SCINet: Time Series Modeling and Forecasting with Sample Convolution and Interaction

https://arxiv.org/abs/2106.09305

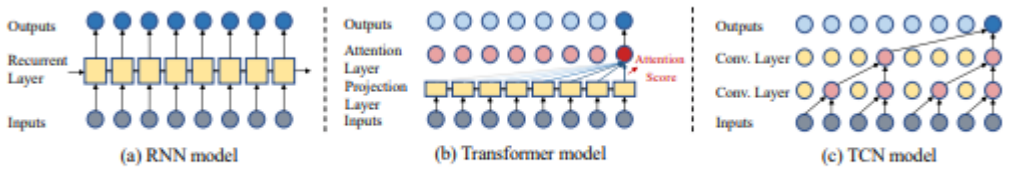
0. Introduction

- 시계열(time series)은 다운샘플링해도 시간적 관계(추세·계절성 등)가 크게 유지됨
- 이 논문은 이러한 특성을 활용한 시계열 예측 모델 SCINet을 제안함
- 목표는 다양한 시간 해상도에서 중요한 정보를 추출하고 상호작용함으로써 복잡한 시계열 동역학을 더 효과적으로 모델링하는 것임

1. Overview

- SCINet은 recursive한 downsample → convolve → interact 구조로 설계됨
- 각 계층에서 입력을 두 개의 하위 시퀀스로 분할한 후, 각각에 다중 컨볼루션 필터 적용
- 서로 다른 해상도에서 추출된 특징을 결합해 시계열의 잠재적 패턴을 효과적으로 학습함

2. Challenges



(a) RNN model (b) Transformer model (c) TCN model

Figure 1: Existing sequence modeling architectures for time series forecasting.

- 기존 RNN, TCN, Transformer 기반 TSF는 시계열 성질을 충분히 활용하지 못함
- 다운샘플링 시 각 하위 시퀀스에 있는 시간적 관계가 유지된다는 점은 잘 고려되지 않

- 단일 필터를 사용하는 구조는 복잡한 시계열의 다양성 있는 패턴을 포착하기 어려움

3. Method

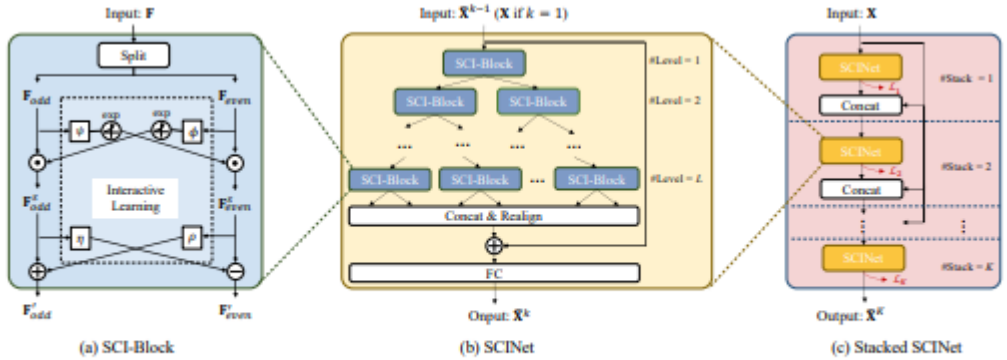


Figure 2: The overall architecture of Sample Convolution and Interaction Network (SCINet).

- SCI-Block
  - 입력 시퀀스를 even-index와 odd-index sub-sequence로 분리함
  - 각 서브시퀀스에 별도의 컨볼루션 필터를 적용해 특징을 추출
  - interactive learning: C↔O 간 affine 변환과 상호 스케일링 통해 정보 손실 보완 형태로 상호작용
- SCINet
  - SCI-Block을 트리 구조로 여러 계층(level) 구성 (binary-tree 스타일)
  - 각 레벨마다 해상도를 분리하고, 특징을 추출·상호작용시킴
  - 추출된 특징을 realign하여 원 시퀀스를 보완하고, decoder MLP로 예측
- Stacked SCINet
  - 여러 SCINet 모듈을 쌓아 intermediate supervision 추가
  - 점진적으로 예측 정확도와 표현력을 향상시킴

