1.036	1.874	1.172	1.659	1.081	**0.305**	**0.396**
	720	46.19%	0.964	0.750	1.033	0.780	**0.643**	**0.601**	1.195	0.841	1.447	0.941	2.478	1.310	1.943	1.206	1.941	1.127	0.823	0.681
Traffic	96	30.15%	**0.410**	0.282	**0.410**	**0.279**	**0.410**	0.282	0.587	0.366	0.613	0.388	0.719	0.391	2.085	0.468	0.684	0.384	2.723	1.079
	192	29.96%	**0.423**	0.287	**0.423**	**0.284**	**0.423**	0.287	0.604	0.373	0.616	0.382	0.696	0.379	0.867	0.467	0.685	0.390	2.756	1.087
	336	29.95%	0.436	0.295	**0.435**	**0.290**	0.436	0.296	0.621	0.383	0.622	0.337	0.777	0.420	0.869	0.469	0.734	0.408	2.791	1.095
	720	25.87%	0.466	0.315	**0.464**	**0.307**	0.466	0.315	0.626	0.382	0.660	0.408	0.864	0.472	0.881	0.473	0.717	0.396	2.811	1.097
Weather	96	18.89%	**0.176**	0.236	0.182	**0.232**	**0.176**	0.237	0.217	0.296	0.266	0.336	0.300	0.384	0.896	0.556	0.458	0.490	0.259	0.254
	192	21.01%	**0.218**	0.276	0.225	**0.269**	0.220	0.282	0.276	0.336	0.307	0.367	0.598	0.544	0.622	0.624	0.658	0.589	0.309	0.292
	336	22.71%	**0.262**	0.312	0.271	**0.301**	0.265	0.319	0.339	0.380	0.359	0.395	0.578	0.523	0.739	0.753	0.797	0.652	0.377	0.338
	720	19.85%	0.326	0.365	0.338	**0.348**	**0.323**	0.362	0.403	0.428	0.419	0.428	1.059	0.741	1.004	0.934	0.869	0.675	0.465	0.394
ILI	24	47.86%	1.947	0.985	**1.683**	**0.858**	2.215	1.081	3.228	1.260	3.483	1.287	5.764	1.677	1.420	2.012	4.480	1.444	6.587	1.701
	36	36.43%	2.182	1.036	**1.703**	**0.859**	1.963	0.963	2.679	1.080	3.103	1.148	4.755	1.467	7.394	2.031	4.799	1.467	7.130	1.884
	48	34.43%	2.256	1.060	**1.719**	**0.884**	2.130	1.024	2.622	1.078	2.669	1.085	4.763	1.469	7.551	2.057	4.800	1.468	6.575	1.798
	60	34.33%	2.390	1.104	**1.819**	**0.917**	2.368	1.096	2.857	1.157	2.770	1.125	5.264	1.564	7.662	2.100	5.278	1.560	5.893	1.677
ETTh1	96	0.80%	0.375	0.397	**0.374**	**0.394**	0.375	0.399	0.376	0.419	0.449	0.459	0.865	0.713	0.664	0.612	0.878	0.740	1.295	0.713
	192	3.57%	0.418	0.429	0.408	**0.415**	**0.405**	0.416	0.420	0.448	0.500	0.482	1.008	0.792	0.790	0.681	1.037	0.824	1.325	0.733
	336	6.54%	0.479	0.476	**0.429**	**0.427**	0.439	0.443	0.459	0.465	0.521	0.496	1.107	0.809	0.891	0.738	1.238	0.932	1.323	0.744
	720	13.04%	0.624	0.592	**0.440**	**0.453**	0.472	0.490	0.506	0.507	0.514	0.512	1.181	0.865	0.963	0.782	1.135	0.852	1.339	0.756
ETTh2	96	19.94%	0.288	0.352	**0.277**	**0.338**	0.289	0.353	0.346	0.388	0.358	0.397	3.755	1.525	0.645	0.597	2.116	1.197	0.432	0.422
	192	19.81%	0.377	0.413	**0.344**	**0.381**	0.383	0.418	0.429	0.439	0.456	0.452	5.602	1.931	0.788	0.683	4.315	1.635	0.534	0.473
	336	25.93%	0.452	0.461	**0.357**	**0.400**	0.448	0.465	0.496	0.487	0.482	0.486	4.721	1.835	0.907	0.747	1.124	1.604	0.591	0.508
	720	14.25%	0.698	0.595	**0.394**	**0.436**	0.605	0.551	0.463	0.474	0.515	0.511	3.647	1.625	0.963	0.783	3.188	1.540	0.588	0.517
ETTm1	96	21.10%	0.308	0.352	0.306	0.348	**0.299**	**0.343**	0.379	0.419	0.505	0.475	0.672	0.571	0.543	0.510	0.600	0.546	1.214	0.665
	192	21.36%	0.340	0.369	0.349	0.375	**0.335**	**0.365**	0.426	0.441	0.553	0.496	0.795	0.669	0.557	0.537	0.837	0.700	1.261	0.690
	336	17.07%	0.376	0.393	0.375	0.388	**0.369**	**0.386**	0.445	0.459	0.621	0.537	1.212	0.871	0.754	0.655	1.124	0.832	1.283	0.707
	720	21.73%	0.440	0.435	0.433	0.422	**0.425**	**0.421**	0.543	0.490	0.671	0.561	1.166	0.823	0.908	0.724	1.153	0.820	1.319	0.729
ETTm2	96	17.73%	0.168	0.262	**0.167**	**0.255**	**0.167**	0.260	0.203	0.287	0.255	0.339	0.365	0.453	0.435	0.507	0.768	0.642	0.266	0.328
	192	17.84%	0.232	0.308	**0.221**	**0.293**	0.224	0.303	0.269	0.328	0.281	0.340	0.533	0.563	0.730	0.673	0.989	0.757	0.340	0.371
	336	15.69%	0.320	0.373	**0.274**	**0.327**	0.281	0.342	0.325	0.366	0.339	0.372	1.363	0.887	1.201	0.845	1.334	0.872	0.412	0.410
	720	12.58%	0.413	0.435	**0.368**	**0.384**	0.397	0.421	0.421	0.415	0.433	0.432	3.379	1.338	3.625	1.451	3.048	1.328	0.521	0.465

