UC San Diego

TARNet: Task-Aware Reconstruction for Time-Series Transformer

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Code is publicly available at https://github.com/ranakroychowdhury/TARNet

Outline

- Motivation
- Related Work
- Proposed Method
- Experimental Results
- Case Study
- Conclusion

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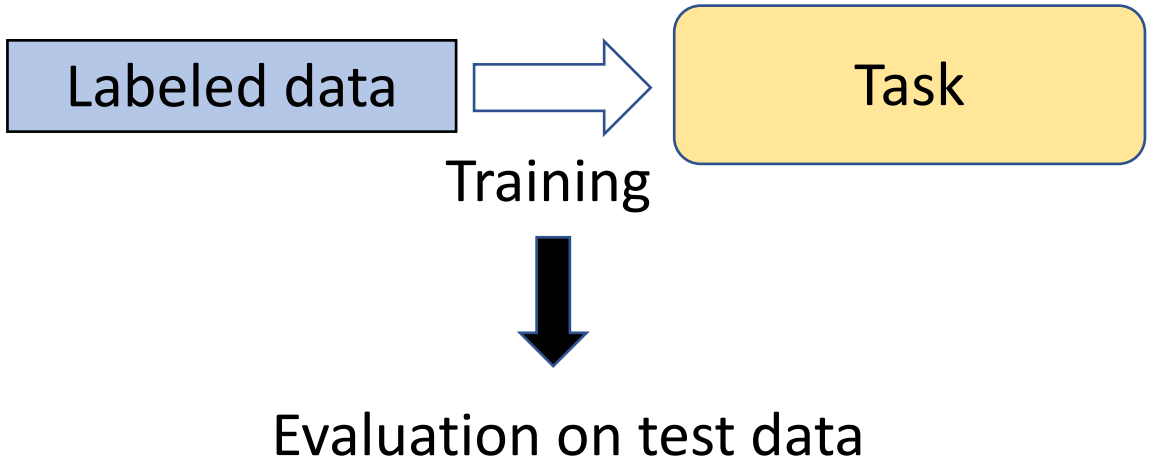
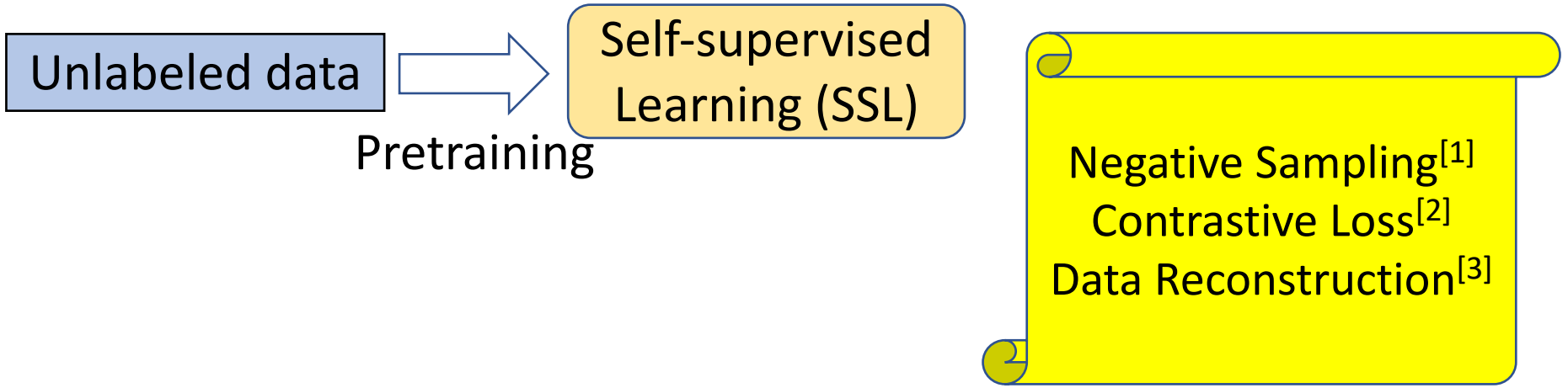
Motivation



