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발표 자료

광운대학교 로봇학과  
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김한서

# 이번 주 진행사항

- CAlformer
  - 논문 리뷰

# CAIFORMER: A CAUSAL INFORMED TRANSFORMER FOR MULTIVARIATE TIME SERIES FORECASTING

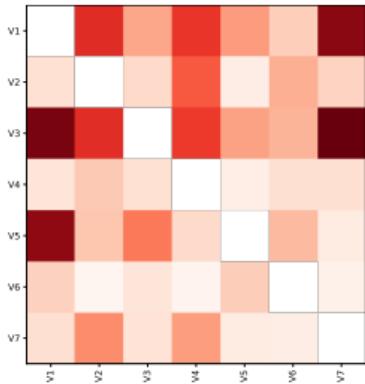
Xingyu Zhang<sup>1,2</sup>, Wenwen Qiang<sup>1,2</sup>, Siyu Zhao<sup>1</sup>, Huijie Guo<sup>1,2</sup>, Jiangmeng Li<sup>1,2</sup>, Chuxiong Sun<sup>1,2</sup> and Changwen Zheng<sup>1,2</sup>

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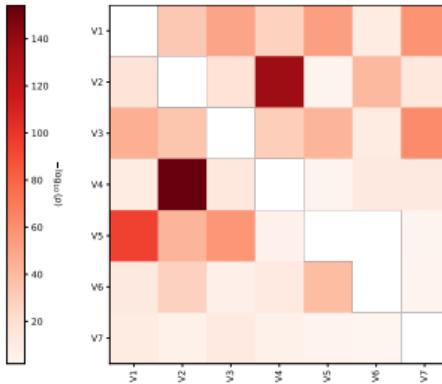
- arXiv 등록일: 2025-05-22
- 인용 수: 3회(Google Scholar, 2026-02-10)
- ICLR 2026 reject
- 링크: <https://openreview.net/pdf?id=Z97AqtNa81>

# CAIformer

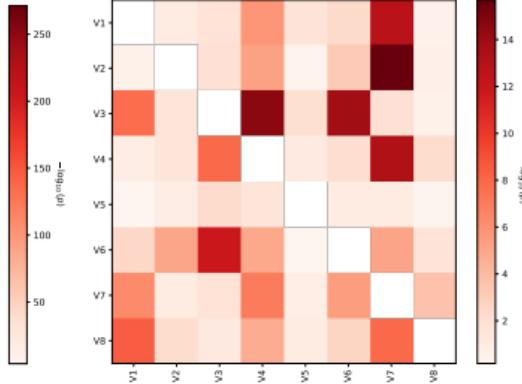
## Background



(a) ETTh1



(b) ETTm1

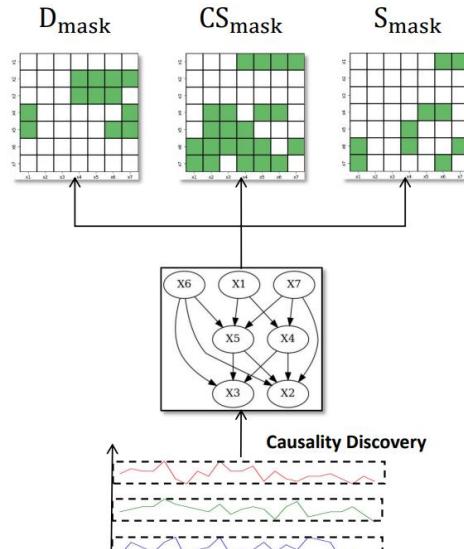


(c) Exchange

- 기존 Transformer 방식
  - All-to-all 예측 방식으로, 인과 관계가 없는 변수들까지 학습하기 때문에 노이즈가 발생하여 일반화 성능이 저하됨
- CAIformer 방식
  - 입력 데이터를 내생적(Endogenous), 직접 인과(Direct Causal), 콜라이더 인과(Collider Causal), 가짜 상관관계(Spurious Correlation)의 세그먼트로 분리, 이후 관계없는 변수들을 입력에서 제외하여 일반화 성능 향상

