

# Less is More

Efficient Time Series Dataset Condensation via Two-fold Modal Matching

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# 1. Introduction

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## 1.1 Motivation

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### Existing Methods

- Coreset construction
- Issues
  - Not optimal
  - Downstream tasks

## 1.2 Problem

### Challenge 1

- Effectiveness
  - Bi-level optimization
  - Capture relevant information
- Generalization
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- Effectiveness
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### Solution

- Curriculum Training Trajectory Matching (CT<sup>2</sup>D)
- Expert trajectories
  - Based on original dataset

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- Complex Temporal Dependencies
  - Existing methods focus on image
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### Solution

- Time Series Feature Extraction (TSFE)
  - Stacked TSOOperators
- Decomposition-Driven Frequency Matching (DDFM)
  - Analyze intermediate TSFE
  - Match to original data

## 1.3 Contributions

### Dataset Condensation

- Novel time series dataset condensation
- TSFE
- DDFM
- CT<sup>2</sup>M

## 2. Methodology

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## 2.1 Overview

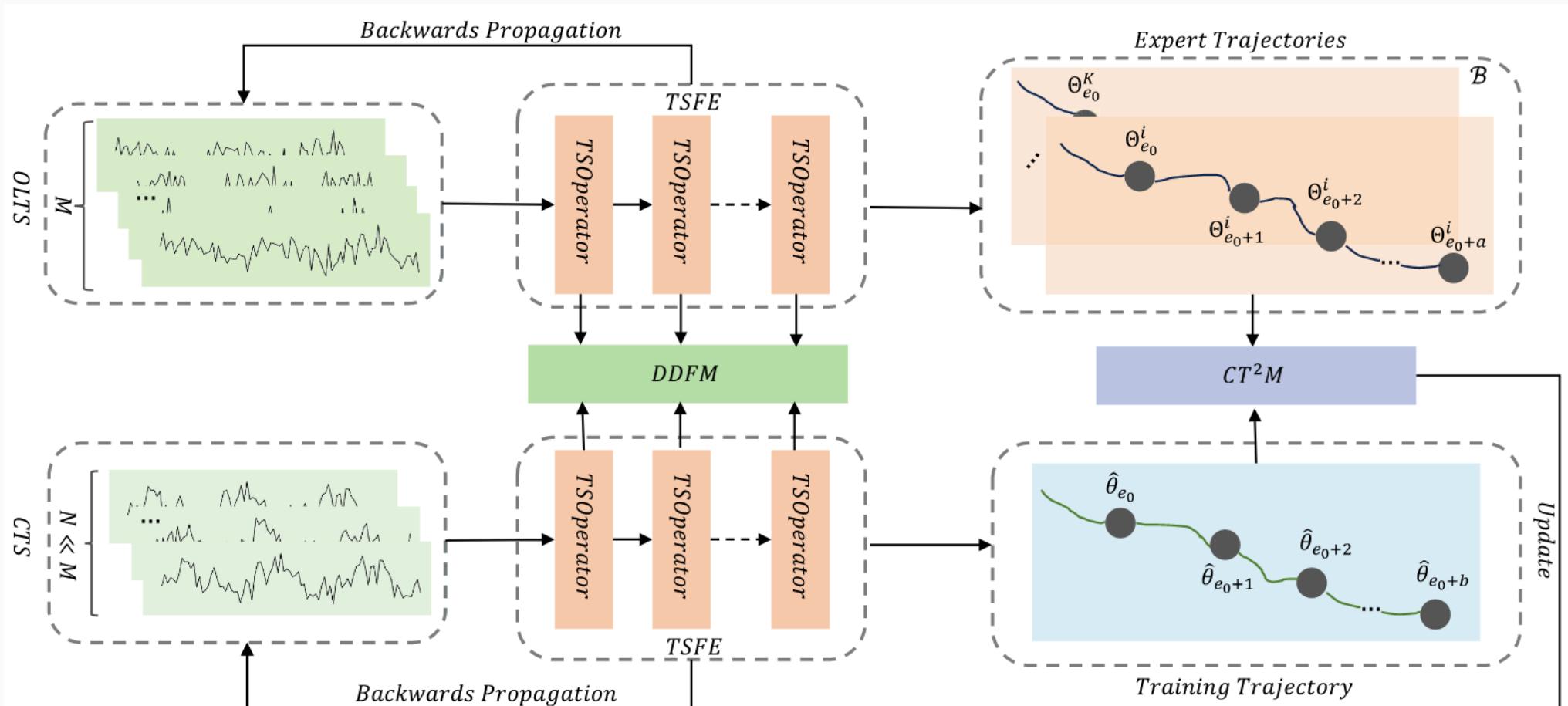


Figure 2: TimeDC Framework Overview

## 2.2 Time Series Feature Extraction

### Architecture

- Channel independent mechanism
  - Split variables
- Patching
  - Combine data
- Stacked TSOoperators
  - Self-attention
  - Fully connected
  - Normalization
- Concatenate to combine variables

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#### Algorithm 1: Time Series Feature Extraction

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**Input:** a batch of time series:  $T_{input} \in \mathcal{B} \times n \times C$ ; the number of  $TSOperators$ :  $N_{op}$ .

**Output:** extracted features:  $h$ .

```
