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

23.04.24

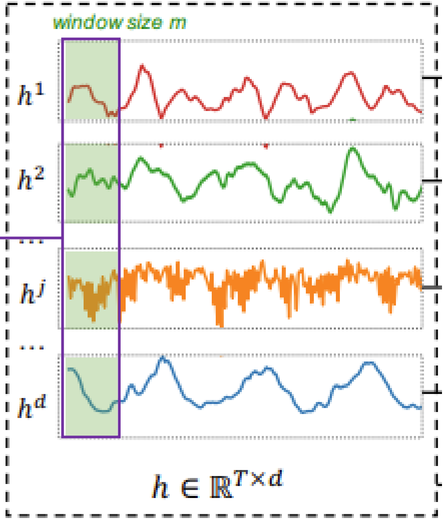
이정민

연구 배경

❖ 기존 연구들의 한계점(Multivariate Time Series)

- **Sub-sequence level**에서의 **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

Local spatial interactions



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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

방법론

❖ Framework(Asymmetric auto-encoder structure)

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

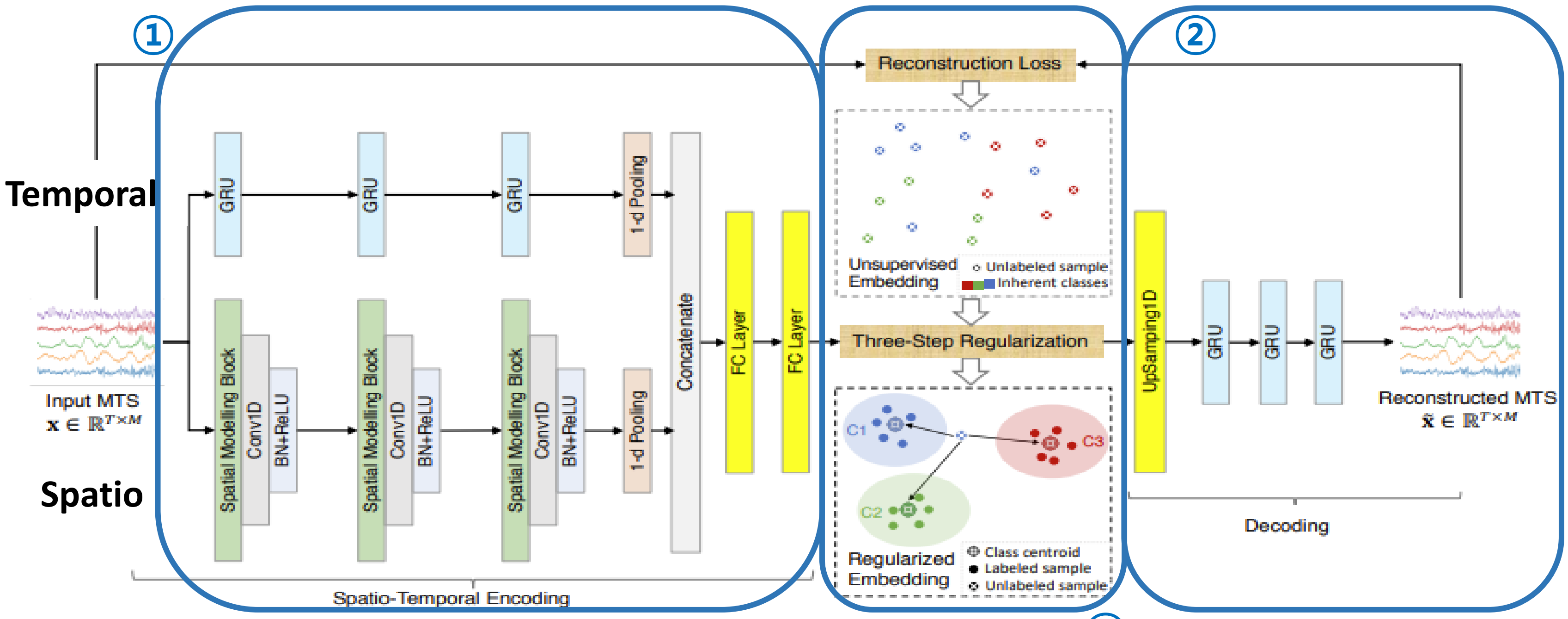

Fig. 1: Model Structure of SMATE

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방법론