# CAIformer

## 마스킹 생성 및 적용 과정



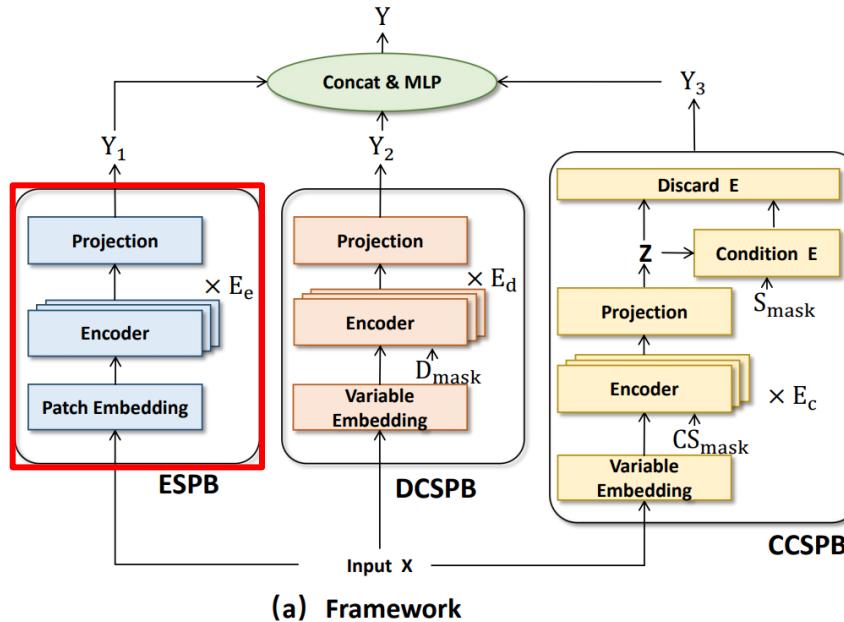
(c) Causal Discovery

- PC(peter-Clark) 알고리즘을 통해 변수 간 인과 관계를 나타내는 DAG(Directed Acyclic Graph) 도출  
이후에 DAG를 수치화하여 인접 행렬  $W_{adjm} \in \{-1, 0, 1\}^{D \times D}$  생성
- 타겟 변수  $V_i$ 를 기준으로 DAG 상의 경로를 분석해 4가지 Segment(ES, DCS, CCS, SCS) 정의
- 각 Segment를 인접 행렬에 적용해  $D_{mask}$ ,  $CS_{mask}$ ,  $S_{mask}$  동시 생성

\*ES (Endogenous): 타겟 변수 자신의 과거 데이터  
 \*DCS (Direct Causal): 직접적인 원인/결과 변수  
 \*CCS (Collider Causal): 콜라이더 구조로 얹힌 변수  
 \*SCS (Spurious Correlation): 인과 관계가 없는 변수