4. Experiments

Datasets	ETTh(1,2)	ETTm1	Traffic	Solar-Energy	Electricity	Exchange-Rate	PEMS03	PEMS04	PEMS07	PEMS08
Variants	7	7	862	137	321	8	358	307	883	170
Timesteps	17,420	69,680	17,544	52,560	26,304	7,588	26,209	16,992	28,224	17,856
Granularity	1hour	15min	1hour	10min	1hour	1day	5min	5min	5min	5min
Start time	7/1/2016	7/1/2016	1/1/2015	1/1/2006	1/1/2012	1/1/1990	5/1/2012	7/1/2017	5/1/2017	3/1/2012
Task type	Multi-step	Multi-step	Single-step	Single-step	Single-step	Single-step	Multi-step	Multi-step	Multi-step	Multi-step
Data partition	Follow [42]		Training/Validation/Testing: 6/2/2				Training/Validation/Testing: 6/2/2			

- 데이터셋: 전력, 교통, 태양광, 환율, ETTh, PeMS 등 11개 시계열 데이터베이스
- 비교 모델: TCN, Transformer 기반 TSF, RNN 등
- 구성 및 설정: 계층 수 및 스택 수 조정, intermediate supervision 사용

5. Results

Table 2: Short-term forecasting performance comparison on the four datasets. The best results are shown in **bold** and second best results are highlighted with underlined blue font. IMP shows the improvement of SCINet over the best model.

Model		SCINet		Autoformer [40]		Informer [42]		Transformer [37]		*TCN [4]		*TCN†		LSTNet [19]		TPA-LSTM [34]		IMP
Metric	τ	RSE	CORR	RSE	CORR	RSE	CORR	RSE	CORR	RSE	CORR	RSE	CORR	RSE	CORR	RSE	CORR	RSE
Solar-Energy	3	**0.1775**	**0.9853**	N/A	N/A	N/A	N/A	N/A	N/A	0.1940	0.9835	0.1900	0.9848	0.1843	0.9843	0.1803	0.9850	1.55%
	6	**0.2301**	**0.9739**	N/A	N/A	N/A	N/A	N/A	N/A	0.2581	0.9602	0.2382	0.9612	0.2559	0.9690	0.2347	0.9742	1.96%
	12	**0.2997**	**0.9550**	N/A	N/A	N/A	N/A	N/A	N/A	0.3512	0.9321	0.3353	0.9432	0.3254	0.9467	0.3214	0.9487	7.33%
	24	**0.4081**	**0.9112**	N/A	N/A	N/A	N/A	N/A	N/A	0.4732	0.8812	0.4676	0.8851	0.4643	0.8870	0.4389	0.9081	7.02%
Traffic	3	**0.4216**	**0.8920**	0.5368	0.8268	0.5175	0.8515	0.5122	0.8555	0.5459	0.8486	0.5361	0.8540	0.4777	0.8721	0.4487	0.8815	6.04%
	6	**0.4414**	**0.8809**	0.5462	0.8191	0.5258	0.8465	0.5455	0.8388	0.6061	0.8205	0.5992	0.8197	0.4893	0.8690	0.4658	0.8717	5.24%
	12	**0.4495**	**0.8772**	0.5623	0.8082	0.5533	0.8279	0.5485	0.8317	0.6367	0.8048	0.6061	0.8205	0.4950	0.8614	0.4641	0.8717	3.15%
	24	**0.4453**	**0.8825**	0.6020	0.7757	0.5883	0.8033	0.5934	0.8048	0.6586	0.7921	0.6456	0.7982	0.4973	0.8588	0.4785	0.8679	6.55%
Electricity	3	**0.0740**	**0.9494**	0.1458	0.9032	0.1524	0.8858	0.1182	0.9055	0.0892	0.9232	0.0852	0.9293	0.0864	0.9283	0.0823	0.9430	10.09%
	6	**0.0845**	**0.9387**	0.1555	0.8957	0.1932	0.8660	0.1328	0.8962	0.0974	0.9121	0.0924	0.9235	0.0931	0.9135	0.0916	0.9337	7.75%
	12	**0.0929**	**0.9305**	0.1541	0.8907	0.1748	0.8585	0.1375	0.8849	0.1053	0.9017	0.0993	0.9173	0.1007	0.9077	0.0964	0.9250	3.63%
	24	**0.0967**	**0.9270**	0.1754	0.8732	0.2110	0.8347	0.1461	0.8774	0.1091	0.9101	0.0989	0.9101	0.1007	0.9119	0.1006	0.9133	3.88%
Exchange Rate	3	**0.0171**	**0.9787**	0.0400	0.9458	0.1302	0.9473	0.0689	0.9759	0.0217	0.9693	0.0202	0.9712	0.0226	0.9735	0.0174	0.9779	1.72%
	6	**0.0240**	0.9704	0.0481	0.9197	0.1548	0.9207	0.0806	0.9671	0.0263	0.9633	0.0257	0.9628	0.0280	0.9658	0.0241	**0.9709**	0.41%
	12	**0.0331**	0.9553	0.0638	0.9054	0.1793	0.8817	0.0893	0.9476	0.0393	0.9531	0.0352	0.9501	0.0356	0.9511	0.0341	**0.9564**	2.93%
	24	**0.0436**	**0.9396**	0.0651	0.8952	0.1998	0.7715	0.1127	0.9213	0.0492	0.9223	0.0487	0.9314	0.0449	0.9354	0.0444	0.9381	1.80%

