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발표 자료

광운대학교 로봇학과
FAIR Lab

김한서

이번 주 진행사항

- TimeMixer
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  - 실험 세팅
  - 실험 결과 및 시각화
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TIMEMIXER: DECOMPOSABLE MULTISCALE MIXING FOR TIME SERIES FORECASTING

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- 인용 수: 651회(Google Scholar, 2025-11-23)
- Published at ICLR 2024
- TimeMixer는 Multiscale-Mixing 관점에서 시계열의 미시/거시적 정보를 분리하고, 이를 PDM(Past-Decomposable-Mixing)과 FMM(Future-Multipredictor-Mixing)으로 활용하는 MLP 기반 모델을 제안

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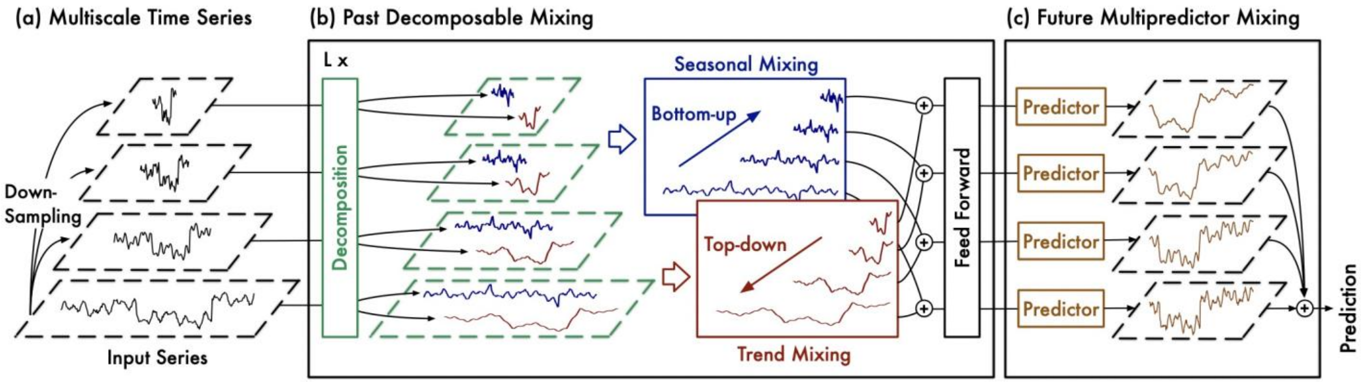
모델 구조



- (a) Multiscale Time Series
  - 시계열 데이터를 Average Pooling을 통해 압축하여 *M*개의 Scale로 다운 샘플링
  - 위로 올라갈수록 정보가 압축되어 Fine scale에서 Coarse scale이 됨
- (b) Past Decomposable Mixing
  - 각 Scale을 Decomposition을 통해 계절성과 추세 성분으로 분해
  - 분리된 계절성과 추세가 각각 Seasonal mixing, Trend mixing을 거친 뒤, 다시 합쳐짐
- (c) Future Multipredictor Mixing
  - 각 Scale별로 독립적인 예측기가 미래를 예측하고, 이를 합하여 최종 결과를 도출

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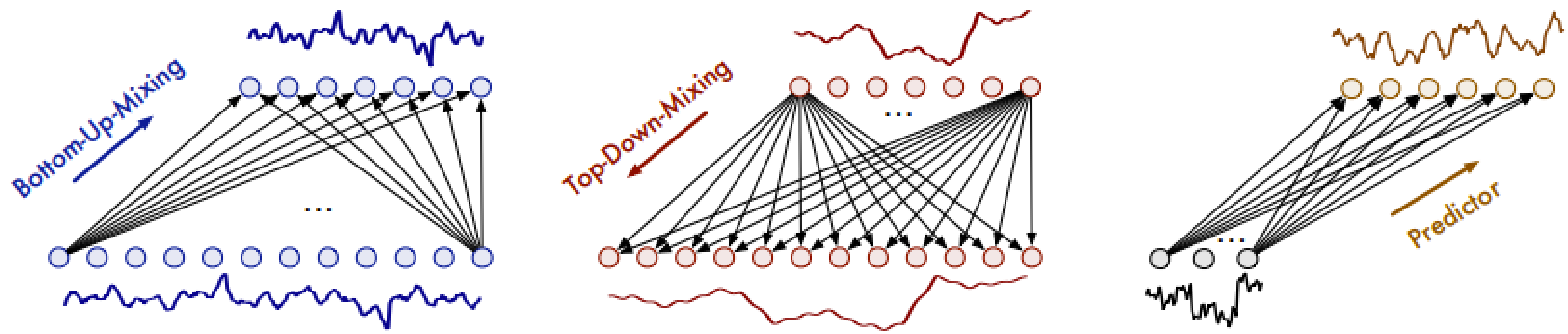
모델 세부 구조