# CAformer

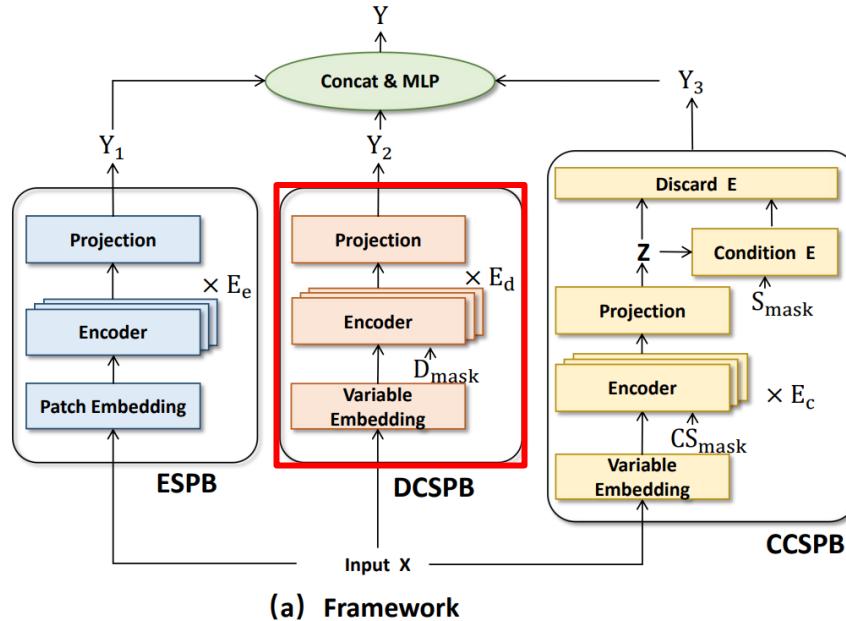
## 모델 구조



- ESPB(Endogenous Sub-segment Prediction Block)
  - Channel Independence 방식 사용
  - 외부 변수 없이, 타겟 변수  $v_i$  자신의 과거 데이터만을 사용하여 노이즈 방지
  - 예측 성능 변화가 변수 내부 요인 때문인지, 외부 요인 때문인지 판단하기 위해 사용

# CAIformer

## 모델 구조

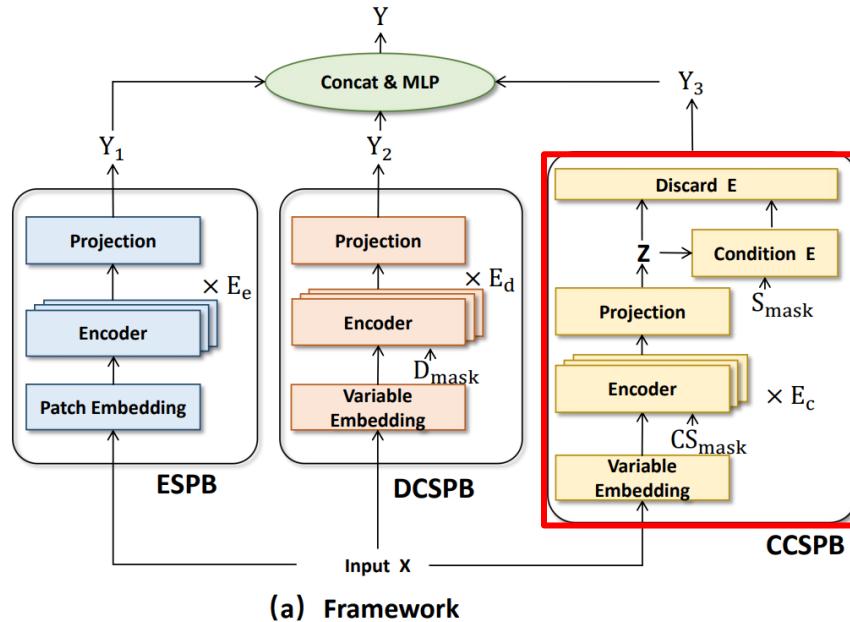


- DCSPB(Direct Causal Sub-segment Prediction Block)

- 각 채널을 하나의 독립된 토큰으로 사용해 채널 간 상관관계 포착
- Attention 과정에서  $D_{mask}$ 를 적용, 이를 통해 직접적인 연관이 없는 변수 간의 Attention을 방지

# CAIformer

## 모델 구조



- CCSPB(Collider Causal Sub-segment Prediction Block)
  - DCSPB와 동일하게 각 채널을 토큰화하여 사용, Attention 과정에서  $CS_{mask}$ 를 적용해 콜라이더 구조( $V_i \rightarrow V_c \leftarrow V_s$ )끼리만 Attention 수행
  - Condition E를 통해 콜라이더 구조에서 발생하는 가짜 상관관계를 분리 및 제거하여 일반화 성능 향상