1  $T_{input}^1, \dots, T_{input}^c, \dots, T_{input}^C \leftarrow$  Separate  $T_{input}$  into  $C$  univariate channel-independent time series with Equation 3;  
2 Split each univariate time series into patches;  
3 for  $1 \leq c \leq C$  do  
4    $h_c^0 \leftarrow T_{input}^c$ ;  
5   for  $0 < j < N_{op}$  do  
6     Feature extraction with Equation 4;  
7      $h_c^j \leftarrow TSOperator(h_c^{j-1})$ ;  
8    $h_c \leftarrow h_c^{N_{op}-1}$ ;  
9  $h \leftarrow$  Concatenate  $\{h_c\}_{c=1}^C$  along the channel;  
10 return  $h$ .
```

---

$$h^j = TSOperator(h^{j-1}) = Norm(FC(MultiHead(h^{j-1}))), \quad (4)$$

## 2.3 Decomposition-Driven Frequency Matching

### Architecture

- Works on intermediate TSFE output
- Splits representation
  - Trends (long-term)
  - Seasonality (the rest)
- Consine similarity to match
- Produces a “data-related” loss term
  - Relevant for back propagation

$$h_{TRE}^j = \text{AvgPool}(\text{Padding}(h^j)), h_{SEA}^j = h^j - h_{TRE}^j, \quad (6)$$

$$\cos(h_{TRE\mathcal{T}}^j, h_{TRE\mathcal{S}}^j) = \frac{h_{TRE\mathcal{T}}^j}{\|h_{TRE\mathcal{T}}^j\|_2} \cdot \frac{h_{TRE\mathcal{S}}^j}{\|h_{TRE\mathcal{S}}^j\|_2} \quad (8)$$

$$\cos(h_{SEA\mathcal{T}}^j, h_{SEA\mathcal{S}}^j) = \frac{h_{SEA\mathcal{T}}^j}{\|h_{SEA\mathcal{T}}^j\|_2} \cdot \frac{h_{SEA\mathcal{S}}^j}{\|h_{SEA\mathcal{S}}^j\|_2},$$

## 2.4 Curriculum Training Trajectory Matching

### Architecture

- Expert buffer and current model
  - Current model is based on expert
- Train current model  $a$  epochs
- Compare cosine for parameter movement
- Rank based on similarity
  - Easy → Hard
- Compute trajectory matching loss

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**Algorithm 2:** Curriculum Training Trajectory Query and Matching

---

**Input:** A buffer  $\mathcal{B}$  with a set of trajectories pre-trained on the original TS dataset  $\mathcal{T}$  parameterized by  $\{\Theta_{\mathcal{T}}^k\}_{k=1}^K$ ; current model parameters  $\tilde{\theta}^S$  on  $S$ .

