2025 12 04
발표 자료

광운대학교 로봇학과
FAIR Lab

김한서

KWANGWOON UNIVERSITY

이번 주 진행사항

FAIR Lab

- Fredformer
  - 논문 리뷰
  - 실험 세팅
  - 실험 결과 및 시각화
  - 결과 정리

Fredformer

KWANGWOON UNIVERSITY

Fredformer: Frequency Debiased Transformer for Time Series Forecasting

Xihao Piao*
SANKEN, Osaka University
Osaka, Japan
park88@sanken.osaka-u.ac.jp

Zheng Chen*
SANKEN, Osaka University
Osaka, Japan
chenz@sanken.osaka-u.ac.jp

Taichi Murayama
SANKEN, Osaka University
Osaka, Japan
taichi@sanken.osaka-u.ac.jp

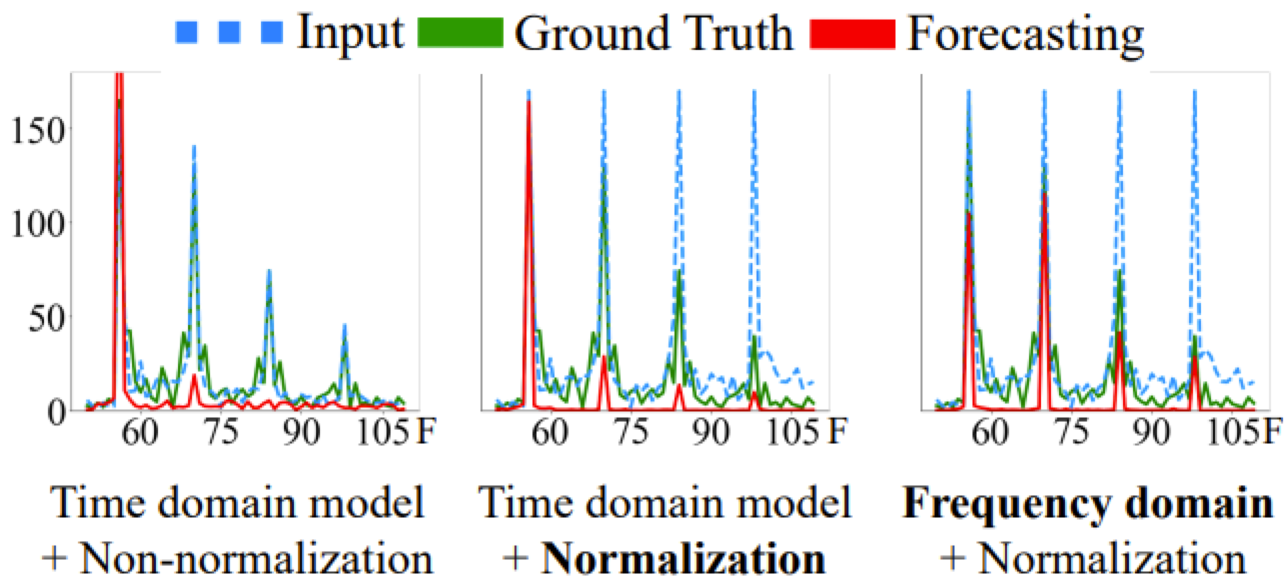
Yasuko Matsubara
SANKEN, Osaka University
Osaka, Japan
yasuko@sanken.osaka-u.ac.jp

Yasushi Sakurai
SANKEN, Osaka University
Osaka, Japan
yasushi@sanken.osaka-u.ac.jp

- arXiv 등록일: 2024-06-13
- 인용 수: 100회(Google Scholar, 2025-11-29)
- Published at KDD 2024
- Fredformer는 기존 Transformer 모델이 데이터의 저주파 특징만 포착하고, 고주파 특징을 간과하는 주파수 편향을 해결하기 위해 주파수 데이터의 Patch별 정규화와 채널별 Attention을 제안

Fredformer

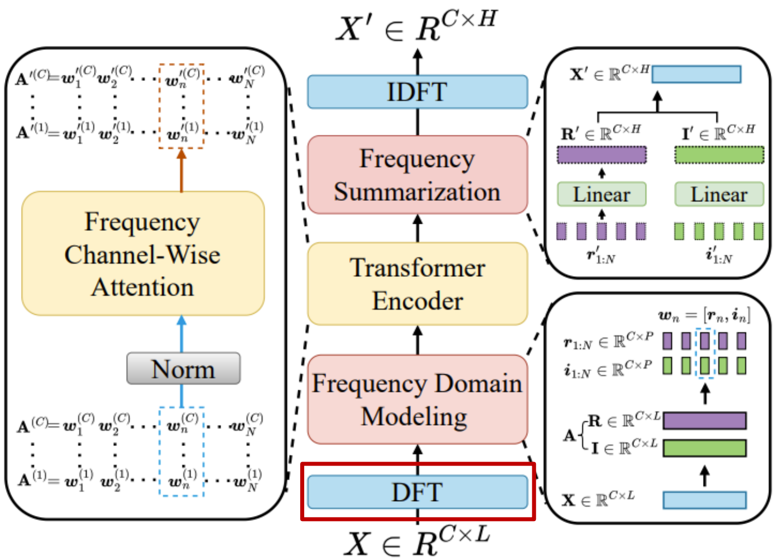
기존 방식과 Fredformer 방식 비교



- Time domain model
  - 진폭이 큰 저주파 위주로만 학습되기 때문에 고주파 정보가 손실됨
- Frequency domain
  - 주파수 데이터의 Patch별로 정규화를 적용하여 저주파 고주파 모두 동일한 비중으로 학습하게 함