(a) Seasonal Mixing (b) Trend Mixing (c) Future Prediction

- (a) Seasonal Mixing
  - Bottom-Up 방식 사용, Fine scale의 세밀한 주기 정보를 Coarse scale에 전달해 계절성을 보정
- (b) Trend Mixing
  - Top-Down 방식 사용, Coarse scale의 전체적인 추세 정보를 Fine scale에 전달해 추세 예측을 가이드
- (c) Future Prediction
  - 계절성과 추세를 다시 합친 스케일을 예측기에 전달해 미래 예측

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주요 모델 성능 비교

Models		TimeMixer (Ours)		PatchTST 2023		TimesNet 2023a		Crossformer 2023		MICN 2023		FiLM 2022a		DLinear 2023		FEDformer 2022b		Stationary 2022b		Autoformer 2021		Informer 2021	
Metric		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Weather	96	0.163	0.209	0.186	0.227	0.172	0.220	0.195	0.271	0.198	0.261	0.195	0.236	0.195	0.252	0.217	0.296	0.173	0.223	0.266	0.336	0.300	0.384
	192	0.208	0.250	0.234	0.265	0.219	0.261	0.209	0.277	0.239	0.299	0.239	0.271	0.237	0.295	0.276	0.336	0.245	0.285	0.307	0.367	0.598	0.544
	336	0.251	0.287	0.284	0.301	0.246	0.337	0.273	0.332	0.285	0.336	0.289	0.306	0.282	0.331	0.339	0.380	0.321	0.338	0.359	0.395	0.578	0.523
	720	0.339	0.341	0.356	0.349	0.365	0.359	0.379	0.401	0.351	0.388	0.361	0.351	0.345	0.382	0.403	0.428	0.414	0.410	0.419	0.428	1.059	0.741
	Avg	0.240	0.271	0.265	0.285	0.251	0.294	0.264	0.320	0.268	0.321	0.271	0.291	0.265	0.315	0.309	0.360	0.288	0.314	0.338	0.382	0.634	0.548
Solar-Energy	96	0.189	0.259	0.265	0.323	0.373	0.358	0.232	0.302	0.257	0.325	0.333	0.350	0.290	0.378	0.286	0.341	0.321	0.380	0.456	0.446	0.287	0.323
	192	0.222	0.283	0.288	0.332	0.397	0.376	0.371	0.410	0.278	0.354	0.371	0.372	0.320	0.398	0.291	0.337	0.346	0.369	0.588	0.561	0.297	0.341
	336	0.231	0.292	0.301	0.339	0.420	0.380	0.495	0.515	0.298	0.375	0.408	0.385	0.353	0.415	0.354	0.416	0.357	0.387	0.595	0.588	0.367	0.429
	720	0.223	0.285	0.295	0.336	0.420	0.381	0.526	0.542	0.299	0.379	0.406	0.377	0.357	0.413	0.380	0.437	0.375	0.424	0.733	0.633	0.374	0.431
	Avg	0.216	0.280	0.287	0.333	0.403	0.374	0.406	0.442	0.283	0.358	0.380	0.371	0.330	0.401	0.328	0.383	0.350	0.390	0.586	0.557	0.331	0.381