- Methods* are implemented by us; Other results are from FEDformer [31].

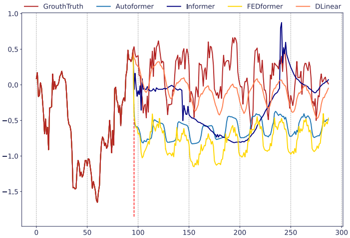
A. Zeng et al., AAAI 2023,
Are Transformers Effective for Time Series Forecasting?



(a) Electricity

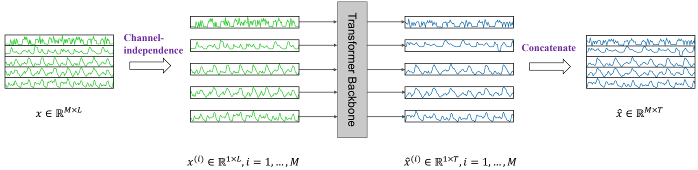


(b) Exchange-Rate



(c) ETTh2

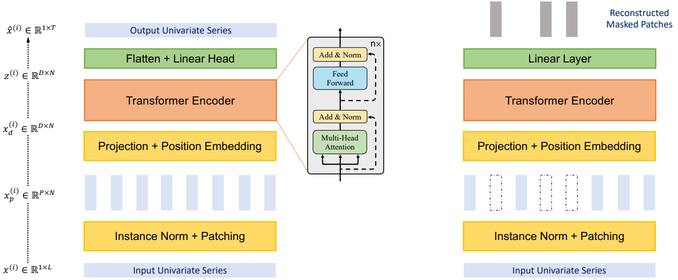
Last of the last: patchTST



(a) PatchTST Model Overview

Current state of the art

- Patch extraction *vs* CNN
- Self-supervision



(b) Transformer Backbone (Supervised) (c) Transformer Backbone (Self-supervised)