Fredformer

모델 구조 (DFT)



- DFT (Discrete Fourier Transform)
  - 입력 데이터를 시간 도메인에서 주파수 도메인으로 변환, 모든 주파수 정보를 담은 복소수 행렬 A 생성

$$X \in R^{C \times L} \longrightarrow A = \mathrm{DFT}(X) \in R^{C \times L}$$

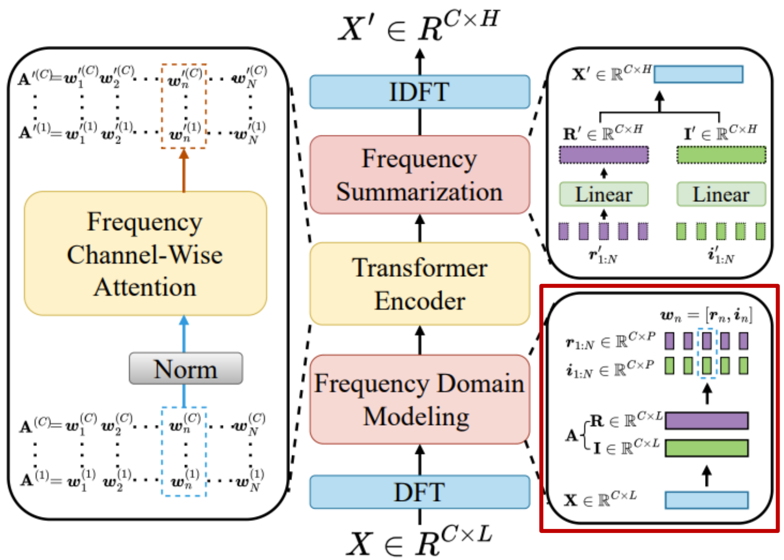
*X : 입력 시계열 데이터
*C : channel 수
*L : Look back window 길이

Fredformer

FAIR Lab

KWANGWOON UNIVERSITY

모델 구조 (Frequency Domain Modeling)

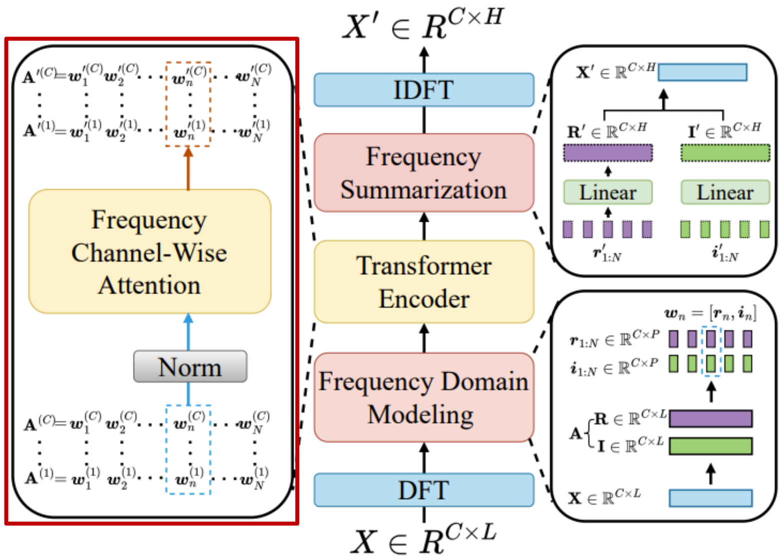


- Frequency Domain Modeling
  - 복소수 A를 실수부(**R**)와 허수부(**I**) 행렬로 분리 $A \longrightarrow \mathrm{R} \in R^{C \times L},\ \mathrm{I} \in R^{C \times L}$
  - 분리된 각 행렬을 Patch단위로 자름 $\mathrm{r1{:}N},\ \mathrm{i1{:}N} \in R^{C \times P}$ $\quad \mathbf{w_n} = [\mathbf{r_n}, \mathbf{i_n}]$
  - 이후 Patch마다 정규화 진행 $\mathbf{w_n^*} = \mathrm{Norm}(\mathbf{w_n})$

*P : Patch 길이
*N : Patch 개수
*r1:N : Patch된 실수부
*i1:N : Patch된 허수부
*Wn : 실수부+허수부 Patch

Fredformer

모델 구조 (Transformer Encoder)