Electricity	96	0.153	0.247	0.190	0.296	0.168	0.272	0.219	0.314	0.180	0.293	0.198	0.274	0.210	0.302	0.193	0.308	0.169	0.273	0.201	0.317	0.274	0.368
	192	0.166	0.256	0.199	0.304	0.184	0.322	0.231	0.322	0.189	0.302	0.198	0.278	0.210	0.305	0.201	0.315	0.182	0.286	0.222	0.334	0.296	0.386
	336	0.185	0.277	0.217	0.319	0.198	0.300	0.246	0.337	0.198	0.312	0.217	0.300	0.223	0.319	0.214	0.329	0.200	0.304	0.231	0.443	0.300	0.394
	720	0.225	0.310	0.258	0.352	0.220	0.320	0.280	0.363	0.217	0.330	0.278	0.356	0.258	0.350	0.246	0.355	0.222	0.321	0.254	0.361	0.373	0.439
	Avg	0.182	0.272	0.216	0.318	0.193	0.304	0.244	0.334	0.196	0.309	0.223	0.302	0.225	0.319	0.214	0.327	0.193	0.296	0.227	0.338	0.311	0.397
Traffic	96	0.462	0.285	0.526	0.347	0.593	0.321	0.644	0.429	0.577	0.350	0.647	0.384	0.650	0.396	0.587	0.366	0.612	0.338	0.613	0.388	0.719	0.391
	192	0.473	0.296	0.522	0.332	0.617	0.336	0.665	0.431	0.589	0.356	0.600	0.361	0.598	0.370	0.604	0.373	0.613	0.340	0.616	0.382	0.696	0.379
	336	0.498	0.296	0.517	0.334	0.629	0.336	0.674	0.420	0.594	0.358	0.610	0.367	0.605	0.373	0.621	0.383	0.618	0.328	0.622	0.337	0.777	0.420
	720	0.506	0.313	0.552	0.352	0.640	0.350	0.683	0.424	0.613	0.361	0.691	0.425	0.645	0.394	0.626	0.382	0.653	0.355	0.660	0.408	0.864	0.472
	Avg	0.484	0.297	0.529	0.341	0.620	0.336	0.667	0.426	0.593	0.356	0.637	0.384	0.625	0.383	0.610	0.376	0.624	0.340	0.628	0.379	0.764	0.416
ETTh1	96	0.375	0.400	0.460	0.447	0.384	0.402	0.423	0.448	0.426	0.446	0.438	0.433	0.397	0.412	0.395	0.424	0.513	0.491	0.449	0.459	0.865	0.713
	192	0.429	0.421	0.512	0.477	0.436	0.429	0.471	0.474	0.454	0.464	0.493	0.466	0.446	0.441	0.469	0.470	0.534	0.504	0.500	0.482	1.008	0.792
	336	0.484	0.458	0.546	0.496	0.638	0.469	0.570	0.546	0.493	0.487	0.547	0.495	0.489	0.467	0.530	0.499	0.588	0.535	0.521	0.496	1.107	0.809
	720	0.498	0.482	0.544	0.517	0.521	0.500	0.653	0.621	0.526	0.526	0.586	0.538	0.513	0.510	0.598	0.544	0.643	0.616	0.514	0.512	1.181	0.865
	Avg	0.447	0.440	0.516	0.484	0.495	0.450	0.529	0.522	0.475	0.480	0.516	0.483	0.461	0.457	0.498	0.484	0.570	0.537	0.496	0.487	1.040	0.795