Y. Nie et al., ICLR 2023,
A Time Series is Worth 64 Words: Long-Term Forecasting With Transformers

Last of the last: patchTST

Great experimental section:

- Good performance
- Numerous ablations
- Transfer seems promising

Models		PatchTST Fine-tuning		PatchTST Lin. Prob.		PatchTST Sup.		DLinear		FEDformer		Autoformer		Informer	
Metric		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Weather	96	**0.144**	**0.193**	0.158	0.209	0.152	0.199	0.176	0.237	0.238	0.314	0.249	0.329	0.354	0.405
	192	**0.190**	**0.236**	0.203	0.249	0.197	0.243	0.220	0.282	0.275	0.329	0.325	0.370	0.419	0.434
	336	**0.244**	**0.280**	0.251	0.285	0.249	0.283	0.265	0.319	0.339	0.377	0.351	0.391	0.583	0.543
	720	**0.320**	**0.335**	0.321	0.336	**0.320**	**0.335**	0.323	0.362	0.389	0.409	0.415	0.426	0.916	0.705
Traffic	96	**0.352**	**0.244**	0.399	0.294	0.367	0.251	0.410	0.282	0.576	0.359	0.597	0.371	0.733	0.410
	192	**0.371**	**0.253**	0.412	0.298	0.385	0.259	0.423	0.287	0.610	0.380	0.607	0.382	0.777	0.435
	336	**0.381**	**0.257**	0.425	0.306	0.398	0.265	0.436	0.296	0.608	0.375	0.623	0.387	0.776	0.434
	720	**0.425**	**0.282**	0.460	0.323	0.434	0.287	0.466	0.315	0.621	0.375	0.639	0.395	0.827	0.466
Electricity	96	**0.126**	**0.221**	0.138	0.237	0.130	**0.222**	0.140	0.237	0.186	0.302	0.196	0.313	0.304	0.393
	192	**0.145**	**0.238**	0.156	0.252	0.148	0.240	0.153	0.249	0.197	0.311	0.211	0.324	0.327	0.417
	336	**0.164**	**0.256**	0.170	0.265	0.167	0.261	0.169	0.267	0.213	0.328	0.214	0.327	0.333	0.422
	720	**0.193**	**0.291**	0.208	0.297	0.202	**0.291**	0.203	0.301	0.233	0.344	0.236	0.342	0.351	0.427

Models		PatchTST Fine-tuning		PatchTST Lin. Prob.		PatchTST Sup.		DLinear		FEDformer		Autoformer		Informer	
Metric		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Weather	96	**0.145**	**0.195**	0.163	0.216	0.152	0.199	0.176	0.237	0.238	0.314	0.249	0.329	0.354	0.405
	192	**0.193**	**0.243**	0.205	0.252	0.197	**0.243**	0.220	0.282	0.275	0.329	0.325	0.370	0.419	0.434
	336	**0.244**	**0.280**	0.253	0.289	0.249	0.283	0.265	0.319	0.339	0.377	0.351	0.391	0.583	0.543
	720	0.321	0.337	**0.320**	0.336	**0.320**	**0.335**	0.323	0.362	0.389	0.409	0.415	0.426	0.916	0.705
Traffic	96	0.388	0.273	0.400	0.288	**0.367**	**0.251**	0.410	0.282	0.576	0.359	0.597	0.371	0.733	0.410
	192	0.400	0.277	0.412	0.293	**0.385**	**0.259**	0.423	0.287	0.610	0.380	0.607	0.382	0.777	0.435
	336	0.408	0.280	0.425	0.307	**0.398**	**0.265**	0.436	0.296	0.608	0.375	0.623	0.387	0.776	0.434
	720	0.447	0.310	0.457	0.317	**0.434**	**0.287**	0.466	0.315	0.621	0.375	0.639	0.395	0.827	0.466

Table 5: Transfer learning task: PatchTST is pre-trained on Electricity dataset and the model is transferred to other datasets. The best results are in **bold** and the second best are underlined.