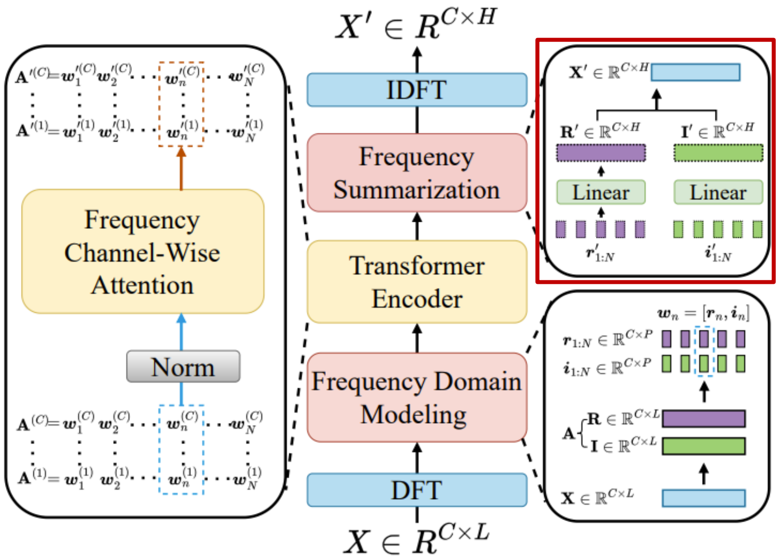


- Transformer Encoder
  - 정규화된 주파수 Patch가 Channel-Wise Attention를 수행 $\mathbf{w}_\mathbf{n}' = \mathrm{Attention}(\mathbf{w}_\mathbf{n}^*)$
  - 같은 주파수 대역 내에서 변수(Channel) 간의 상관관계가 학습된 특징 벡터 $\mathbf{w}_\mathbf{n}'$ 생성

*w_*^n : 정규화된 Patch
*w_n' : Attention 결과 Patch

Fredformer

모델 구조 (Frequency Summarization)



- Frequency Summarization
  - 현재 데이터를 Linear Layer를 통과시켜 예측하고자 하는 길이 H로 변환

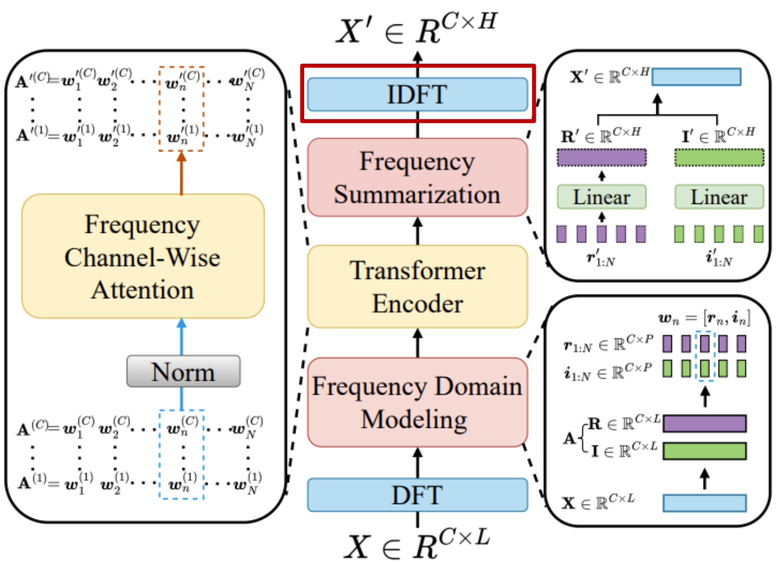
    $\mathbf{R}' = \mathrm{Linear}(\mathbf{r}'1{:}N), \quad \mathbf{I}' = \mathrm{Linear}(\mathbf{i}'1{:}N)$
  - 이때 실수부와 허수부를 각각 처리한 후 다시 하나의 복소수 형태로 합침

    $A' = \mathbf{R}' + \mathrm{j}\mathbf{I}'$

*R' : 선형 변환된 실수부
*I' : 선형 변환된 허수부
*j : 허수 단위

Fredformer

모델 구조 (IDFT)



- IDFT (Inverse DFT)
  - 처리가 완료된 주파수 도메인을 다시 시간 도메인으로 변환 $X' = IDFT(A') \in R^{C\times H}$
  - 최종 예측 결과 $X' \in R^{C\times H}$ 출력