ETTh2	96	0.289	0.341	0.308	0.355	0.340	0.374	0.745	0.584	0.372	0.424	0.322	0.364	0.340	0.394	0.358	0.397	0.476	0.458	0.346	0.388	3.755	1.525
	192	0.372	0.392	0.393	0.405	0.402	0.414	0.877	0.656	0.492	0.492	0.404	0.414	0.482	0.479	0.429	0.439	0.512	0.493	0.456	0.452	5.602	1.931
	336	0.386	0.414	0.427	0.436	0.452	0.452	1.043	0.731	0.607	0.555	0.435	0.445	0.591	0.541	0.496	0.487	0.552	0.551	0.482	0.486	4.721	1.835
	720	0.412	0.434	0.436	0.450	0.462	0.468	1.104	0.763	0.824	0.655	0.447	0.458	0.839	0.661	0.463	0.474	0.562	0.560	0.515	0.511	3.647	1.625
	Avg	0.364	0.395	0.391	0.411	0.414	0.427	0.942	0.684	0.574	0.531	0.402	0.420	0.563	0.519	0.437	0.449	0.526	0.516	0.450	0.459	4.431	1.729
ETTm1	96	0.320	0.357	0.352	0.374	0.338	0.375	0.404	0.426	0.365	0.387	0.353	0.370	0.346	0.374	0.379	0.419	0.386	0.398	0.505	0.475	0.672	0.571
	192	0.361	0.381	0.390	0.393	0.374	0.387	0.450	0.451	0.403	0.408	0.389	0.387	0.382	0.391	0.426	0.441	0.459	0.444	0.553	0.496	0.795	0.669
	336	0.390	0.404	0.421	0.414	0.410	0.411	0.532	0.515	0.436	0.431	0.421	0.408	0.415	0.415	0.445	0.459	0.495	0.464	0.621	0.537	1.212	0.871
	720	0.454	0.441	0.462	0.449	0.478	0.450	0.666	0.589	0.489	0.462	0.481	0.441	0.473	0.451	0.543	0.490	0.585	0.516	0.671	0.561	1.166	0.823
	Avg	0.381	0.395	0.406	0.407	0.400	0.406	0.513	0.495	0.423	0.422	0.411	0.402	0.404	0.408	0.448	0.452	0.481	0.456	0.588	0.517	0.961	0.734
ETTm2	96	0.175	0.258	0.183	0.270	0.187	0.267	0.287	0.366	0.197	0.296	0.183	0.266	0.193	0.293	0.203	0.287	0.192	0.274	0.255	0.339	0.365	0.453
	192	0.237	0.299	0.255	0.314	0.249	0.309	0.414	0.492	0.284	0.361	0.248	0.305	0.284	0.361	0.269	0.328	0.280	0.339	0.281	0.340	0.533	0.563
	336	0.298	0.340	0.309	0.347	0.321	0.351	0.597	0.542	0.381	0.429	0.309	0.343	0.382	0.429	0.325	0.366	0.334	0.361	0.339	0.372	1.363	0.887
	720	0.391	0.396	0.412	0.404	0.408	0.403	1.730	1.042	0.549	0.522	0.410	0.400	0.558	0.525	0.421	0.415	0.417	0.413	0.433	0.432	3.379	1.338
	Avg	0.275	0.323	0.290	0.334	0.291	0.333	0.757	0.610	0.353	0.402	0.287	0.329	0.354	0.402	0.305	0.349	0.306	0.347	0.327	0.371	1.410	0.810