- Autoformer, Informer and Transformer achieved by Autoformer [40] requires pre-prossessed datasets for training.
- N/A denotes no pre-prossessed dataset for training.
- * denotes re-implementation. † denotes the variant with normal convolutions.

Table 3: Long-term forecasting performance comparison with Transformer-based models.

Model		SCINet		Autoformer [38]		*Pyraformer [25]		Informer [42]		Transformer [37]		LogTrans [21]		Reformer [18]		IMP
Metric		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE
Exchange Rate	96	**0.061**	**0.188**	0.197	0.323	1.748	1.105	0.847	0.752	0.559	0.587	0.968	0.812	1.065	0.829	68.98%
	192	**0.106**	**0.244**	0.300	0.369	1.874	1.151	1.204	0.895	1.168	0.835	1.040	0.851	1.188	0.906	64.70%
	336	**0.181**	**0.323**	0.509	0.524	1.943	1.172	1.672	1.036	1.423	0.949	1.659	1.081	1.357	0.976	64.36%
	720	**0.525**	**0.571**	1.447	0.941	2.085	1.206	2.478	2.478	2.160	1.150	1.941	1.127	1.510	1.016	63.72%
Electricity	96	**0.168**	**0.253**	0.201	0.317	0.386	0.449	0.274	0.368	0.263	0.359	0.258	0.357	0.312	0.402	16.42%
	192	**0.175**	**0.262**	0.222	0.334	0.378	0.443	0.296	0.296	0.273	0.374	0.266	0.368	0.348	0.433	21.17%
	336	**0.189**	**0.278**	0.231	0.338	0.376	0.443	0.300	0.394	0.277	0.373	0.280	0.380	0.350	0.433	18.19%
	720	**0.231**	**0.316**	0.254	0.361	0.376	0.445	0.373	0.439	0.290	0.378	0.283	0.376	0.340	0.420	9.06%
Traffic	96	**0.613**	0.395	**0.613**	**0.388**	0.867	0.468	0.719	0.391	0.638	0.354	0.684	0.384	0.732	0.423	0.00%
	192	**0.535**	**0.355**	0.616	0.382	0.869	0.467	0.696	0.379	0.647	0.354	0.685	0.390	0.733	0.420	13.15%
	336	**0.540**	**0.359**	0.622	0.337	0.881	0.469	0.777	0.420	0.669	0.364	0.733	0.408	0.742	0.420	13.18%
	720	**0.620**	**0.394**	0.660	0.408	0.896	0.473	0.864	0.472	0.707	0.386	0.717	0.396	0.755	0.423	6.06%

- * denotes re-implementation.