*X' :최종 예측 결과
*C : channel 수
*H : 미래 예측 길이

Fredformer

주요 모델 성능 비교

Models		Fredformer (Ours)		iTransformer [2024]		RLinear [2023]		PatchTST [2023]		Crossformer [2023]		TiDE [2023]		TimesNet [2023]		DLinear [2023]		SCINet [2022]		FEDformer [2022]		Stationary [2022a]		Autoformer [2021]	
Metric		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTm1	96	0.326	0.361	0.334	0.368	0.355	0.376	0.329	0.367	0.404	0.426	0.364	0.387	0.338	0.375	0.345	0.372	0.418	0.438	0.379	0.419	0.386	0.398	0.505	0.475
	192	0.363	0.380	0.377	0.391	0.391	0.392	0.367	0.385	0.450	0.451	0.398	0.404	0.374	0.387	0.380	0.389	0.439	0.450	0.426	0.441	0.459	0.444	0.553	0.496
	336	0.395	0.403	0.426	0.420	0.424	0.415	0.399	0.410	0.532	0.515	0.428	0.425	0.410	0.411	0.413	0.413	0.490	0.485	0.445	0.459	0.495	0.464	0.621	0.537
	720	0.453	0.438	0.491	0.459	0.487	0.450	0.454	0.439	0.666	0.589	0.487	0.461	0.478	0.450	0.474	0.453	0.595	0.550	0.543	0.490	0.585	0.516	0.671	0.561
	Avg	0.384	0.395	0.407	0.410	0.414	0.407	0.387	0.400	0.513	0.496	0.419	0.419	0.400	0.406	0.403	0.407	0.485	0.481	0.448	0.452	0.481	0.456	0.588	0.517
ETTm2	96	0.177	0.259	0.180	0.264	0.182	0.265	0.175	0.259	0.287	0.366	0.207	0.305	0.187	0.267	0.193	0.292	0.286	0.377	0.203	0.287	0.192	0.274	0.255	0.339
	192	0.243	0.301	0.250	0.309	0.246	0.304	0.241	0.302	0.414	0.492	0.290	0.364	0.249	0.309	0.284	0.362	0.399	0.445	0.269	0.328	0.280	0.339	0.281	0.340
	336	0.302	0.340	0.311	0.348	0.307	0.342	0.305	0.343	0.597	0.542	0.377	0.422	0.321	0.351	0.369	0.427	0.637	0.591	0.325	0.366	0.334	0.361	0.339	0.372
	720	0.397	0.396	0.412	0.407	0.407	0.398	0.402	0.400	1.730	1.042	0.558	0.524	0.408	0.403	0.554	0.522	0.960	0.735	0.421	0.415	0.417	0.413	0.433	0.432
	Avg	0.279	0.324	0.288	0.332	0.286	0.327	0.281	0.326	0.757	0.610	0.358	0.404	0.291	0.333	0.350	0.401	0.571	0.537	0.305	0.349	0.306	0.347	0.327	0.371
ETTh1	96	0.373	0.392	0.386	0.405	0.386	0.395	0.414	0.419	0.423	0.448	0.479	0.464	0.384	0.402	0.386	0.400	0.654	0.599	0.376	0.419	0.513	0.491	0.449	0.459
	192	0.433	0.420	0.441	0.436	0.437	0.424	0.460	0.445	0.471	0.474	0.525	0.492	0.436	0.429	0.437	0.432	0.719	0.631	0.420	0.448	0.534	0.504	0.500	0.482
	336	0.470	0.437	0.487	0.458	0.479	0.446	0.501	0.466	0.570	0.546	0.565	0.515	0.491	0.469	0.481	0.459	0.778	0.659	0.459	0.465	0.588	0.535	0.521	0.496
	720	0.467	0.456	0.503	0.491	0.481	0.470	0.500	0.488	0.653	0.621	0.594	0.558	0.521	0.500	0.519	0.516	0.836	0.699	0.506	0.507	0.643	0.616	0.514	0.512
	Avg	0.435	0.426	0.454	0.447	0.446	0.434	0.469	0.454	0.529	0.522	0.541	0.507	0.458	0.450	0.456	0.452	0.747	0.647	0.440	0.460	0.570	0.537	0.496	0.487
ETTh2	96	0.293	0.342	0.297	0.349	0.288	0.338	0.302	0.348	0.745	0.584	0.400	0.440	0.340	0.374	0.333	0.387	0.707	0.621	0.358	0.397	0.476	0.458	0.346	0.388
	192	0.371	0.389	0.380	0.400	0.374	0.390	0.388	0.400	0.877	0.656	0.528	0.509	0.402	0.414	0.477	0.476	0.860	0.689	0.429	0.439	0.512	0.493	0.456	0.452
	336	0.382	0.409	0.428	0.432	0.415	0.426	0.426	0.433	1.043	0.731	0.643	0.571	0.452	0.452	0.594	0.541	1.000	0.744	0.496	0.487	0.552	0.551	0.482	0.486
	720	0.415	0.434	0.427	0.445	0.420	0.440	0.431	0.446	1.104	0.763	0.874	0.679	0.462	0.468	0.831	0.657	1.249	0.838	0.463	0.474	0.562	0.560	0.515	0.511