**Output:** Trajectory matching loss  $L_{tmm}$ .

```
1 Distance list  $DT \leftarrow []$ ;  
2 Pre-update  $\tilde{\theta}^S$  for  $a$ -steps with Equation 13;  
3  $\tilde{\theta}_{e_0+a} \leftarrow \tilde{\theta}_{e_0} - \sum_{s=1}^a (\alpha \nabla \mathcal{L}(f_{\theta^S}, \mathcal{S}))$ ;  
4 for  $\Theta_{\mathcal{T}}^k \in \{\Theta_{\mathcal{T}}^k\}_{k=1}^K$  do  
5   Compute the distance  $disk$  between  $\tilde{\theta}|_{e_0}^a$  and  $\Theta_{\mathcal{T}}^k$  with  
   Equation 15;  
6    $disk \leftarrow -D(\tilde{\theta}|_{e=e_0}^a, \theta^k|_{e=e_0}^a)$ ;  
7    $DT \leftarrow (k, disk)$ ;  
8 Rank  $DT$  in a descending order;  
9  $\beta \leftarrow 0$   
10 while  $\beta < K$  do  
11    $k \leftarrow DT[\beta][0]$   
12    $L_{tmm} \leftarrow$  Sample trajectory  $\Theta_{\mathcal{T}}^k$  and match the training  
   trajectory according to Equation 11;  
13    $\beta \leftarrow \beta + 1$ ;  
14 return  $L_{tmm}$ 
```

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## 2.5 Loss

### Loss

- Task specific loss
  - ▶ How good is the data?
- Frequency related loss
  - ▶ How similar is the data?
- Trajectory matching loss
  - ▶ How does data affect training?

$$L_{\text{all}} = \mathcal{L} + L_{\text{Fre}} + L_{\text{tmm}} \quad (16)$$

### 3. Experiments

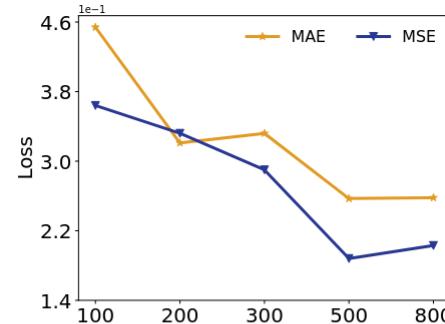
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### 3.1 Dataset Condensation

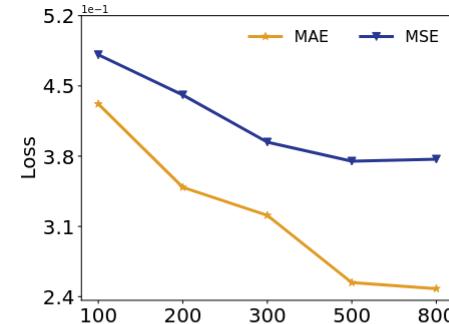
**Table 1: Overall Performance Comparison on Seven Datasets**