Table 4: Multivariate time-series forecasting results on the *ETT* datasets.

Methods	Metrics	ETTh1					ETTh2					ETTm1				
		Horizon					Horizon					Horizon				
		24	48	168	336	720	24	48	168	336	720	24	48	96	288	672
LogTrans [21]	MSE	0.686	0.766	1.002	1.362	1.397	0.828	1.806	4.070	3.875	3.913	0.419	0.507	0.768	1.462	1.669
	MAE	0.604	0.757	0.846	0.952	1.291	0.750	1.034	1.681	1.763	1.552	0.412	0.583	0.792	1.320	1.461
Reformer [18]	MSE	0.991	1.313	1.824	2.117	2.415	1.531	1.871	4.660	4.028	5.381	0.724	1.098	1.433	1.820	2.187
	MAE	0.754	0.906	1.138	1.280	1.520	1.613	1.735	1.846	1.688	2.015	0.607	0.777	0.945	1.094	1.232
LSTMa [2]	MSE	0.650	0.702	1.212	1.424	1.960	1.143	1.671	4.117	3.434	3.963	0.621	1.392	1.339	1.740	2.736
	MAE	0.624	0.675	0.867	0.994	1.322	0.813	1.221	1.674	1.549	1.788	0.629	0.939	0.913	1.124	1.555
LSTNet [19]	MSE	1.293	1.456	1.997	2.655	2.143	2.742	3.567	3.242	2.544	4.625	1.968	1.999	2.762	1.257	1.917
	MAE	0.901	0.960	1.214	1.369	1.380	1.457	1.687	2.513	2.591	3.709	L1700	1.215	1.542	2.076	2.941
Informer [42]	MSE	0.577	0.685	0.931	1.128	1.215	0.720	1.457	3.489	2.723	3.467	0.323	0.494	0.678	1.056	1.192
	MAE	0.549	0.625	0.752	0.873	0.896	0.665	1.001	1.515	1.340	1.473	0.369	0.503	0.614	0.786	0.926
*TCN [4]	MSE	0.511	0.515	0.694	0.814	0.944	0.444	0.617	2.405	2.486	2.608	0.229	0.239	0.260	0.768	2.732
	MAE	0.549	0.529	0.617	0.682	0.778	0.478	0.615	1.266	1.312	1.276	0.282	0.360	0.363	0.646	1.371
*Pyraformer [25]	MSE	0.479	0.518	0.758	0.891	0.963	0.477	0.934	3.913	0.907	0.963	0.332	0.492	0.543	0.656	0.901
	MAE	0.499	0.520	0.665	0.738	0.782	0.537	0.764	1.557	0.747	0.783	0.383	0.475	0.510	0.598	0.720
Autoformer [38]	MSE	0.406	0.478	0.493	0.515	**0.499**	0.360	0.311	0.466	0.472	0.480	0.408	0.499	0.540	0.636	0.699
	MAE	0.440	0.462	0.481	0.492	**0.500**	0.339	0.372	0.458	0.478	**0.488**	0.424	0.464	0.489	0.533	0.564
SCINet	MSE	**0.300**	**0.361**	**0.408**	**0.504**	0.544	**0.180**	**0.230**	**0.342**	**0.365**	**0.475**	**0.106**	**0.136**	**0.165**	**0.253**	**0.346**
	MAE	**0.342**	**0.388**	**0.417**	**0.495**	0.537	**0.263**	**0.303**	**0.380**	**0.409**	**0.488**	**0.202**	**0.230**	**0.252**	**0.315**	**0.376**
IMP	MSE	26.11%	24.48%	17.34%	2.14%	-9.02%	50.77%	25.81%	26.61%	22.67%	1.04%	38.71%	22.83%	21.40%	49.59%	40.18%

- * denotes re-implementation.