Y. Nie et al., ICLR 2023,
A Time Series is Worth 64 Words: Long-Term Forecasting With Transformers

Conclusion

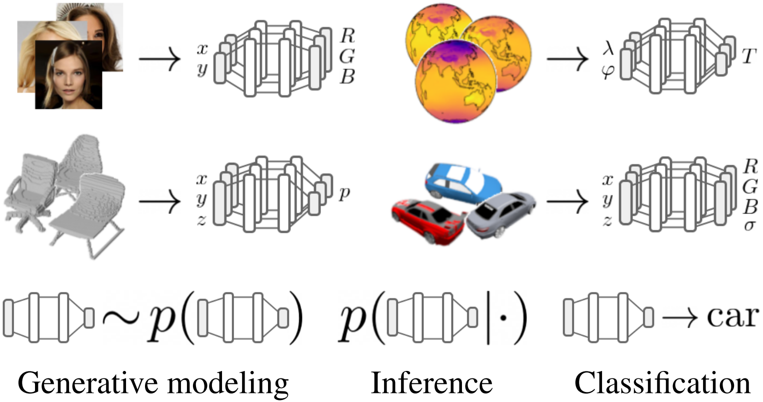
- Transformers are going to improve time series analysis (forecasting, classification...)
- ... And probably through discretization/patch decomposition
- Implementations also improve quickly:
  Librairy Gluon.ai:
  `https://ts.gluon.ai/stable/api/gluonts/gluonts.torch.model.patch_tst.html`

Continuous modeling: Implicit Neural Representation

Implicit Neural Representation

1 instance = 1 neural network

⇒ Multiple applications: video games, image coding, ... & time series?



Dupont et al., ICML 2022,
From data to functa: Your data point is a function and you can treat it like one

Implicit Neural Representation

Compression ability:

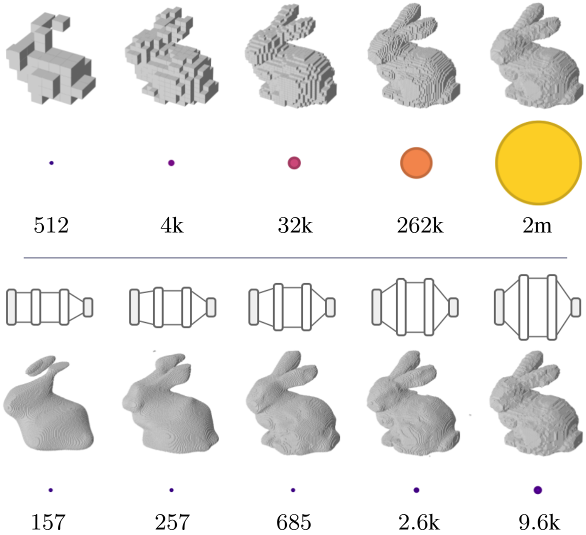


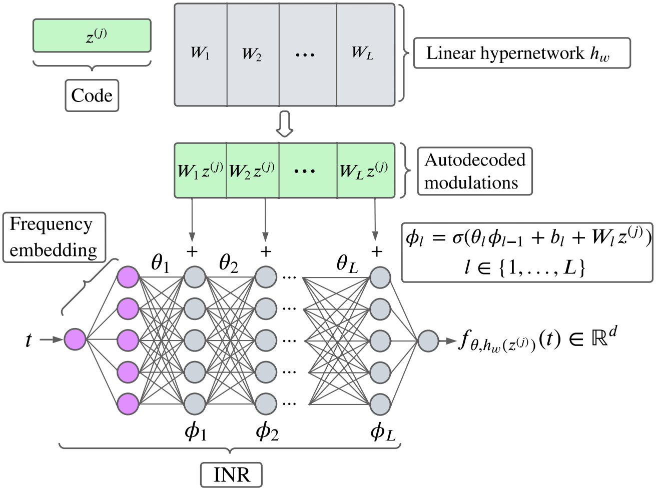
Figure 2. Functa scale much more gracefully with resolution than

$$f_\theta : \mathcal{X} \to \mathcal{F}$$

mapping coordinates $x \in \mathcal{X}$
(e.g. pixel locations)
to features $f \in \mathcal{F}$
(e.g. RGB values)
with parameters θ

