# SMATE: Semi-Supervised Spatio-Temporal Representation Learning on Multivariate Time Series

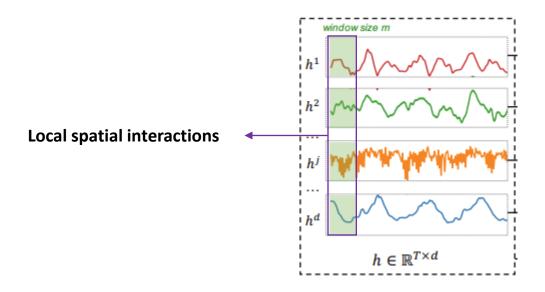
23,04,24

이정민

# 연구 배경

### ❖ 기존 연구들의 한계점(Multivariate Time Series)

- Sub-sequence level에서의 local spatial interactions 무시(Spatial dynamics)
- Supervised loss에만 치중하면 unlabeled 데이터가 실제 features에서 벗어나게 되어 성능 저하를 야기할 수 있음
- 학습된 representation에 대한 해석을 제공할 수 없음

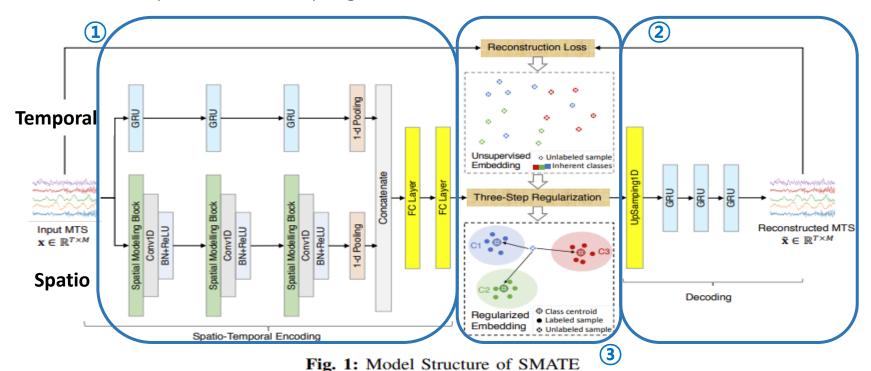


# 기여점

- SMATE(Semi-supervised spatio-temporal representation learning on Multivariate Time sEries)
  - 시계열 특징 뿐만 아니라 features의 공간적 특징도 반영(**Sptaio-Temporal dynamic features**)
  - Semi-supervised 기반의 three-step Regularization Process를 통해 class-sepecific한 representation 학습 가능
  - Embedding 공간에서 visual interpretability 제공

### Framework(Asymmetric auto-encoder structure)

- Spatio-Temporal dynamic encoder
- Sequential decoder
- Semi-supervised three-step regularization



1 Spatio-Temporal dynamic encoder

### Spatial Modeling Block(SMB)

- T: Window +, 첫 번째 block에서는 d = M
- Pooling
  - ho  $s_H(i) = avg([h_{i-\frac{m}{2}}:h_{i+\frac{m}{2}}]), i:time stick$

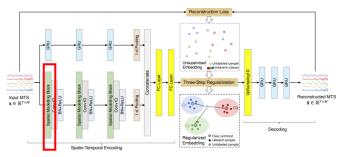


Fig. 1: Model Structure of SMATE

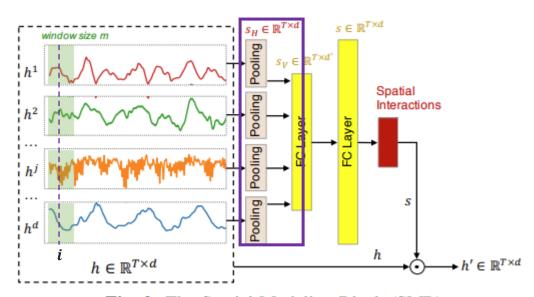


Fig. 2: The Spatial Modeling Block (SMB)

1 Spatio-Temporal dynamic encoder

### Spatial Modeling Block(SMB)

- FC Layer
  - $ightharpoonup s_H$ 를 vertical 방향으로 압축하여 **h간의 interactions**이 반영된  $s_V$  생성
  - $> s_V$ 를 초기 차원에 맞게 s로 remapping

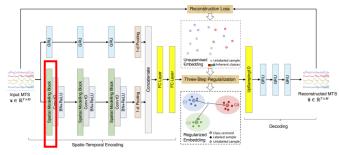


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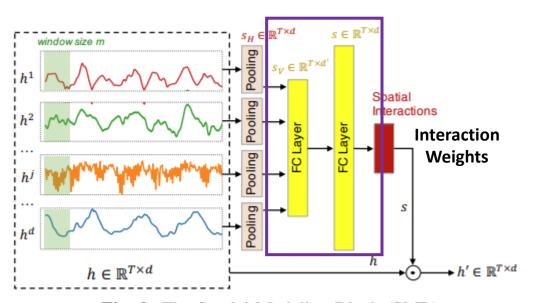


Fig. 2: The Spatial Modeling Block (SMB)

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### Temporal channel(GRU based)