Table 6: Performance comparison of different approaches on the *PeMS* datasets.

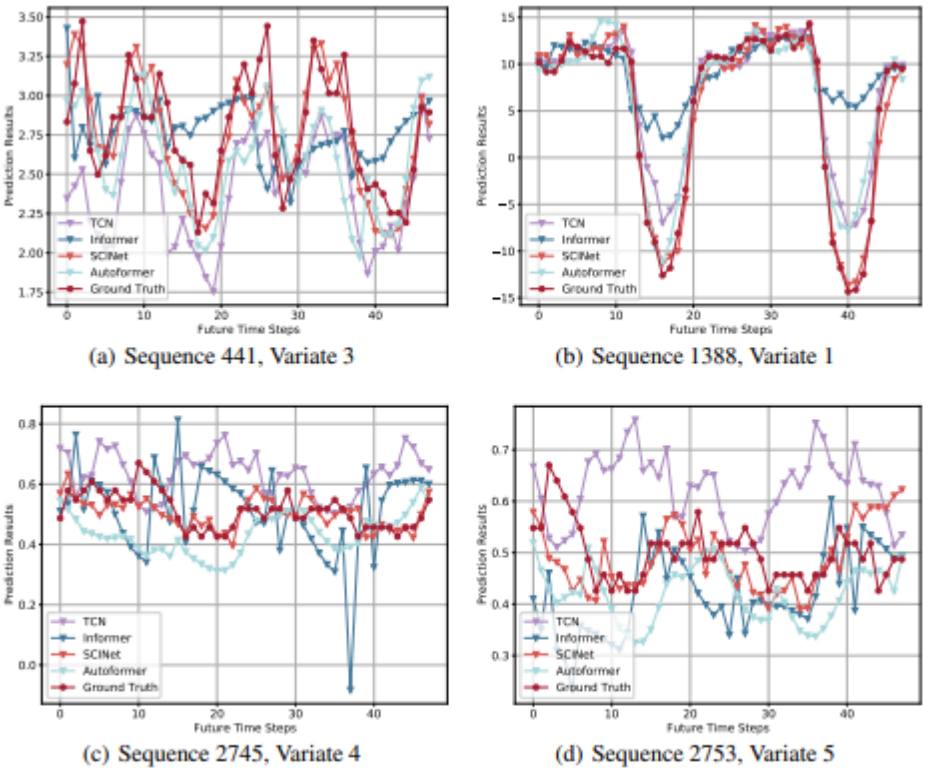
Datasets	Metrics	Methods												IMP
		*LSTM	*TCN	*TCN†	DCRNN	STGCN	ASTGCN(r)	GraphWaveNet	STSGCN	STFGNN	AGCRN	LSGCN	SCINet	MAE
PEMS03	MAE	21.33	19.32	18.87	18.18	17.49	17.69	19.85	17.48	16.77	*15.98	-	**14.98**	6.26%
	MAPE	21.33	19.93	18.63	18.91	17.15	19.40	19.31	16.78	16.30	*15.23	-	**14.11**	7.36%
	RMSE	35.11	33.55	32.24	30.31	30.12	29.66	32.94	29.21	28.34	*28.25	-	**24.08**	8.37%
PEMS04	MAE	25.14	25.22	22.81	24.70	22.70	22.93	25.45	21.19	19.83	19.83	21.53	**18.95**	4.44%
	MAPE	20.33	15.59	14.31	17.12	14.59	16.56	17.29	13.90	13.02	12.97	13.18	**11.86**	8.56%
	RMSE	39.59	37.26	36.87	38.12	35.55	35.22	39.70	33.65	31.88	32.30	33.86	**30.89**	4.40%
PEMS07	MAE	29.98	32.72	30.53	28.30	25.38	28.05	26.85	24.26	22.07	*22.37	-	**21.19**	5.27%
	MAPE	15.33	14.26	13.88	11.66	11.08	13.92	12.12	10.21	9.21	*9.12	-	**8.83**	3.18%
	RMSE	42.84	42.23	41.02	38.58	38.78	42.57	42.78	39.03	35.80	*36.55	-	**34.03**	6.89%
PEMS08	MAE	22.20	22.72	21.42	17.86	18.02	18.61	19.13	17.13	16.64	15.95	17.73	**15.72**	1.44%
	MAPE	15.32	14.03	13.09	11.45	11.40	13.08	12.68	10.96	10.60	10.09	11.20	**9.80**	2.87%
	RMSE	32.06	35.79	34.03	27.83	27.83	28.16	31.05	26.80	26.22	25.22	26.76	**24.76**	1.82%