# CAIformer

## 주요 모델 성능 비교

Models	Metric	CAIFormer (Ours)		TimePro (2025)		SEMPo (2025)		TFPS (2025)		iTtransformer (2024)		PatchTST (2023)		RLinear (2023)		Crossformer (2023)		TIDE (2023)		TimesNet (2023)		DLinar (2023)		FEDformer (2022)		Autoformer (2021)				
		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE			
ETThm1	96	0.327	<b>0.364</b>	0.466	0.443	0.327	0.367	0.334	0.368	0.329	0.367	0.355	0.376	0.404	0.426	0.364	0.387	0.338	0.375	0.345	0.372	0.379	0.419	0.505	0.475	0.339				
	192	<b>0.361</b>	0.377	0.367	0.383	0.484	0.455	<b>0.374</b>	0.395	0.377	0.391	0.367	0.385	0.391	0.392	0.450	0.451	0.404	0.374	0.387	0.380	0.389	0.426	0.441	0.553	0.496	0.339			
	336	<b>0.391</b>	0.402	0.402	0.409	0.506	0.469	0.401	0.408	0.426	0.420	0.399	0.410	0.424	0.415	0.532	0.515	0.428	0.425	0.410	0.411	0.413	0.445	0.459	0.621	0.537	0.339			
	720	<b>0.449</b>	0.437	0.469	0.446	0.557	0.498	0.479	0.456	0.491	0.459	<b>0.454</b>	0.439	0.487	0.450	0.666	0.589	0.487	0.461	0.478	0.450	0.474	0.453	0.543	0.490	0.671	0.561	0.339		
	Avg	<b>0.382</b>	<b>0.395</b>	0.391	<b>0.400</b>	0.503	0.466	0.395	0.406	0.407	0.410	<b>0.387</b>	<b>0.400</b>	0.414	0.407	0.513	0.496	0.419	0.419	0.400	0.406	0.403	0.407	0.448	0.452	0.588	0.517	0.339		
ETThm2	96	<b>0.168</b>	<b>0.255</b>	0.178	0.260	0.196	0.286	0.170	<b>0.255</b>	0.180	0.264	0.175	0.259	0.182	0.265	0.287	0.366	0.207	0.305	0.187	0.267	0.193	0.292	0.203	0.287	0.255	0.339	0.339		
	192	<b>0.240</b>	<b>0.302</b>	0.242	0.303	0.252	0.323	<b>0.235</b>	0.296	0.250	0.309	0.241	<b>0.302</b>	0.246	0.304	0.414	0.492	0.290	0.364	0.249	0.309	0.284	0.362	0.269	0.328	0.281	0.340	0.340		
	336	0.300	0.339	0.303	0.342	0.306	0.354	<b>0.297</b>	<b>0.335</b>	0.311	0.348	0.305	0.343	0.307	0.342	0.597	0.542	0.377	0.422	0.321	0.351	0.369	0.427	0.325	0.366	0.339	0.372	0.339		
	720	0.398	<b>0.397</b>	0.400	0.399	<b>0.391</b>	0.404	0.401	<b>0.397</b>	0.412	0.407	0.402	0.400	0.407	0.399	1.730	1.042	0.558	0.524	0.408	0.403	0.554	0.522	0.421	0.415	0.433	0.432	0.339		
	Avg	<b>0.276</b>	0.323	<b>0.281</b>	0.326	0.286	0.341	0.276	<b>0.321</b>	0.288	0.332	<b>0.281</b>	0.326	0.286	0.327	0.757	0.610	0.358	0.404	0.291	0.333	0.350	0.401	0.305	0.349	0.327	0.371	0.339		
ETTh1	96	<b>0.372</b>	0.399	0.375	0.398	0.384	0.408	0.398	<b>0.413</b>	0.386	0.405	0.414	0.419	0.386	<b>0.395</b>	0.423	0.448	0.479	0.464	0.384	0.402	0.386	0.400	0.376	0.419	0.449	0.459	0.459		
	192	0.429	0.426	<b>0.427</b>	<b>0.429</b>	<b>0.409</b>	0.426	<b>0.423</b>	0.423	0.441	0.436	0.460	0.445	0.437	0.424	0.471	0.474	0.525	0.492	0.436	0.429	0.437	0.432	0.420	0.448	0.500	0.482	0.482		