	Avg	0.365	0.393	0.383	0.407	0.374	0.398	0.387	0.407	0.942	0.684	0.611	0.550	0.414	0.427	0.559	0.515	0.954	0.723	0.437	0.449	0.526	0.516	0.450	0.459
ECL	96	0.147	0.241	0.148	0.240	0.201	0.281	0.195	0.285	0.219	0.314	0.237	0.329	0.168	0.272	0.197	0.282	0.247	0.345	0.193	0.308	0.169	0.273	0.201	0.317
	192	0.165	0.258	0.162	0.253	0.201	0.283	0.199	0.289	0.231	0.322	0.236	0.330	0.184	0.289	0.196	0.285	0.257	0.355	0.201	0.315	0.182	0.286	0.222	0.334
	336	0.177	0.273	0.178	0.269	0.215	0.298	0.215	0.305	0.246	0.337	0.249	0.344	0.198	0.300	0.209	0.301	0.269	0.369	0.214	0.329	0.200	0.304	0.231	0.338
	720	0.213	0.304	0.225	0.317	0.257	0.331	0.256	0.337	0.280	0.363	0.284	0.373	0.220	0.320	0.245	0.333	0.299	0.390	0.246	0.355	0.222	0.321	0.254	0.361
	Avg	0.175	0.269	0.178	0.270	0.219	0.298	0.216	0.304	0.244	0.334	0.251	0.344	0.192	0.295	0.212	0.300	0.268	0.365	0.214	0.327	0.193	0.296	0.227	0.338
Traffic	96	0.406	0.277	0.395	0.268	0.649	0.389	0.544	0.359	0.522	0.290	0.805	0.493	0.593	0.321	0.650	0.396	0.788	0.499	0.587	0.366	0.612	0.338	0.613	0.388
	192	0.426	0.290	0.417	0.276	0.601	0.366	0.540	0.354	0.530	0.293	0.756	0.474	0.617	0.336	0.598	0.370	0.789	0.505	0.604	0.373	0.613	0.340	0.616	0.382
	336	0.432	0.281	0.433	0.283	0.609	0.369	0.551	0.358	0.558	0.305	0.762	0.477	0.629	0.336	0.605	0.373	0.797	0.508	0.621	0.383	0.618	0.328	0.622	0.337
	720	0.463	0.300	0.467	0.302	0.647	0.387	0.586	0.375	0.589	0.328	0.719	0.449	0.640	0.350	0.645	0.394	0.841	0.523	0.626	0.382	0.653	0.355	0.660	0.408
	Avg	0.431	0.287	0.428	0.282	0.626	0.378	0.555	0.362	0.550	0.304	0.760	0.473	0.620	0.336	0.625	0.383	0.804	0.509	0.610	0.376	0.624	0.340	0.628	0.379
Weather	96	0.163	0.207	0.174	0.214	0.192	0.232	0.177	0.218	0.158	0.230	0.202	0.261	0.172	0.220	0.196	0.255	0.221	0.306	0.217	0.296	0.173	0.223	0.266	0.336
	192	0.211	0.251	0.221	0.254	0.240	0.271	0.225	0.259	0.206	0.277	0.242	0.298	0.219	0.261	0.237	0.296	0.261	0.340	0.276	0.336	0.245	0.285	0.307	0.367
	336	0.267	0.292	0.278	0.296	0.292	0.307	0.278	0.297	0.272	0.335	0.287	0.335	0.280	0.306	0.283	0.335	0.309	0.378	0.339	0.380	0.321	0.338	0.359	0.395
	720	0.343	0.341	0.358	0.349	0.364	0.353	0.354	0.348	0.398	0.418	0.351	0.386	0.365	0.359	0.345	0.381	0.377	0.427	0.403	0.428	0.414	0.410	0.419	0.428
	Avg	0.246	0.272	0.258	0.279	0.272	0.291	0.259	0.281	0.259	0.315	0.271	0.320	0.259	0.287	0.265	0.317	0.292	0.363	0.309	0.360	0.288	0.314	0.338	0.382
Solar-Energy	96	0.185	0.233	0.203	0.237	0.322	0.339	0.234	0.286	0.310	0.331	0.312	0.399	0.250	0.292	0.290	0.378	0.237	0.344	0.242	0.342	0.215	0.249	0.884	0.711
	192	0.227	0.253	0.233	0.261	0.359	0.356	0.267	0.310	0.734	0.725	0.339	0.416	0.296	0.318	0.320	0.398	0.280	0.380	0.285	0.380	0.254	0.272	0.834	0.692
	336	0.246	0.284	0.248	0.273	0.397	0.369	0.290	0.315	0.750	0.735	0.368	0.430	0.319	0.330	0.353	0.415	0.304	0.389	0.282	0.376	0.290	0.296	0.941	0.723
	720	0.247	0.276	0.249	0.275	0.397	0.356	0.289	0.317	0.769	0.765	0.370	0.425	0.338	0.337	0.356	0.413	0.308	0.388	0.357	0.427	0.285	0.295	0.882	0.717
	Avg	0.226	0.261	0.233	0.262	0.369	0.356	0.270	0.307	0.641	0.639	0.347	0.417	0.301	0.319	0.330	0.401	0.282	0.375	0.291	0.381	0.261	0.381	0.885	0.711
1st Count		29	31	4	8	1	1	2	1	2	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0