- PatchTST, DLinear 등 기존 모델들과 비교했을 때, 전체적으로 TimeMixer가 더 좋은 성능을 보임
- 변동성이 큰 Weather 데이터셋에서도 TimeMixer가 가장 좋은 성능을 보임

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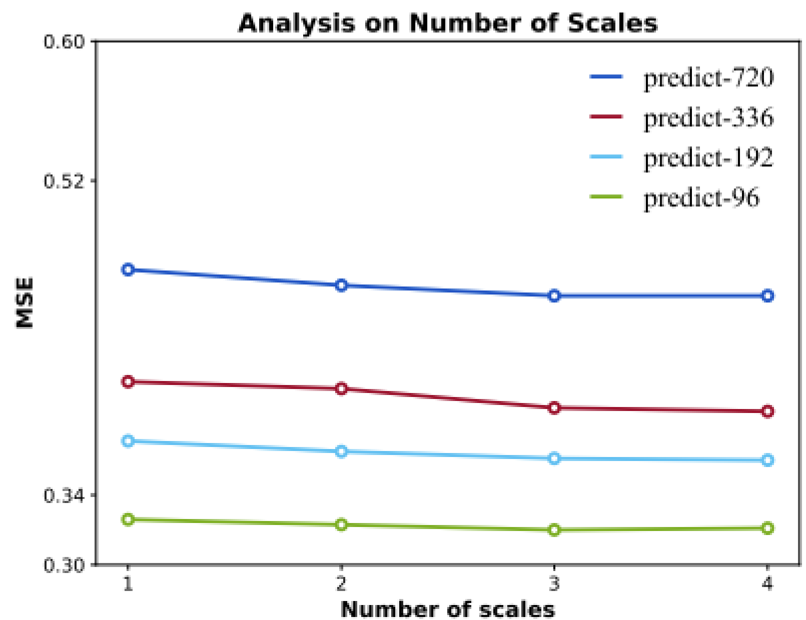
Scale 개수에 따른 성능 변화



- Scale 개수가 늘어날수록 전반적으로 오차가 감소하는 것을 확인
- 단기 예측인 96보다 장기 예측인 720에서의 성능 향상 폭이 더 큼,
  Coarse scale의 전체적인 추세 정보가 장기 예측에 중요하게 작용한 것을 확인

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실험 세팅

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

Experiment	ETTh1, Weather
Learning rate	10^{-2}
Epoch	10
Batch size	128
Loss function	MSE Loss
Seq_len	96
Down Sampling Layers	3
Pred_len	96/192/336/720
d_model	16
d_ff	32

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TimeMixer 재현 실험 (ETTh1, Weather)

- 오차가 어느정도 있지만, 전체적으로 논문 수치와 비슷한 결과가 나온 것을 확인하였음

	ETTh1 Paper		ETTh1 Reproduction		Weather Paper		Weather Reproduction	
Pred len	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
96	0.375	0.400	0.378	0.398	0.163	0.209	0.162	0.208
192	0.429	0.421	0.440	0.430	0.208	0.250	0.209	0.253
336	0.484	0.458	0.500	0.460	0.251	0.287	0.263	0.290
720	0.498	0.482	0.478	0.472	0.339	0.341	0.343	0.345