Baseline		Random		K-Center		Herding		DC		MTT		TimeDC		Whole Dataset	
Dataset	PL	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE
Weather	96	0.731	1.256	0.452	0.687	0.478	0.677	0.361	0.514	0.295	0.244	<b>0.257</b>	<b>0.188</b>	0.239	0.182
	192	0.786	1.302	0.487	0.723	0.512	0.688	0.413	0.527	0.344	0.301	<b>0.285</b>	<b>0.247</b>	0.261	0.195
	336	0.794	1.311	0.524	0.756	0.554	0.712	0.444	0.567	0.368	0.328	<b>0.330</b>	<b>0.287</b>	0.282	0.241
Traffic	96	0.675	1.125	0.503	0.576	0.483	0.554	0.375	0.603	0.279	0.403	<b>0.254</b>	<b>0.375</b>	0.247	0.337
	192	0.712	1.144	0.514	0.604	0.517	0.606	0.432	0.633	0.336	0.442	<b>0.297</b>	<b>0.405</b>	0.265	0.338
	336	0.729	1.117	0.523	0.611	0.553	0.654	0.449	0.676	0.355	0.471	<b>0.312</b>	<b>0.423</b>	0.297	0.360
Electricity	96	0.421	0.669	0.448	0.583	0.501	0.592	0.376	0.513	0.296	0.283	<b>0.274</b>	<b>0.267</b>	0.252	0.268
	192	0.450	0.743	0.476	0.601	0.534	0.628	0.419	0.532	0.315	0.337	<b>0.285</b>	<b>0.294</b>	0.239	0.255
	336	0.491	0.853	0.506	0.622	0.569	0.477	0.436	0.544	0.339	0.356	<b>0.304</b>	<b>0.322</b>	0.271	0.285
ETTh1	96	0.523	0.745	0.554	0.698	0.536	0.656	0.503	<u>0.442</u>	0.456	0.464	<b>0.413</b>	<b>0.401</b>	0.354	0.386
	192	0.557	0.786	0.578	0.722	0.589	0.698	0.552	0.508	<u>0.504</u>	0.471	<b>0.436</b>	<b>0.428</b>	0.362	0.355
	336	0.588	0.802	0.604	0.745	0.603	0.723	0.556	0.513	<u>0.498</u>	0.464	<b>0.447</b>	<b>0.431</b>	0.409	0.387
ETTh2	96	0.487	0.655	0.589	0.711	0.521	0.589	0.463	0.524	<u>0.388</u>	0.342	<b>0.368</b>	<b>0.271</b>	0.324	0.255
	192	0.509	0.673	0.605	0.732	0.553	0.621	0.488	0.536	<u>0.416</u>	0.384	<b>0.389</b>	<b>0.302</b>	0.332	0.257
	336	0.524	0.689	0.623	0.744	0.564	0.640	0.505	0.540	<u>0.435</u>	0.455	<b>0.411</b>	<b>0.334</b>	0.376	0.296
ETTm1	96	0.743	1.124	0.525	0.492	0.607	0.554	0.603	0.665	<u>0.512</u>	0.453	<b>0.503</b>	<b>0.442</b>	0.453	0.403
	192	0.764	1.245	0.566	0.510	0.628	0.571	0.597	0.647	<u>0.563</u>	0.501	<b>0.512</b>	<b>0.465</b>	0.464	0.432
	336	0.801	1.128	0.571	0.523	0.644	0.582	0.624	0.668	<u>0.552</u>	0.488	<b>0.500</b>	<b>0.483</b>	0.477	0.455
ETTm2	96	0.664	0.795	0.486	0.623	0.524	0.558	0.472	0.535	<u>0.376</u>	0.421	<b>0.354</b>	<b>0.391</b>	0.347	0.381
	192	0.687	0.804	0.512	0.643	0.549	0.583	0.488	0.567	<u>0.453</u>	0.479	<b>0.401</b>	<b>0.421</b>	0.358	0.403
	336	0.702	0.823	0.558	0.661	0.598	0.624	0.493	0.556	<u>0.473</u>	0.523	<b>0.453</b>	<b>0.474</b>	0.406	0.435