- 대부분의 데이터셋에서 차이가 크진 않지만 가장 좋은 성능을 보여주었음
- 입력 길이가 길어져도 수치가 안정적으로 나오는 것을 확인

Fredformer

실험 세팅

- 사용한 모델: Fredformer
- 재현 실험 데이터셋: ETTh1, Weather

Experiment	ETTh1, Weather
Learning rate	$10^{-4}/10^{-3}$
Epoch	100
Batch size	128
Loss function	MSE Loss
Seq_len	96
Pred_len	96/192/336/720
d_model	24
d_ff	128
Patch length	4
Stride	4

Fredformer

Fredformer 재현 실험 (ETTh1, Weather)

- ETTh1의 경우, 예측 길이가 길어질수록 어느 정도의 오차가 발생하였지만 Weather는 논문과 거의 비슷한 수치가 나온 것을 확인

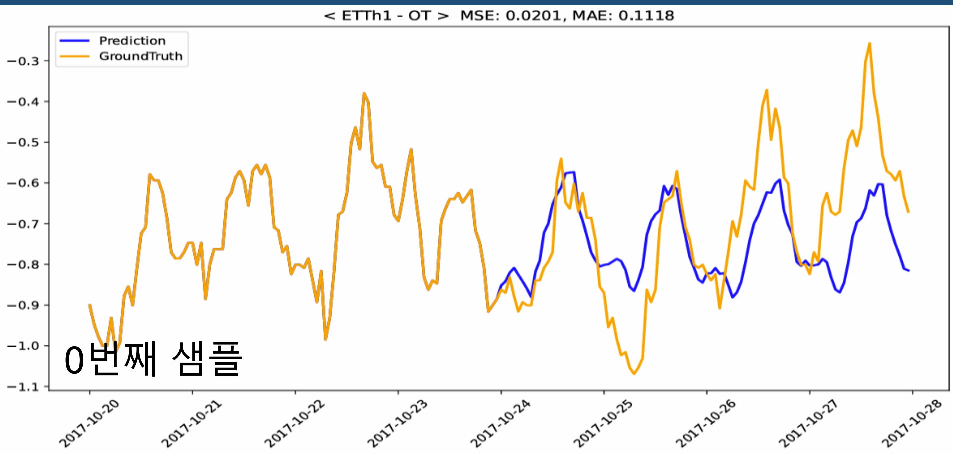
	ETTh1 Paper		ETTh1 Reproduction		Weather Paper		Weather Reproduction	
Pred len	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
96	0.373	0.392	0.376	0.394	0.163	0.207	0.160	0.204
192	0.433	0.420	0.440	0.426	0.211	0.251	0.211	0.252
336	0.470	0.437	0.475	0.441	0.267	0.292	0.264	0.291
720	0.467	0.456	0.496	0.472	0.343	0.341	0.340	0.340