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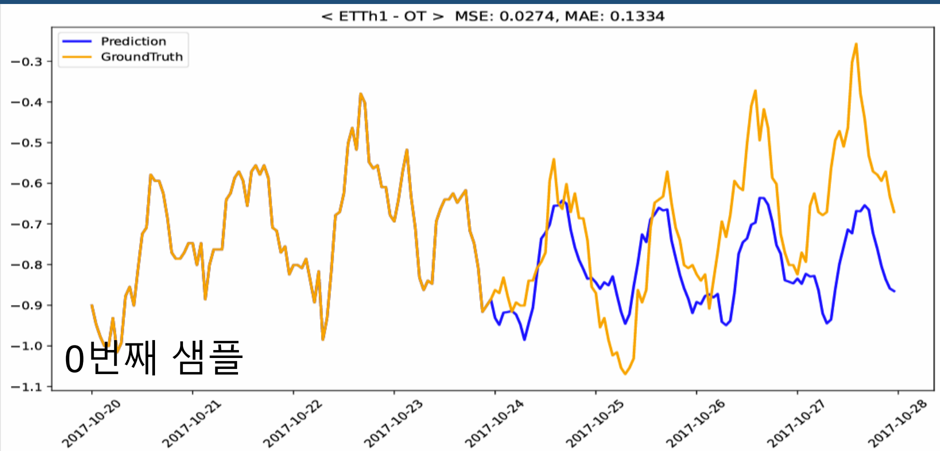
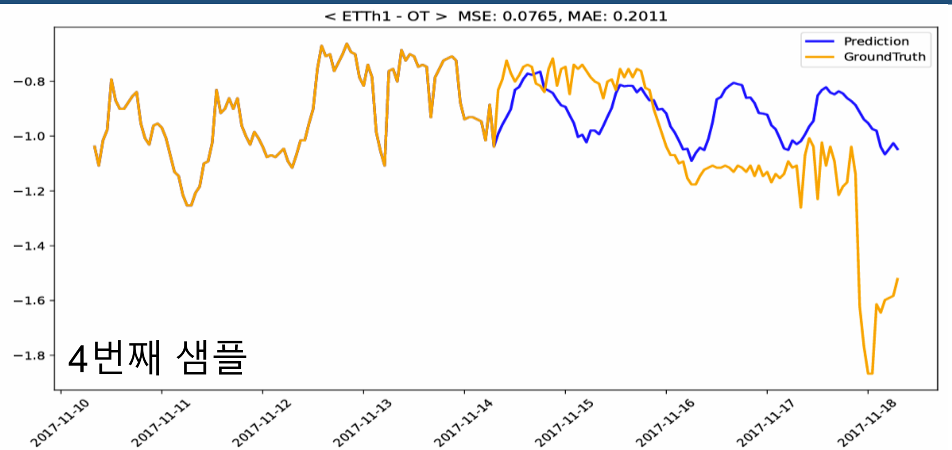
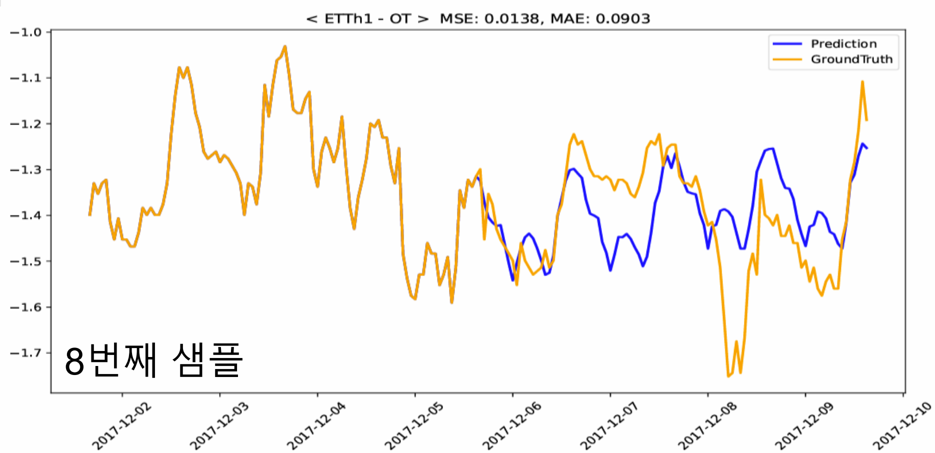
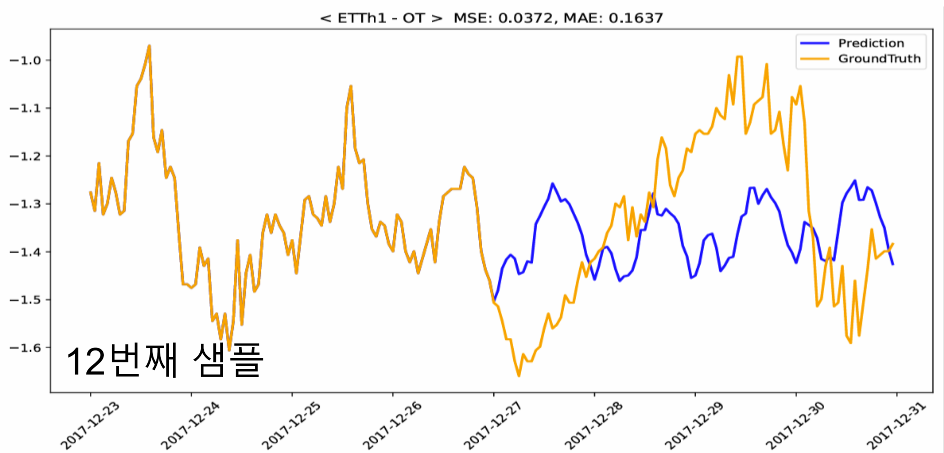
TimeMixer 재현 실험 시각화 (ETTh1)