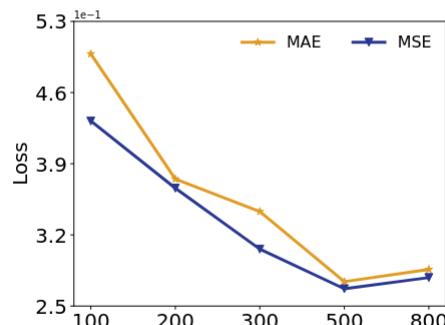
### 3.2 Size of Condensed Dataset



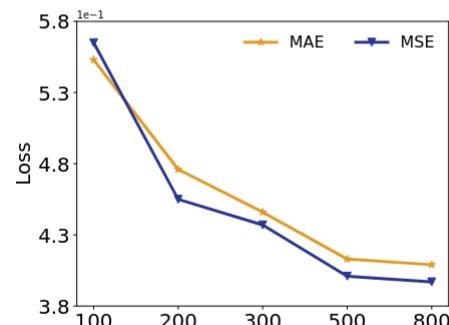
(a) Weather



(b) Traffic



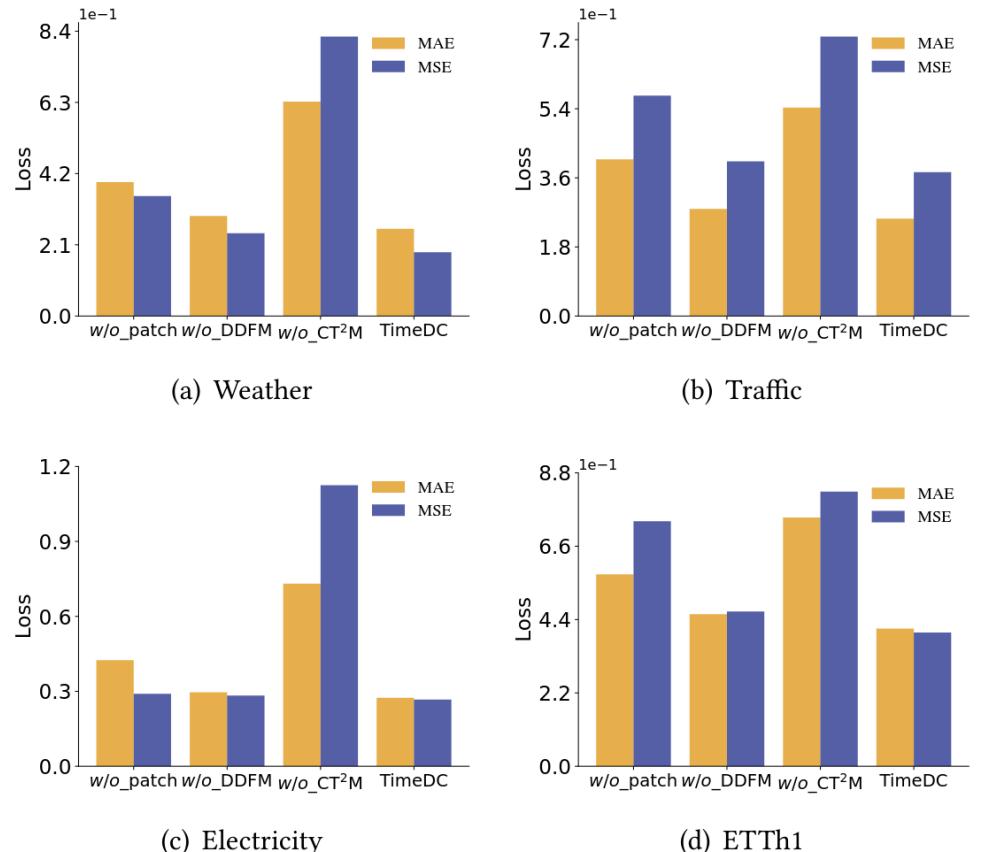
(c) Electricity



(d) ETTh1

**Figure 5: Effect of the Size of Condensed TS Dataset on Four Datasets ( $PL = 96$ )**

### 3.3 Ablation Study



**Figure 6: Performance of TimeDC and Its Variants on Four Datasets ( $PL = 96$ )**

### 3.4 Condensed Dataset Generalization

**Table 2: Cross-Architecture Performance Comparison**

Method	Metric	PL	Weather	Traffic	Electricity	ETT			
						ETTh1	ETTh2	ETTm1	ETTm2
TimeDC	MAE	96	<b>0.257</b>	<b>0.254</b>	<b>0.274</b>	<b>0.413</b>	<b>0.368</b>	<b>0.503</b>	<b>0.354</b>
		192	<b>0.285</b>	<b>0.297</b>	<b>0.285</b>	<b>0.436</b>	<b>0.389</b>	<b>0.512</b>	<b>0.401</b>
	MSE	96	<b>0.188</b>	<b>0.375</b>	<b>0.267</b>	<b>0.401</b>	<b>0.271</b>	<b>0.442</b>	<b>0.391</b>
		192	<b>0.247</b>	<b>0.405</b>	<b>0.294</b>	<b>0.428</b>	<b>0.302</b>	<b>0.465</b>	<b>0.421</b>
Autoformer	MAE	96	<u>0.312</u>	<u>0.370</u>	<u>0.343</u>	<u>0.453</u>	<u>0.473</u>	<u>0.548</u>	<u>0.342</u>
		192	<u>0.381</u>	<u>0.385</u>	<u>0.355</u>	<u>0.478</u>	<u>0.491</u>	<u>0.550</u>	<u>0.334</u>
	MSE	96	<u>0.255</u>	0.597	<u>0.236</u>	<u>0.465</u>	<u>0.412</u>	<u>0.542</u>	<u>0.265</u>
		192	<u>0.334</u>	0.613	<u>0.264</u>	<u>0.493</u>	<u>0.488</u>	<u>0.532</u>	<u>0.287</u>
Informer	MAE	96	0.423	0.430	0.428	0.773	0.842	0.576	0.552
		192	0.482	0.476	0.446	0.788	0.954	0.597	0.532
	MSE	96	0.354	0.643	0.253	0.992	1.032	0.624	0.402
		192	0.478	0.710	0.271	0.987	1.055	0.653	0.432
Transformer	MAE	96	0.389	0.412	0.398	0.632	0.506	0.563	0.555
		192	0.588	0.431	0.422	0.612	0.513	0.588	0.576
	MSE	96	0.344	<u>0.578</u>	0.267	0.785	0.579	0.615	0.479
		192	0.524	<u>0.567</u>	0.288	0.732	0.542	0.643	0.455