•  $h(T) \in R^{L*d_g}$ ,  $L = \frac{T}{P}$ , P: pool sampleing size

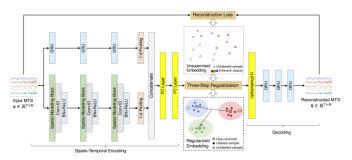
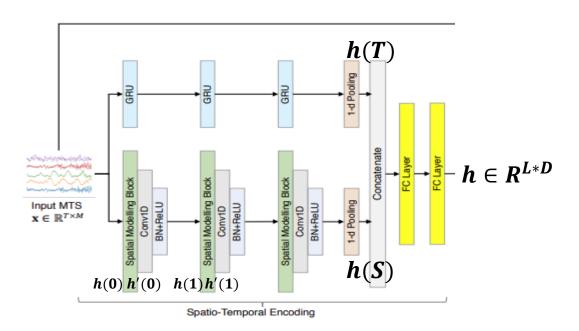


Fig. 1: Model Structure of SMATE

### Spatial channel

- $h'(l) = SMB(h(l)), h(l+1) = ReLU(BN(W \otimes h'(l) + b))$ 
  - 1-D convolutional kernel

•  $h(S) \in R^{L*d_C}$ 



Zuo, J., Zeitouni, K., & Taher, Y. (2021, December). Smate: Semi-supervised spatio-temporal representation learning on multivariate time series. In 2021 IEEE International Conference on Data Mining (ICDM) (pp. 1565-1570). IEEE.

3 Semi-supervised three-step regularization

### Joint Model Optimization

Class-Specific한 특징을 더 잘 반영하기 위함

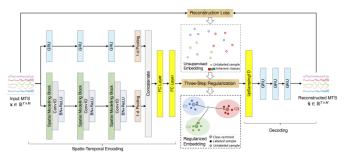
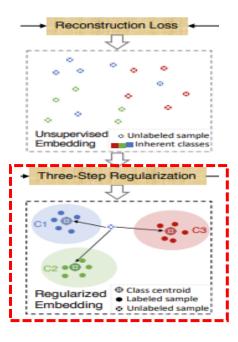


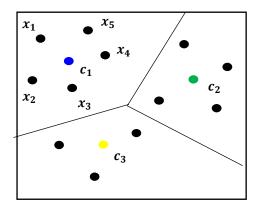
Fig. 1: Model Structure of SMATE



3 Semi-supervised three-step regularization

## Joint Model Optimization(Class-specific)

- 1. Supervised Centroids Initialization
- 2. Supervised Centroids Adjustment
- 3. Unsupervised Centroids Adjustment



< Labeled dataset >

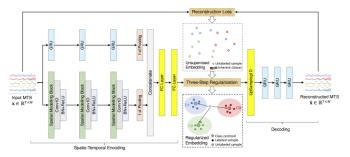


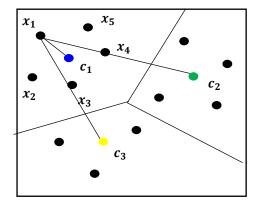
Fig. 1: Model Structure of SMATE

- ✓ Labeled set으로 초기 centroids $(c_k)$  구축
- $\checkmark H^k = f_\theta(X^k)$
- $\checkmark$   $c_k = mean(H^k)$

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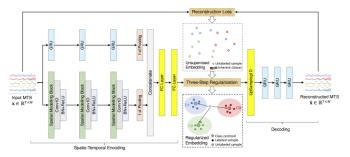


Fig. 1: Model Structure of SMATE

- ✓ Euclidean Distance로  $h_i^k$ ,  $c_k$ 간의 weight 설정
- ✓ 설정된 weight로 새로운 centroids 형성

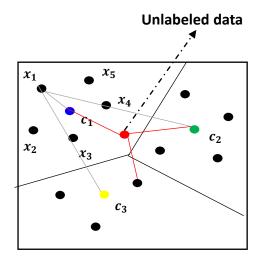
$$\checkmark W_{k,i} = 1 - \frac{ED(h_i^k, c_k)}{\sum_{j=1}^K ED(h_i^k, c_j)}$$

$$\checkmark c_k = \sum_{i=1}^{N_K} W_{k,i} h_i^k$$

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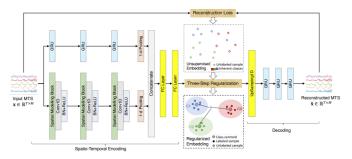


Fig. 1: Model Structure of SMATE

✓ ED로 unlabeled data에 대한 클래스별 확률 값 계산

$$\checkmark \quad \widehat{p_{\theta}}(y = k | \widehat{x_i}) = 1 - \frac{ED(f_{\theta}(\widehat{x_i}), c_k)}{\sum_{j=1}^{K} ED(f_{\theta}(\widehat{x_i}), c_j)}$$

✓ Labeled data와 unlabeled data를 같이 이용하여
새로운 centroids 설정

$$\mathbf{c}_{k} = \frac{N_{k}}{N_{k} + \hat{N}_{k}} \sum_{i=1}^{N_{k}} W_{k,i} \cdot \mathbf{h}_{i}^{k} + \frac{\hat{N}_{k}}{N_{k} + \hat{N}_{k}} \sum_{i=1}^{\hat{N}_{k}} \hat{p}_{k,i} \cdot \hat{\mathbf{h}}_{i}^{k}$$

### Training Loss

### Total Loss

- Reconstruction Loss( $L_R$ )
- Regularization Loss  $(L_{Reg})$

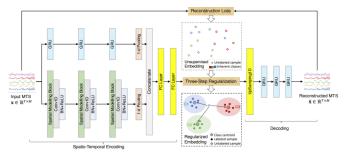


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# Total dataset $L_R = \sum_t \left| |x_t - \widetilde{x_t}| \right|_2 \qquad \qquad L_{Reg} = -\sum_k log W_\theta(y=k|x)$

$$\min_{\theta} L_R + \lambda L_{Reg}$$