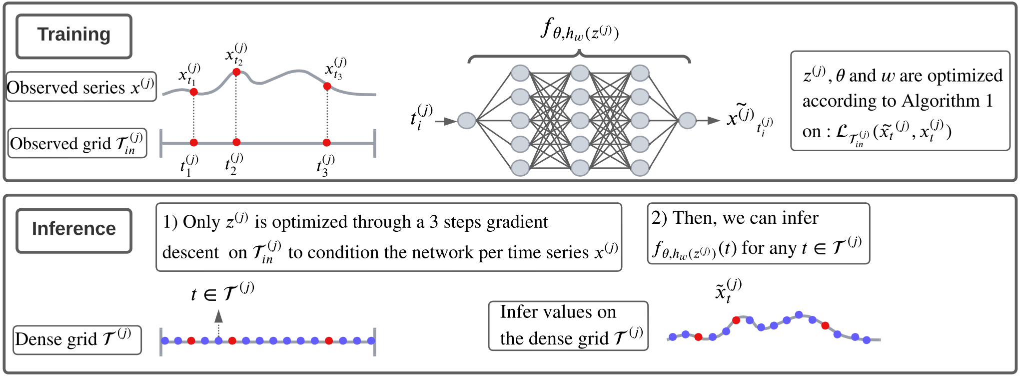
Time series modeling: TimeFlow [LeNaour, 2023]

- Dealing with irregularly sampled look-back windows
- Continuous modeling
- Perform both imputation & forecasting



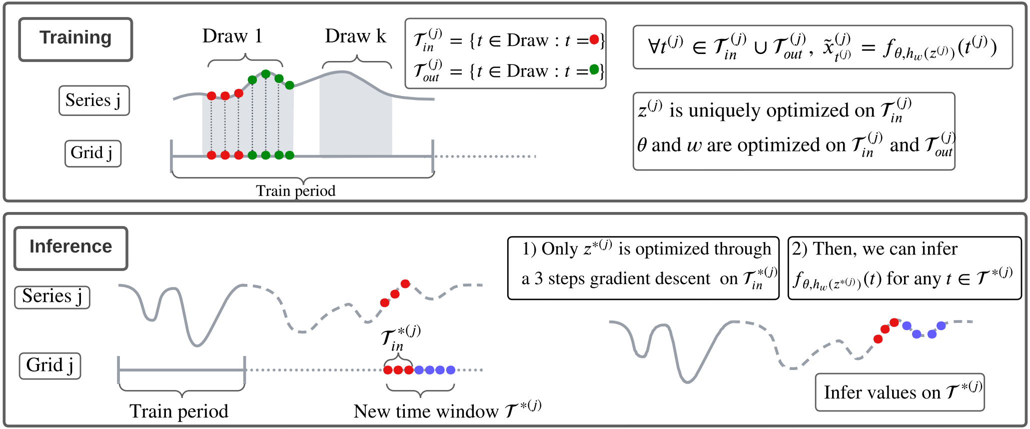
LeNaour et al., arXiv 2023,
Time Series Continuous Modeling for Imputation and Forecasting with Implicit Neural Representations

Time series modeling: TimeFlow [LeNaour, 2023]