## 4. Critique

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## 4.1 Terminology

### TimeDC

- Condensation framework
- TSFE prediction architecture
- Interchangable
  - Understand from context

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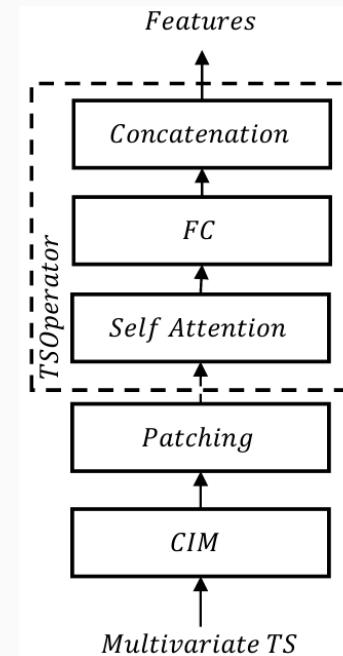
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	MAE	96	<b>0.312</b>	<b>0.370</b>	<b>0.343</b>	<b>0.453</b>	<b>0.473</b>	<b>0.548</b>	<b>0.342</b>
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		192	<b>0.482</b>	<b>0.476</b>	<b>0.446</b>	<b>0.788</b>	<b>0.954</b>	<b>0.597</b>	<b>0.532</b>
	MAE	96	<b>0.354</b>	<b>0.643</b>	<b>0.253</b>	<b>0.992</b>	<b>1.032</b>	<b>0.624</b>	<b>0.402</b>
		192	<b>0.478</b>	<b>0.710</b>	<b>0.271</b>	<b>0.987</b>	<b>1.055</b>	<b>0.653</b>	<b>0.432</b>
Informer	MAE	96	<b>0.389</b>	<b>0.412</b>	<b>0.398</b>	<b>0.632</b>	<b>0.506</b>	<b>0.563</b>	<b>0.555</b>
		192	<b>0.588</b>	<b>0.431</b>	<b>0.422</b>	<b>0.612</b>	<b>0.513</b>	<b>0.588</b>	<b>0.576</b>
	MSE	96	<b>0.344</b>	<b>0.578</b>	<b>0.267</b>	<b>0.785</b>	<b>0.579</b>	<b>0.615</b>	<b>0.479</b>
		192	<b>0.524</b>	<b>0.567</b>	<b>0.288</b>	<b>0.732</b>	<b>0.542</b>	<b>0.643</b>	<b>0.455</b>
Transformer	MAE	96	<b>0.257</b>	<b>0.287</b>	<b>0.288</b>	<b>0.321</b>	<b>0.321</b>	<b>0.321</b>	<b>0.321</b>
		192	<b>0.334</b>	<b>0.363</b>	<b>0.363</b>	<b>0.393</b>	<b>0.393</b>	<b>0.393</b>	<b>0.393</b>

## 4.2 Method

### TSOperator Structure

- Figure 3
  - Self-attention
  - Fully connected
  - Concatenation
- Equation 4 + Algorithm 1
  - Self-attention
  - Fully connected
  - Normalization



$$h^j = \text{TSOperator}(h^{j-1}) = \text{Norm}(\text{FC}(\text{MultiHead}(h^{j-1}))), \quad (4)$$

## 4.2 Method

### DDFM

- No details on comparison
  - Full condensed dataset?
  - Single time series from original?
  - Average similarity?