- dash denotes that the methods do not implement on this dataset. * denotes re-implementation or re-training. † denotes the variant with normal convolutions.

Table 7: Permutation entropy comparison before and after SCINet.

Permutation Entropy		Datasets								
		ETTh1	Traffic	Solar-Energy	Electricity	Exc-rate	PEMS03	PEMS04	PEMS07	PEMS08
Parameters	m (τ = 1)*	6	6	7	6	6	6	6	6	6
Value	Original Input	0.8878	0.9371	0.4739	0.9489	0.8260	0.9649	0.9203	0.9148	0.9390
	Enhanced Representation	0.7096	0.8832	0.3537	0.8901	0.7836	0.8377	0.8749	0.8330	0.8831

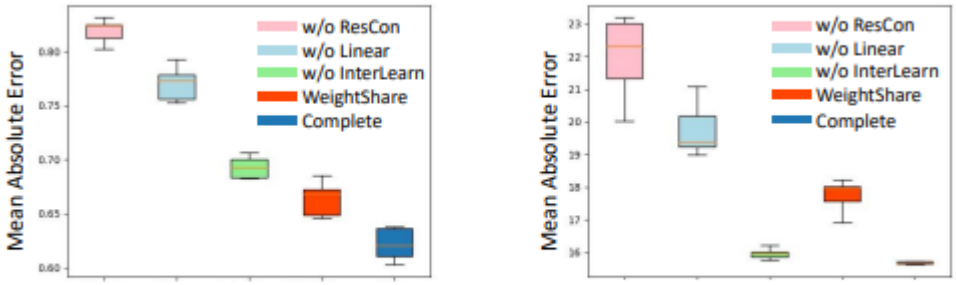
* m (embedding dimension) and τ (time-lag) are two parameters used for calculating PE, and the values are selected following [30, 16].



(a) Sequence 441, Variate 3 (b) Sequence 1388, Variate 1

(c) Sequence 2745, Variate 4 (d) Sequence 2753, Variate 5

Figure 3: The prediction results (Horizon = 48) of SCINet, Autoformer, Informer, and TCN on randomly-selected sequences from ETTh1 dataset.



(a) ETTh1(H = 720) (b) PEMS08(H = 12)

Figure 4: Component analysis of SCINet on two datasets. Smaller values are better. See Section 4.3.

- 다양한 real-world 데이터에서 기존 convolution 및 Transformer 기반 모델 대비 예측 성능 상당히 향상됨
- spatial-temporal task (예: PeMS)에서도 별도 공간 처리 없이 우수한 성능 달성

6. Insight

- 시계열의 다운샘플링 특성을 활용한 구조 설계가 효과적임
- multi-resolution convolution과 상호작용(interaction) 전략이 장기·단기 패턴을 모두 포착함
- interactive learning을 통한 정보 보완 방식이 TCN 기반 단일 필터 방식의 한계를 극복함
- Stacked 구조로 intermediate supervision을 도입해 더 깊은 모델의 안정적인 학습 가능
- 한계: irregular 간격, 결측 데이터, 확률적 예측, 공간 모델 통합 등에 대한 확장은 추후 과제