① Spatio-Temporal dynamic encoder

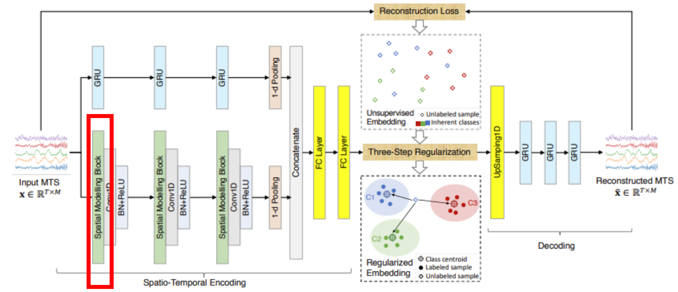

Fig. 1: Model Structure of SMATE

❖ Spatial Modeling Block(SMB)

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

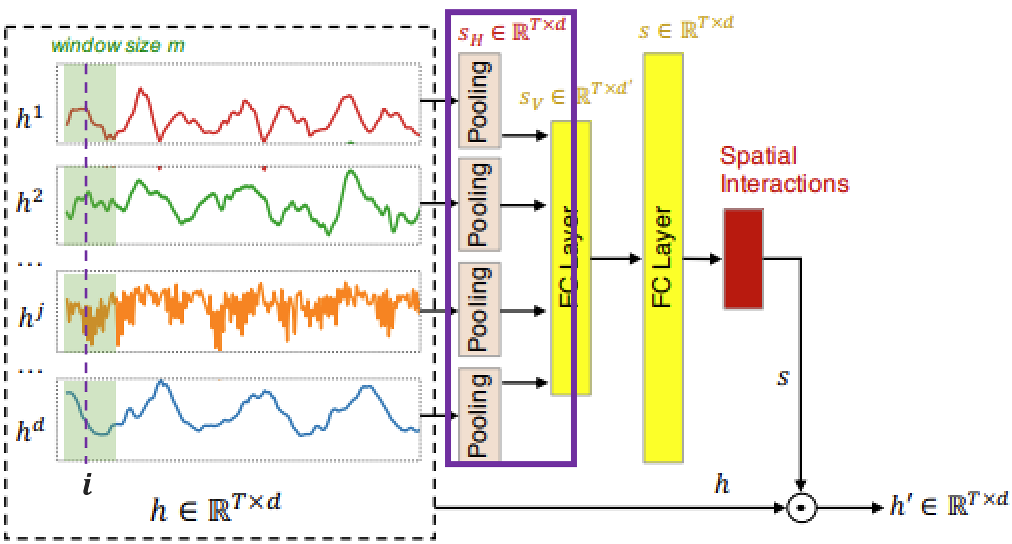

Fig. 2: The Spatial Modeling Block (SMB)

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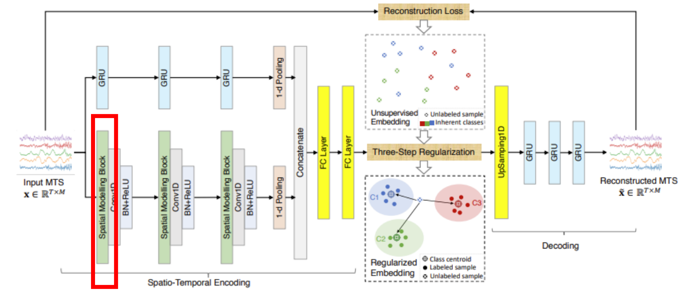
① Spatio-Temporal dynamic encoder

❖ Spatial Modeling Block(SMB)

- FC Layer
  - ➢ s_H를 vertical 방향으로 압축하여 **h간의 interactions**이 반영된 s_V 생성
  - ➢ s_V를 초기 차원에 맞게 $s\,(T \times d)$로 remapping
  - ➢ $h' = h \odot s$ (elementwise multiply), $h' \in R^{T \times d}$