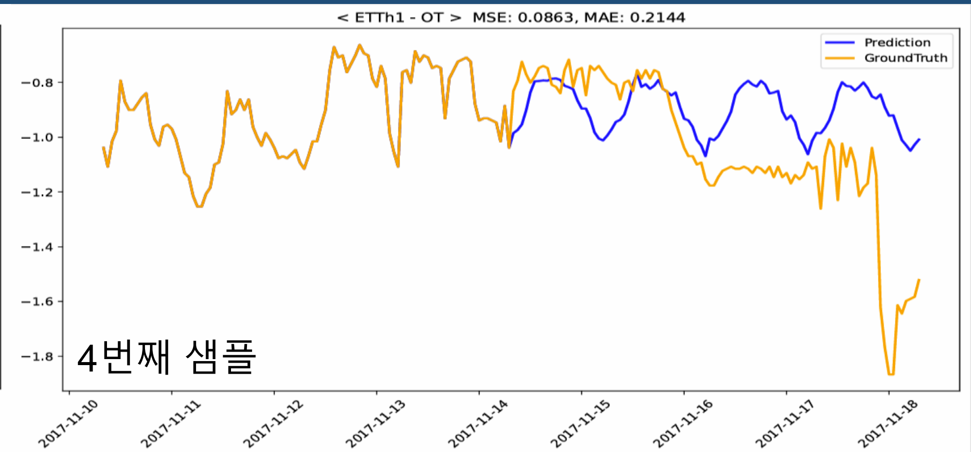
Fredformer

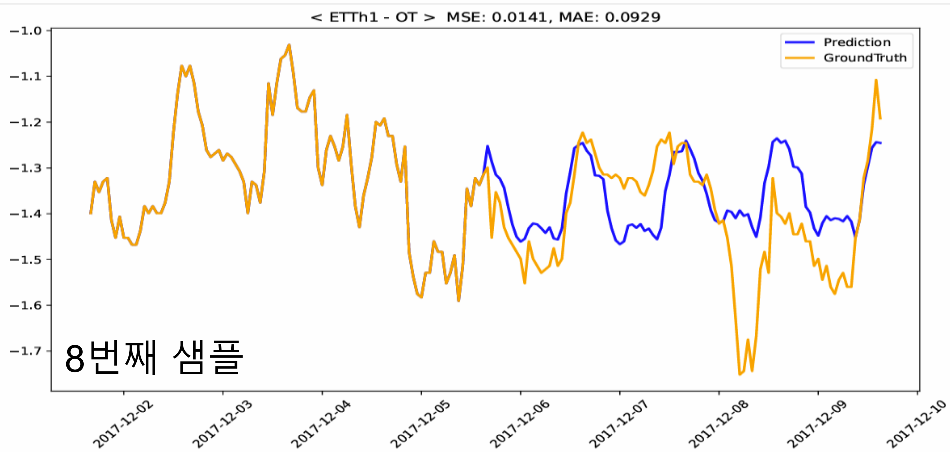
FAIR Lab

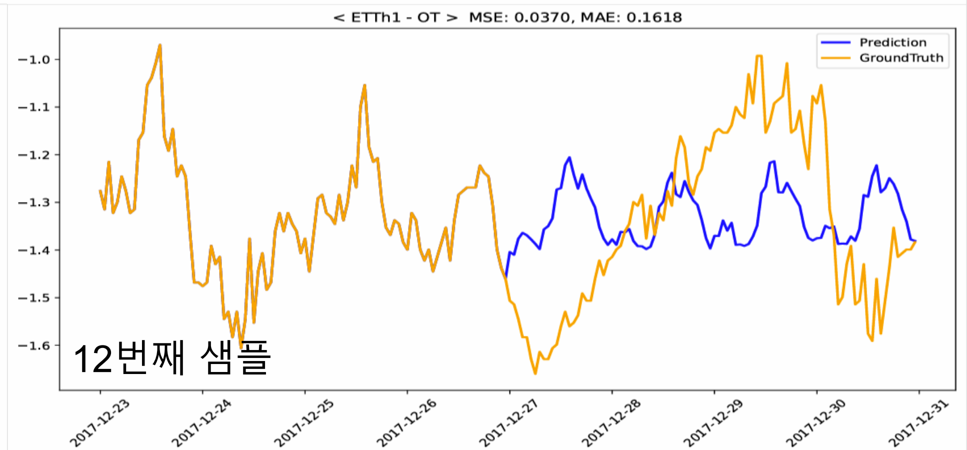
KWANGWOON UNIVERSITY

Fredformer 재현 실험 시각화 (ETTh1)