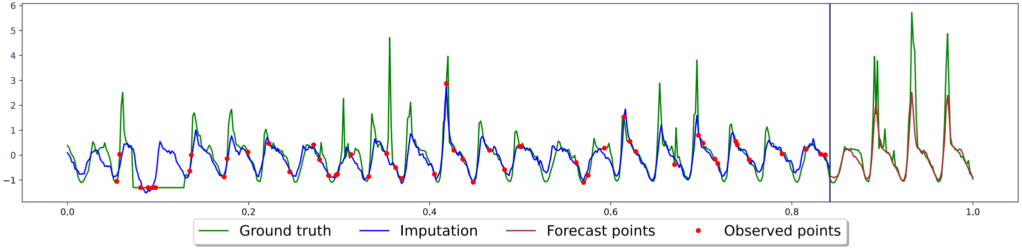
LeNaour et al., arXiv 2023,
Time Series Continuous Modeling for Imputation and Forecasting with Implicit Neural Representations

Time series modeling: TimeFlow [LeNaour, 2023]



LeNaour et al., arXiv 2023,
Time Series Continuous Modeling for Imputation and Forecasting with Implicit Neural Representations

Time series modeling: TimeFlow [LeNaour, 2023]



	H	Continuous methods: TimeFlow	DeepTime	Neural Process	Discrete methods: Patch-TST	DLinear	AutoFormer	Informer
Electricity	96	0.228 ± 0.028	0.244 ± 0.026	0.392 ± 0.045	**0.221** ± **0.023**	0.241 ± 0.030	0.546 ± 0.277	0.603 ± 0.255
	192	0.238 ± 0.020	0.252 ± 0.019	0.401 ± 0.046	**0.229** ± **0.020**	0.252 ± 0.025	0.500 ± 0.190	0.690 ± 0.291
	336	0.270 ± 0.031	0.284 ± 0.034	0.434 ± 0.076	**0.251** ± **0.027**	0.288 ± 0.038	0.523 ± 0.188	0.736 ± 0.271
	720	0.316 ± 0.055	0.359 ± 0.051	0.607 ± 0.150	**0.297** ± **0.039**	0.365 ± 0.059	0.631 ± 0.237	0.746 ± 0.265
SolarH	96	**0.190** ± **0.013**	**0.190** ± **0.020**	0.221 ± 0.048	0.262 ± 0.070	0.208 ± 0.014	0.245 ± 0.045	0.248 ± 0.022
	192	**0.202** ± **0.020**	0.204 ± 0.028	0.244 ± 0.048	0.253 ± 0.051	0.217 ± 0.022	0.333 ± 0.107	0.270 ± 0.031
	336	0.209 ± 0.017	**0.199** ± **0.026**	0.240 ± 0.006	0.259 ± 0.071	0.217 ± 0.026	0.334 ± 0.079	0.328 ± 0.048
	720	**0.218** ± **0.041**	0.229 ± 0.024	0.403 ± 0.147	0.267 ± 0.064	0.249 ± 0.034	0.351 ± 0.055	0.337 ± 0.037
Traffic	96	0.217 ± 0.032	0.228 ± 0.032	0.283 ± 0.027	**0.203** ± **0.037**	0.228 ± 0.033	0.319 ± 0.059	0.372 ± 0.078
	192	0.212 ± 0.028	0.220 ± 0.022	0.292 ± 0.024	**0.197** ± **0.030**	0.221 ± 0.023	0.368 ± 0.057	0.511 ± 0.247
	336	0.238 ± 0.034	0.245 ± 0.038	0.305 ± 0.039	**0.222** ± **0.039**	0.250 ± 0.040	0.434 ± 0.061	0.561 ± 0.263
	720	0.279 ± 0.050	0.290 ± 0.052	0.339 ± 0.038	**0.269** ± **0.057**	0.300 ± 0.057	0.462 ± 0.062	0.638 ± 0.067
TimeFlow improvement		/	3.74 %	29.06 %	3.23 %	6.92 %	42.09 %	48.57 %

Conclusion

Conclusion

- Historical approaches mainly rely on seasonality...
- ML chains are fast, reliable & powerful
  - Build performing features, use efficient algorithms (XGBoost?)
  - ... Just care about information leaks
- Deep learning is moving fast and we perceive the transfer
  - Look for foundation models with time series !