## 4.2 Method

### CT<sup>2</sup>M

- Unclear how loss works
  - Accumulated?
  - Sequential backpropagation?
- Why order similarity?

---

**Algorithm 2:** Curriculum Training Trajectory Query and Matching

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**Input:** A buffer  $\mathcal{B}$  with a set of trajectories pre-trained on the original TS dataset  $\mathcal{T}$  parameterized by  $\{\Theta_{\mathcal{T}}^k\}_{k=1}^K$ ; current model parameters  $\tilde{\theta}^S$  on  $\mathcal{S}$ .

**Output:** Trajectory matching loss  $L_{tmm}$ .

```
1 Distance list  $DT \leftarrow []$ ;
2 Pre-update  $\tilde{\theta}^S$  for  $a$ -steps with Equation 13;
3  $\tilde{\theta}_{e_0+a} \leftarrow \tilde{\theta}_{e_0} - \sum_{s=1}^a (\alpha \nabla \mathcal{L}(f_{\theta^s}, S))$ ;
4 for  $\Theta_{\mathcal{T}}^k \in \{\Theta_{\mathcal{T}}^k\}_{k=1}^K$  do
5   Compute the distance  $disk$  between  $\tilde{\theta}|_{e_0}^a$  and  $\Theta_{\mathcal{T}}^k$  with
      Equation 15;
6    $disk \leftarrow -D(\tilde{\theta}|_{e=e_0}^a, \theta^k|_{e=e_0}^a)$ ;
7    $DT \leftarrow (k, disk)$ ;
8 Rank  $DT$  in a descending order;
9  $\beta \leftarrow 0$ 
10 while  $\beta < K$  do
11    $k \leftarrow DT[\beta][0]$ 
12    $L_{tmm} \leftarrow$  Sample trajectory  $\Theta_{\mathcal{T}}^k$  and match the training
      trajectory according to Equation 11;
13    $\beta \leftarrow \beta + 1$ ;
14 return  $L_{tmm}$ 
```

---

## 4.3 Experiments and Results

### Dataset Condensation Performance (Table 1)

- All datasets
- 96, 192, 336 PL

### Generalization Performance (Table 2)

- All datasets
- 96, 192 PL
  - No explanation for 336 missing

### Dynamic Memory Cost (Table 3)

- Only 4 datasets
- Only ETTh1 as sub-dataset

## 4.3 Experiments and Results

### Condensed Dataset Size (Figure 5)

- Only 4 datasets
- Only ETTh1 as sub-dataset
- Only 96 PL
  - ▶ No explanation
- Same for ablation study (Figure 6)

### Training Time for Dataset Condensation

- Only 4 datasets (same as others)
- 96, 192, 336 PL again

## 5. Project & Course

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## 5. Project & Course

### Current Project

- Kind of opposites
  - We have little data, would like more
- Explore how “dense” our data is
  - New usecase for TimeDC

## 5. Project & Course

### Current Project

- Kind of opposites
  - We have little data, would like more
- Explore how “dense” our data is
  - New usecase for TimeDC

### Previous Projects

- Trajectory simplification
- Not synthesized data
- Also focused on use case
  - Query-driven trajectory simplification

## 5. Project & Course

### Course

- Memformer
- Three shared authors
- Time series forecasting (long-term)
- Patching
- Channel independence

## 6. Evaluation

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## 6. Evaluation

### Idea

- Logical methodology
  - Data loss (DDFM)
  - Training loss ( $CT^2M$ )
  - Usecase loss (downstream prediction task)
- Focus on efficiency
  - Faster training
  - Less data
  - Lower memory usage

## 6. Evaluation

### Execution

- Inconsistencies
  - TSOoperator structure
  - TimeDC terminology
- Missing details
  - Loss in CT<sup>2</sup>M
- Cherry-picked results
  - Datasets
  - Forecasting horizons
  - Bold in Table 2
- Resource constrained environments
  - Edge computing?
  - Embedded?
  - Moved computation to offline