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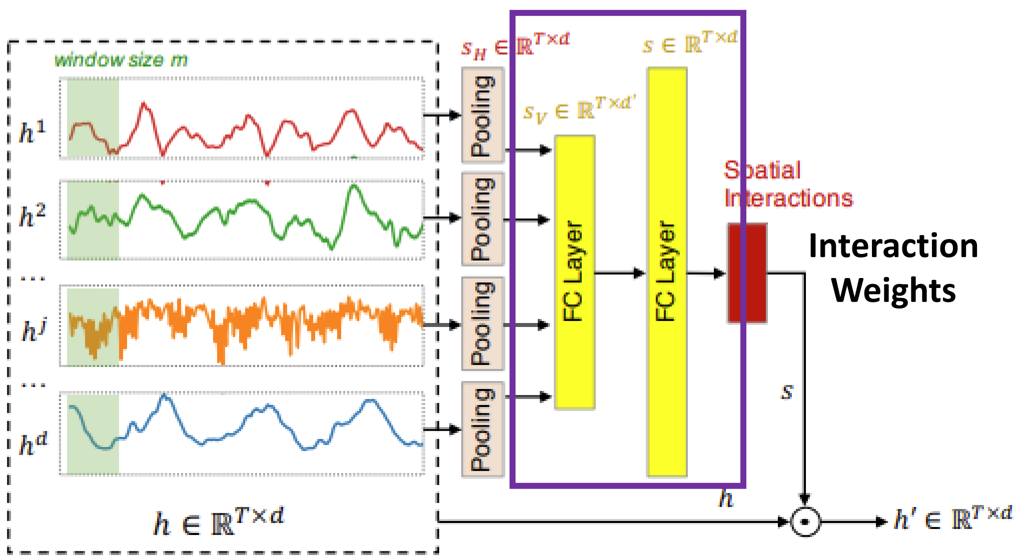

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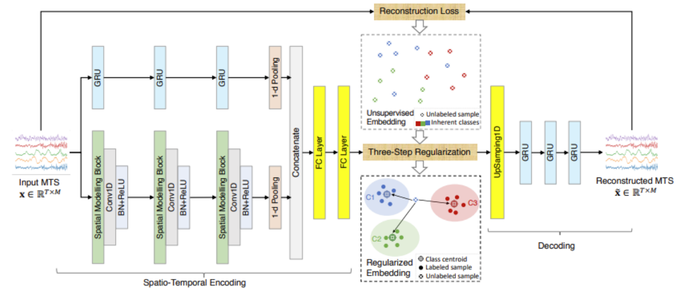


Fig. 1: Model Structure of SMATE

❖ Temporal channel(GRU based)

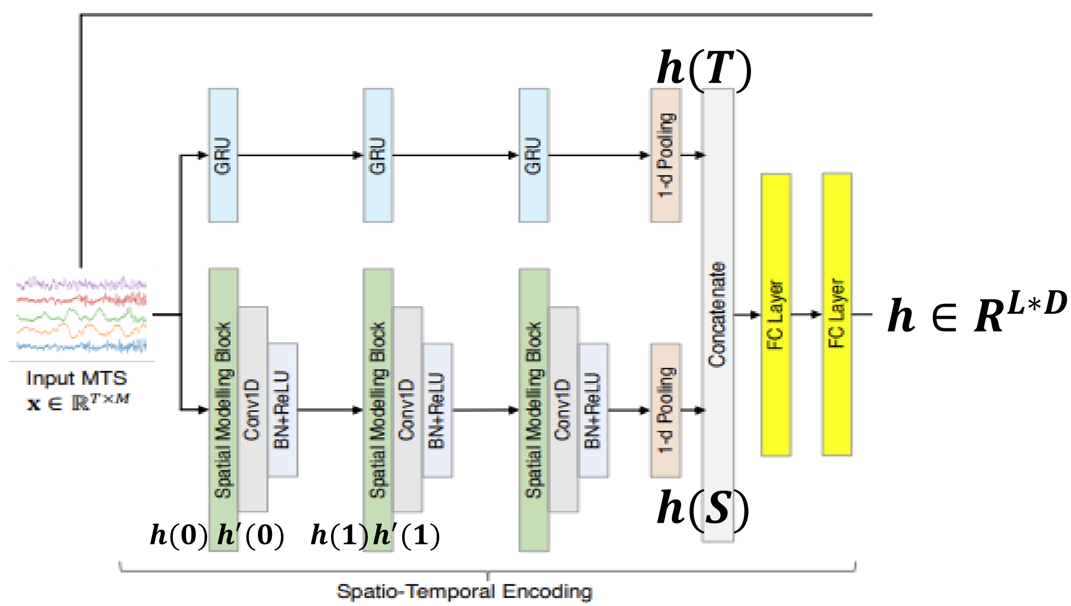
- $h(T) \in R^{L \times d_g}, L = \frac{T}{P}, P\text{: } pool\ sampleing\ size$