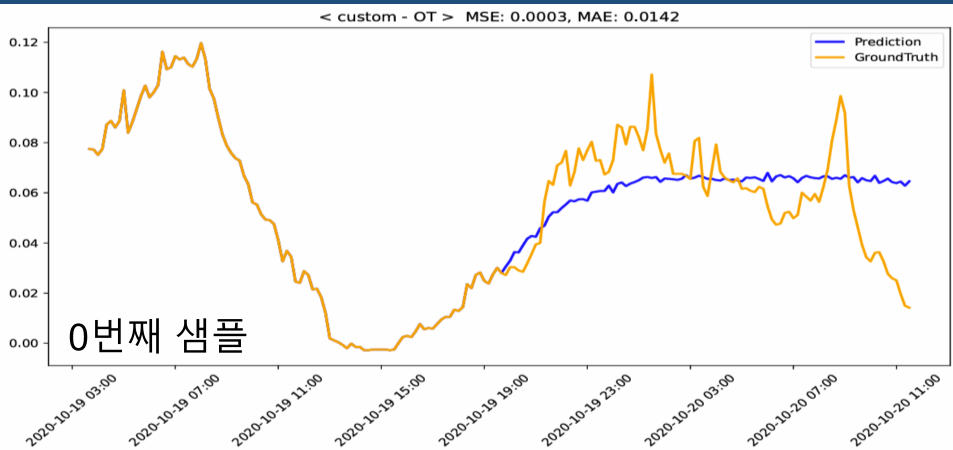
Seq_len → 96
Pred_len → 96

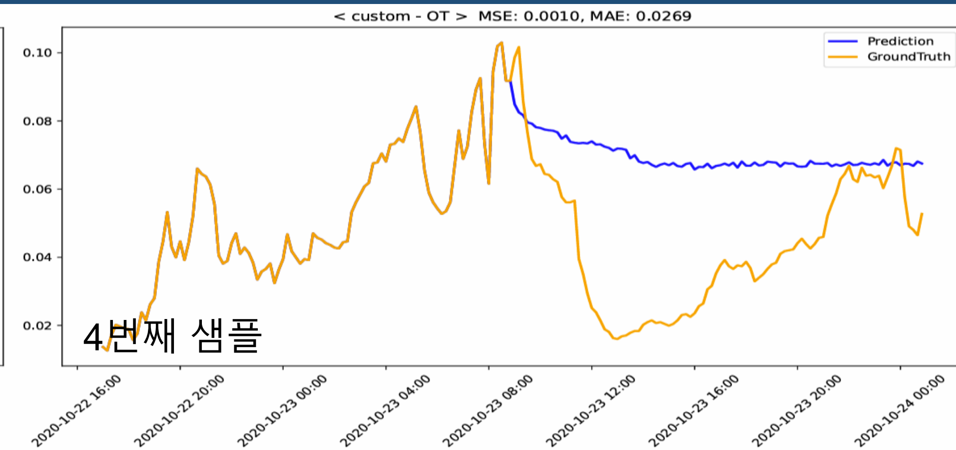
Fredformer

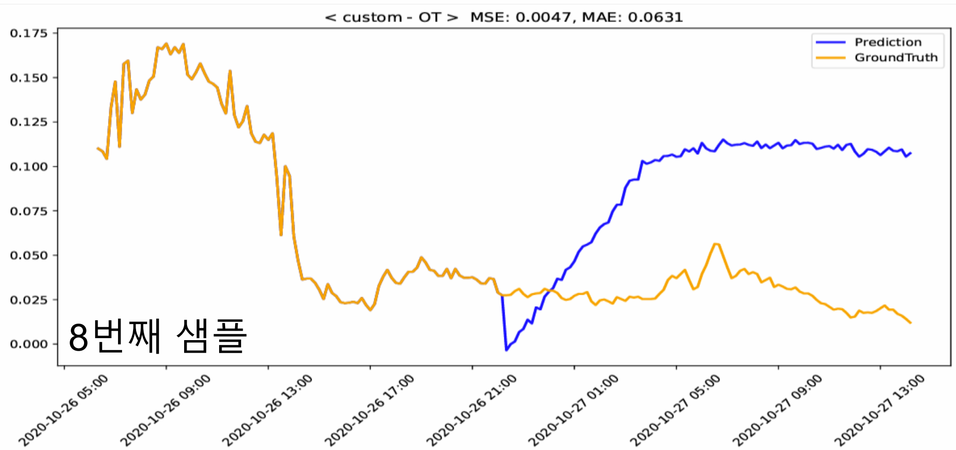
FAIR Lab

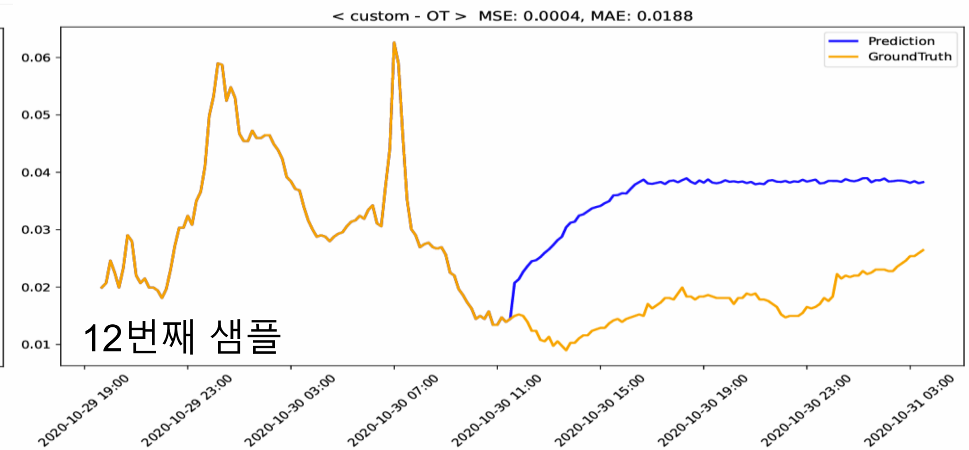
KWANGWOON UNIVERSITY

Fredformer 재현 실험 시각화 (Weather)









Seq_len → 96
Pred_len → 96

Fredformer

Fredformer, iTransformer, DLinear 비교 실험 (ETTh1)

- 논문 수치와 동일하게 ETTh1 데이터셋에서의 성능이 Fredformer가 가장 좋은 것을 확인

	Fredformer ETTh1		iTransformer ETTh1		DLinear ETTh1	
Pred len	MSE	MAE	MSE	MAE	MSE	MAE
96	**0.376**	**0.394**	0.385	0.404	0.396	0.410
192	**0.440**	**0.426**	**0.440**	0.436	0.445	0.440
336	**0.475**	**0.441**	0.491	0.460	0.487	0.465
720	**0.496**	**0.472**	0.509	0.493	0.512	0.510

Fredformer

실험 결과 정리

- 재현 실험
  - ETTh1, Weather 데이터셋 모두 논문 수치와 비슷한 수치가 나옴
- 시각화
  - ETTh1의 경우, 예측값이 변동을 잘 따라가는 모습을 보였지만, 변동성이 큰 Weather는 예측값이 변동을 잘 따라가지 못하는 모습을 보임
- 비교 실험
  - Fredformer가 기존 모델인 iTransformer, DLinear보다 전체적으로 더 뛰어난 성능을 보여줌