Seq_len → 96
Pred_len → 96

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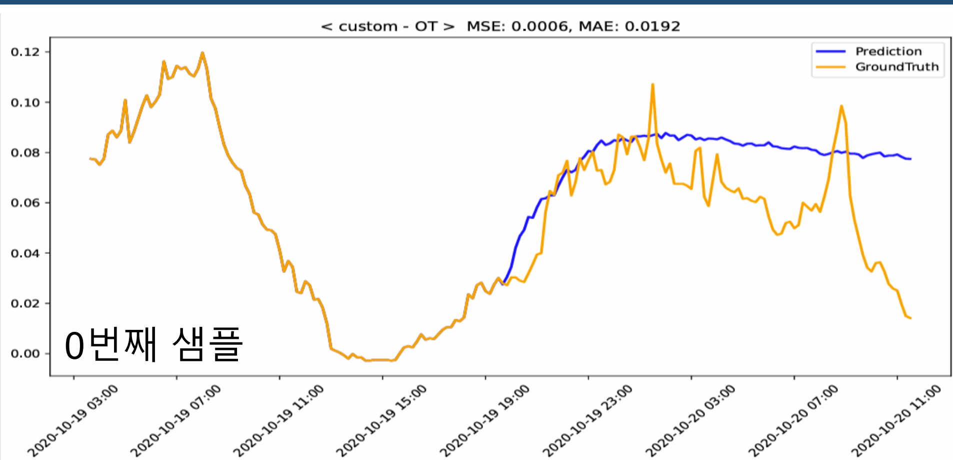
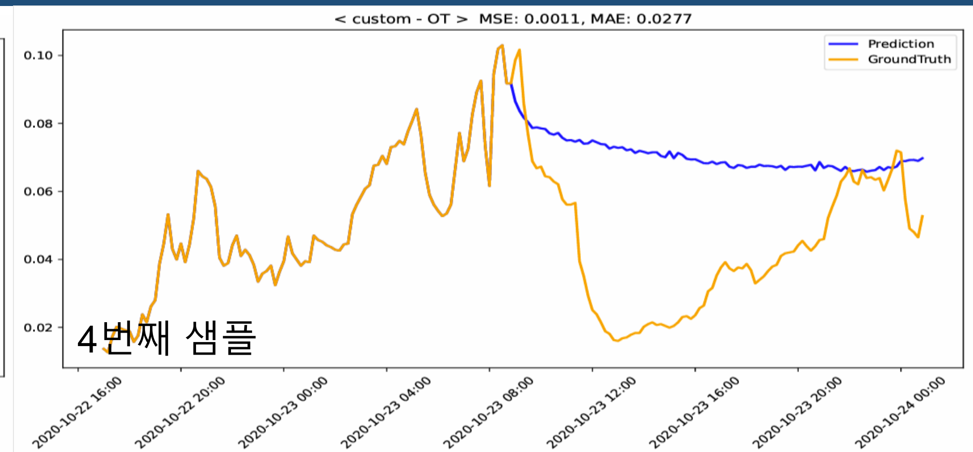
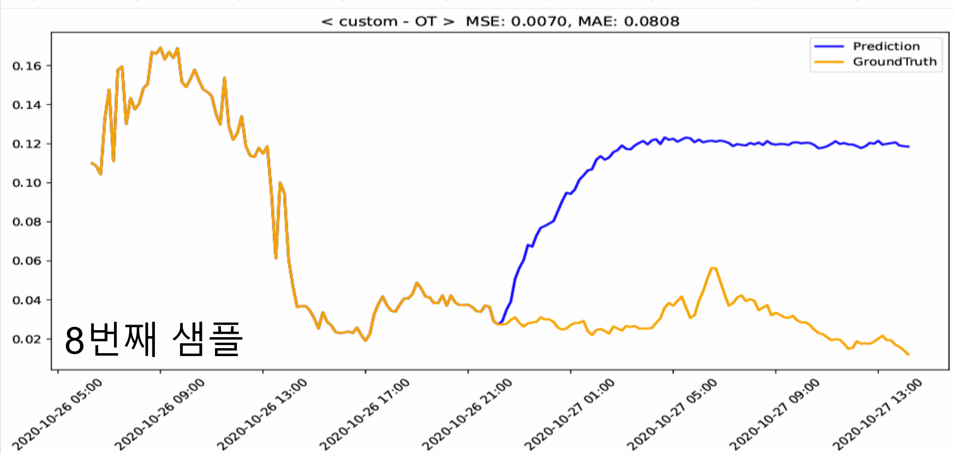
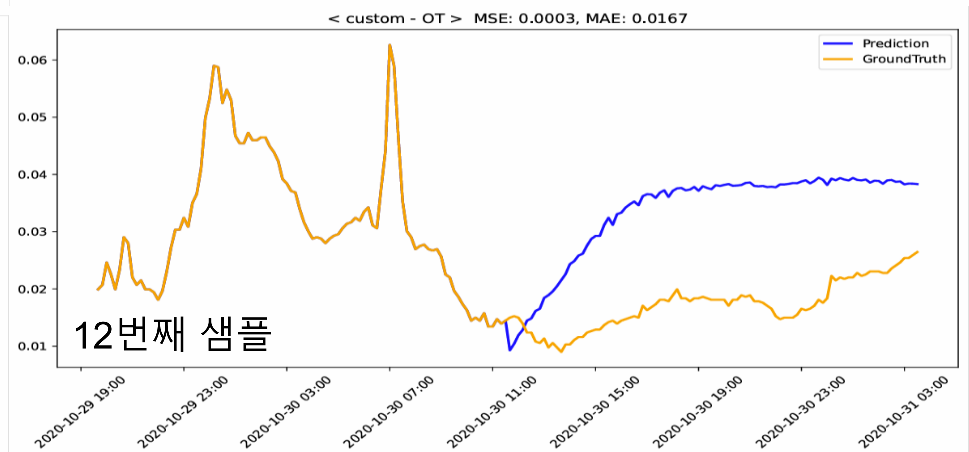
TimeMixer 재현 실험 시각화 (Weather)