❖ Spatial channel

- $h'(l) = SMB\big(h(l)\big),\ h(l+1) = ReLU(BN(\underline{W} \otimes h'(l) + b)$

  1-D convolutional kernel

- $h(S) \in R^{L \times d_c}$



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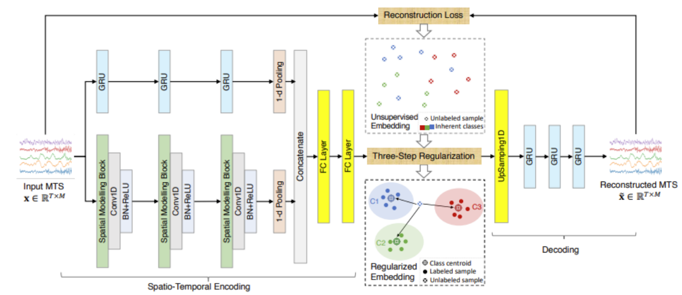
③ Semi-supervised three-step regularization

❖ Joint Model Optimization

- Class-Specific한 특징을 더 잘 반영하기 위함



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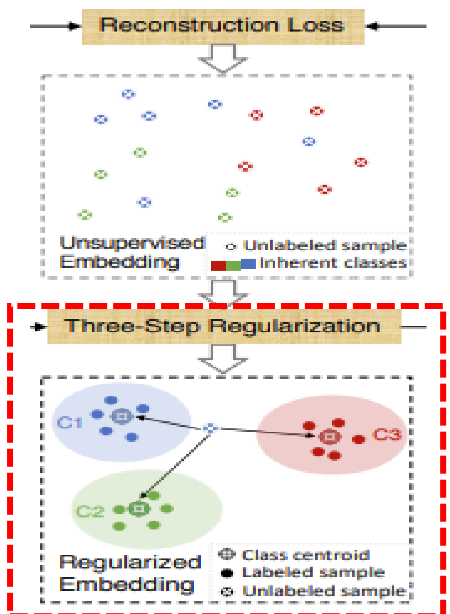

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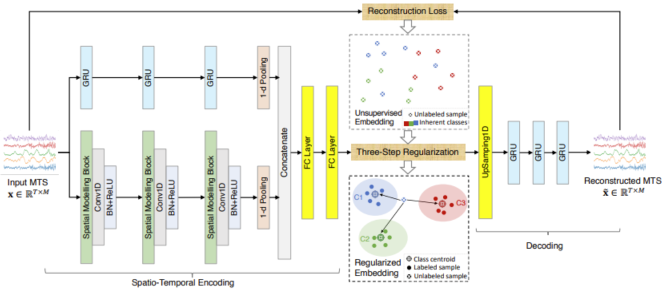
③ Semi-supervised three-step regularization

❖ Joint Model Optimization(Class-specific)

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



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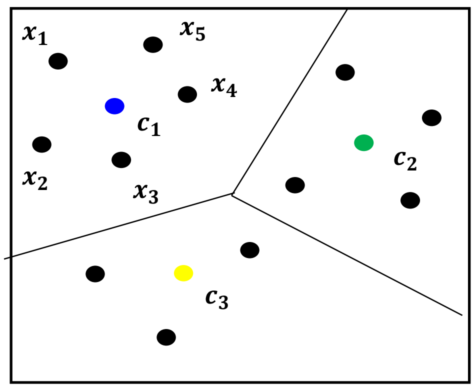