	336	0.464	0.449	0.472	0.450	<b>0.417</b>	<b>0.433</b>	0.484	0.461	0.487	0.458	0.501	0.466	0.479	0.446	0.570	0.546	0.565	0.515	0.491	0.469	0.481	0.459	0.465	0.521	0.496	0.496	0.496		
	720	0.495	0.483	<b>0.476</b>	0.474	<b>0.432</b>	<b>0.454</b>	0.488	0.476	0.503	0.491	0.500	0.488	0.481	0.470	0.653	0.594	0.558	0.521	0.500	0.519	0.516	0.506	0.507	0.514	0.512	0.496			
	Avg	0.439	0.439	<b>0.438</b>	0.438	<b>0.410</b>	<b>0.430</b>	0.448	0.443	0.454	0.447	0.469	0.454	0.446	0.434	0.529	0.522	0.541	0.507	0.458	0.450	0.456	0.452	0.440	0.460	0.496	0.487	0.487		
ETTh2	96	0.294	0.344	0.293	0.345	<b>0.282</b>	0.342	0.313	<b>0.355</b>	0.297	0.349	0.302	0.348	0.288	<b>0.338</b>	0.745	0.584	0.400	0.440	0.340	0.374	0.333	0.387	0.358	0.397	0.346	0.388	0.388	0.388	
	192	0.377	0.398	0.367	0.394	<b>0.334</b>	<b>0.384</b>	0.405	0.410	0.380	0.400	0.388	0.400	0.374	0.390	0.877	0.656	0.528	0.509	0.402	0.414	0.477	0.476	0.429	0.439	0.456	0.452	0.452	0.452	
	336	0.425	0.430	<b>0.419</b>	0.431	<b>0.355</b>	<b>0.403</b>	0.392	<b>0.415</b>	0.428	0.432	0.426	0.433	<b>0.415</b>	0.426	1.043	0.731	0.643	0.571	0.452	0.452	0.594	0.541	0.496	0.487	0.482	0.486	0.486	0.486	
	720	0.424	0.442	<b>0.427</b>	0.445	<b>0.395</b>	<b>0.435</b>	0.410	<b>0.433</b>	0.427	0.445	0.431	0.446	<b>0.420</b>	0.440	1.104	0.763	0.874	0.679	0.462	0.468	0.831	0.657	0.463	0.474	0.515	0.511	0.496	0.496	
	Avg	0.380	0.403	<b>0.377</b>	0.403	<b>0.341</b>	<b>0.391</b>	0.380	0.403	0.383	0.407	0.387	0.407	<b>0.374</b>	0.398	0.942	0.684	0.611	0.550	0.414	0.427	0.559	0.515	0.437	0.449	0.450	0.459	0.459	0.459	
Exchange	96	<b>0.083</b>	<b>0.201</b>	0.085	0.204	-	-	<b>0.083</b>	0.205	0.086	0.206	0.088	0.205	0.093	0.217	0.256	0.367	0.094	0.218	0.107	0.234	0.088	0.218	0.148	0.278	0.197	0.323			
	192	<b>0.173</b>	<b>0.295</b>	0.178	0.299	-	-	0.174	0.297	0.177	0.299	0.176	0.299	0.184	0.307	0.470	0.509	0.184	0.307	0.226	0.344	0.176	0.315	0.271	0.315	0.300	0.369	0.300	0.369	
	336	<b>0.292</b>	<b>0.395</b>	0.328	0.414	-	-	0.310	0.398	0.331	0.417	0.301	0.397	0.351	0.432	1.268	0.883	0.349	0.431	0.367	0.448	0.313	0.427	0.460	0.427	0.509	0.524	0.496	0.496	0.496
	720	0.832	0.688	<b>0.817</b>	<b>0.679</b>	-	-	1.011	0.756	0.847	0.691	0.901	0.714	0.886	0.714	1.767	1.068	0.852	0.698	0.964	0.746	0.839	0.695	1.195	0.695	1.447	0.941	0.941	0.941	
	Avg	<b>0.345</b>	<b>0.395</b>	<b>0.352</b>	<b>0.399</b>	-	-	0.395	0.414	0.360	0.403	0.367	0.404	0.378	0.417	0.940	0.707	0.730	0.413	0.416	0.443	0.354	0.414	0.519	0.429	0.613	0.539	0.539	0.539	