Seq_len → 96
Pred_len → 96

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TimeMixer, DLinear, PatchTST 비교 실험 (ETTh1, Weather)

- ETTh1 데이터셋과 변동성이 큰 Weather 데이터셋에서도 TimeMixer가 가장 좋은 성능을 보인다는 것을 확인하였음

	TimeMixer ETTh1		DLinear ETTh1		PatchTST ETTh1		TimeMixer Weather		DLinear Weather		PatchTST Weather	
Pred len	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
96	**0.378**	**0.398**	<u>0.396</u>	<u>0.410</u>	0.475	0.457	**0.162**	**0.208**	0.195	0.255	<u>0.175</u>	<u>0.219</u>
192	**0.440**	**0.430**	<u>0.445</u>	<u>0.440</u>	0.516	0.479	**0.209**	**0.253**	0.238	0.299	<u>0.221</u>	<u>0.256</u>
336	<u>0.500</u>	**0.460**	**0.487**	<u>0.465</u>	0.551	0.498	**0.263**	**0.290**	0.281	0.330	<u>0.280</u>	<u>0.298</u>
720	**0.478**	**0.472**	<u>0.512</u>	<u>0.510</u>	0.551	0.518	**0.343**	**0.345**	<u>0.345</u>	0.381	0.357	<u>0.349</u>

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실험 결과 정리

- 재현 실험
  - ETTh1, Weather 데이터셋 모두 논문과 비슷한 수치가 나온 것을 확인
  - 비교 실험에서, 기존 모델인 DLinear과 PatchTST보다 더 뛰어난 성능을 보임
- 시각화
  - ETTh1에서는 예측값이 정답값을 어느정도 잘 따라가는 모습을 보였지만, 변동성이 큰 Weather에서는 잘 따라가지 못 하는 모습을 보임