< Labeled dataset >

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

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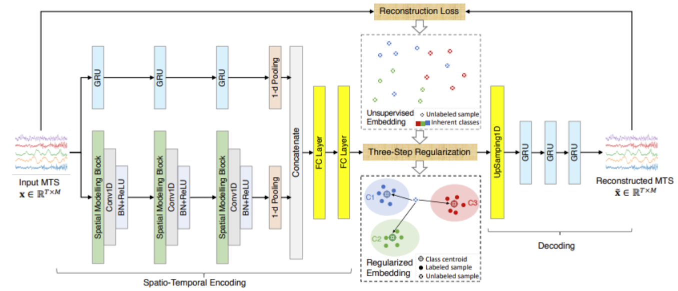

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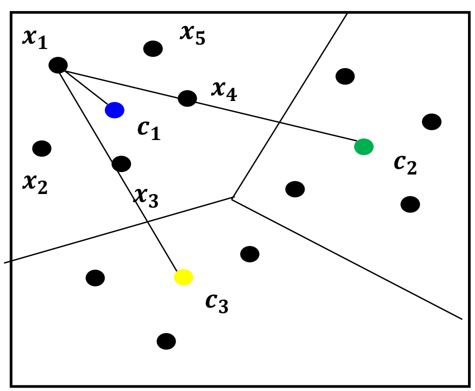

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- ✓ Euclidean Distance로 h_i^k, c_k간의 weight 설정
- ✓ 설정된 weight로 새로운 centroids 형성
- ✓ $W_{k,i} = 1 - \frac{ED\left(h_i^k, c_k\right)}{\sum_{j=1}^{K} ED\left(h_i^k, c_j\right)}$
- ✓ $c_k = \sum_{i=1}^{N_K} W_{k,i} h_i^k$

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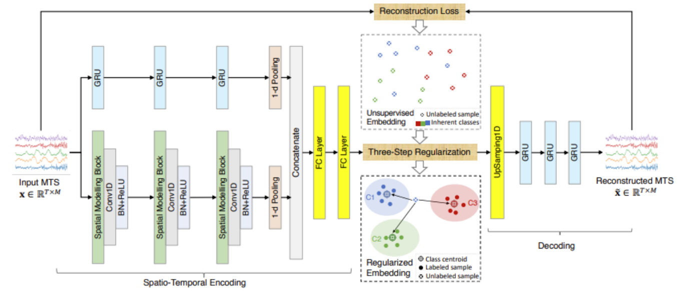

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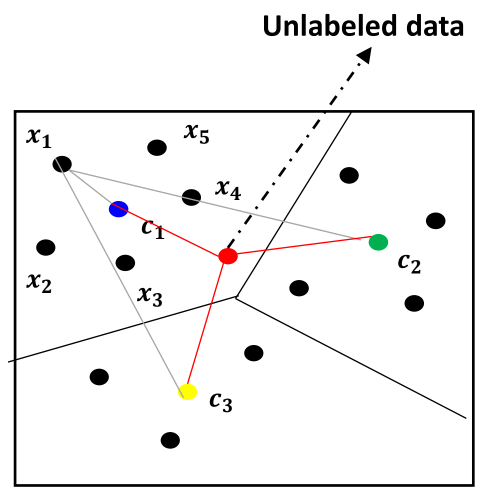

< Labeled dataset >

✓ ED로 unlabeled data에 대한 클래스별 확률 값 계산

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

✓ Labeled data와 unlabeled data를 같이 이용하여 새로운 centroids 설정

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

Labeled data **Unlabeled data**

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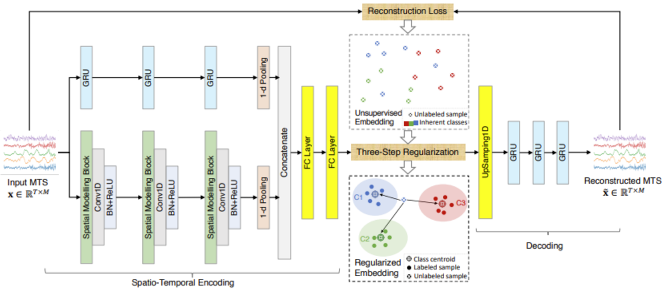
Training Loss

❖ Total Loss

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



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Total dataset

$$L_R = \sum_t ||x_t - \widetilde{x_t}||_2$$

Labeled dataset

$$L_{Reg} = -\sum_k logW_\theta(y = k|x)$$

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

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