Weather	96	<b>0.147</b>	0.205	0.166	0.207	0.171	0.228	<b>0.154</b>	<b>0.202</b>	0.174	0.214	0.177	0.218	0.192	0.232	0.158	0.230	0.202	0.261	0.172	0.220	0.196	0.255	0.217	0.296	0.266	0.336	0.336		
	192	<b>0.195</b>	<b>0.243</b>	0.216	0.254	0.218	0.269	<b>0.205</b>	<b>0.249</b>	0.221	0.254	0.225	0.259	0.240	0.271	0.206	0.277	0.242	0.298	0.219	0.261	0.237	0.296	0.276	0.336	0.307	0.367	0.367		
	336	0.269	<b>0.285</b>	0.273	0.296	<b>0.267</b>	0.304	<b>0.262</b>	<b>0.289</b>	0.278	0.296	0.278	0.297	0.292	0.307	0.272	0.335	0.287	0.335	0.280	0.306	0.283	0.335	0.339	0.380	0.359	0.395	0.395		
	720	0.345	<b>0.340</b>	0.351	0.346	<b>0.336</b>	0.350	<b>0.344</b>	<b>0.342</b>	0.358	0.349	0.354	0.348	0.364	0.353	0.398	0.418	0.351	0.386	0.365	0.359	0.345	0.381	0.403	0.428	0.419	0.428			
	Avg	<b>0.239</b>	<b>0.268</b>	<b>0.251</b>	<b>0.276</b>	0.248	<b>0.287</b>	<b>0.241</b>	<b>0.271</b>	0.258	0.279	0.259	0.281	0.272	0.291	0.259	0.315	0.271	0.320	0.259	0.287	0.265	0.317	0.309	0.360	0.338	0.382	0.382		
ECL	96	<b>0.139</b>	0.235	<b>0.139</b>	<b>0.234</b>	0.168	0.271	0.149	<b>0.236</b>	0.148	0.240	0.181	0.270	0.201	0.281	0.219	0.314	0.237	0.329	0.168	0.272	0.197	0.282	0.193	0.308	0.201	0.317	0.211		
	192	<b>0.155</b>	<b>0.245</b>	0.156	0.249	0.183	0.283	0.162	<b>0.253</b>	0.188	0.274	0.201	0.283	0.231	0.322	0.236	0.330	0.184	0.289	0.196	0.285	0.201	0.315	0.222	0.334	0.222	0.334	0.222		
	336	0.171	<b>0.262</b>	0.172	<b>0.267</b>	0.198	0.297	0.200	<b>0.310</b>	0.178	0.269	0.204	0.293	0.215	0.298	0.246	0.337	0.249	0.344	0.198	0.300	0.209	0.301	0.214	0.329	0.231	0.338	0.231		
	720	0.209	0.303	<b>0.209</b>	<b>0.299</b>	0.238	0.329	0.220	<b>0.320</b>	0.225	0.317	0.246	0.324	0.257	0.331	0.280	0.363	0.284	0.373	0.220	0.320	0.245	0.333	0.246	0.355	0.254	0.361			
	Avg	<b>0.168</b>	<b>0.261</b>	<b>0.169</b>	<b>0.262</b>	0.196	<b>0.295</b>	0.183	<b>0.280</b>	0.178	0.270	0.205	0.290	0.219	0.294	0.244	0.334	0.251	0.344	0.192	0.295	0.212	0.300	0.214	0.327	0.227	0.338	0.238		
Traffic	96	<b>0.388</b>	<b>0.261</b>	-	-	0.441	<b>0.333</b>	-	-	0.395	<b>0.268</b>	0.462	0.295	0.649	0.522</															

# CAIformer

## Ablation Study

ESPB	DCSPB	CCSPB	Shuffle Mask	Weather		ETTh1		Exchange	
				MSE	MAE	MSE	MAE	MSE	MAE
w	w	w	No	0.239	0.268	0.439	0.439	0.345	0.395
w/o	w/o	w	No	0.354	0.345	0.533	0.527	0.448	0.497
w	w/o	w/o	No	0.259	0.281	0.469	0.454	0.367	0.404
w/o	w	w/o	No	0.282	0.326	0.491	0.483	0.415	0.463
w/o	w/o	w	Yes	0.378	0.369	0.551	0.548	0.471	0.522
w/o	w	w/o	Yes	0.331	0.370	0.512	0.509	0.439	0.487

- 핵심 모듈을 모두 적용했을 때의 성능 향상이 가장 큰 것을 확인하였음  
또한, ESPB 모듈의 성능 기여도가 가장 높은 것을 확인