Motivation



[1] Jean-Yves Franceschi, Aymeric Dieuleveut, and Martin Jaggi. 2019. Unsupervised scalable representation learning for multivariate time series. arXiv preprint arXiv:1901.10738 (2019).
[2] Zhihan Yue, Yujing Wang, Juanyong Duan, Tianmeng Yang, Congrui Huang, and Bixiong Xu. 2021. Learning Timestamp-Level Representations for Time Series with Hierarchical Contrastive Loss. arXiv preprint arXiv:2106.10466 (2021).
[3] George Zerveas, Srideepika Jayaraman, Dhaval Patel, Anuradha Bhamidipaty, and Carsten Eickhoff. [n. d.]. A Transformer-based Framework for Multivariate Time Series Representation Learning. In KDD, pages=2114–2124, year=2021.

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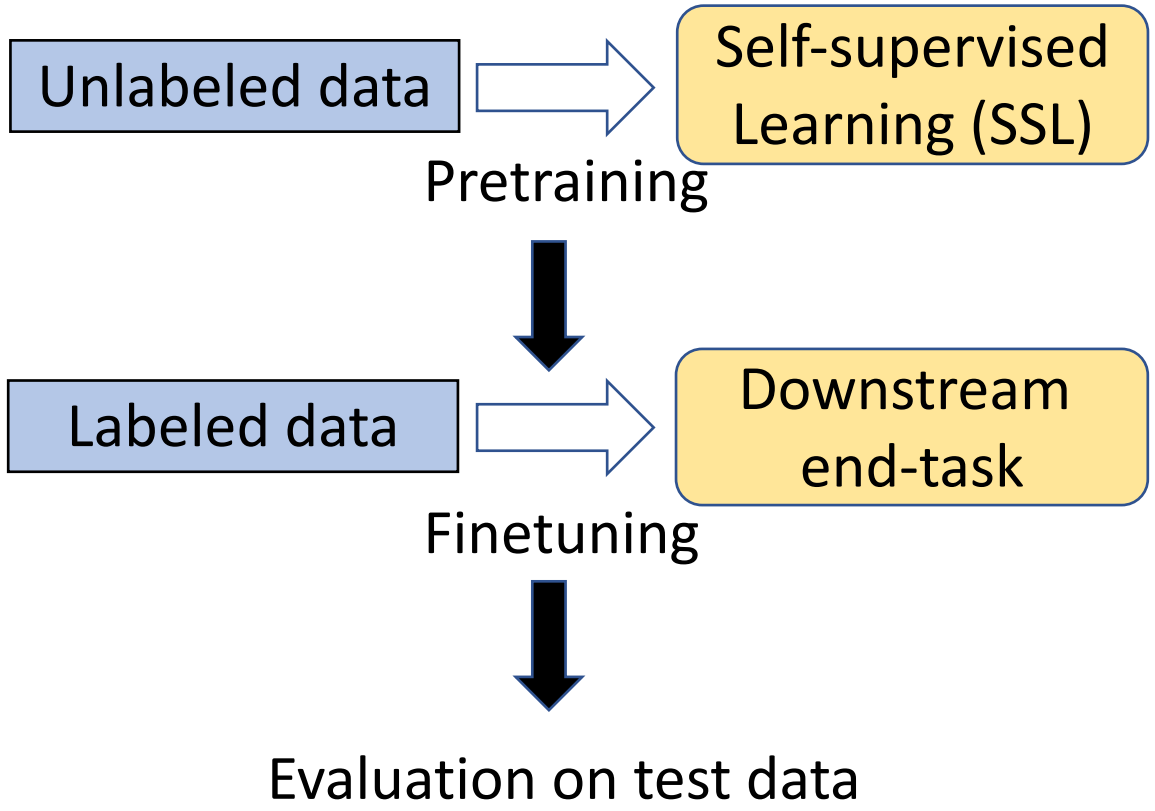
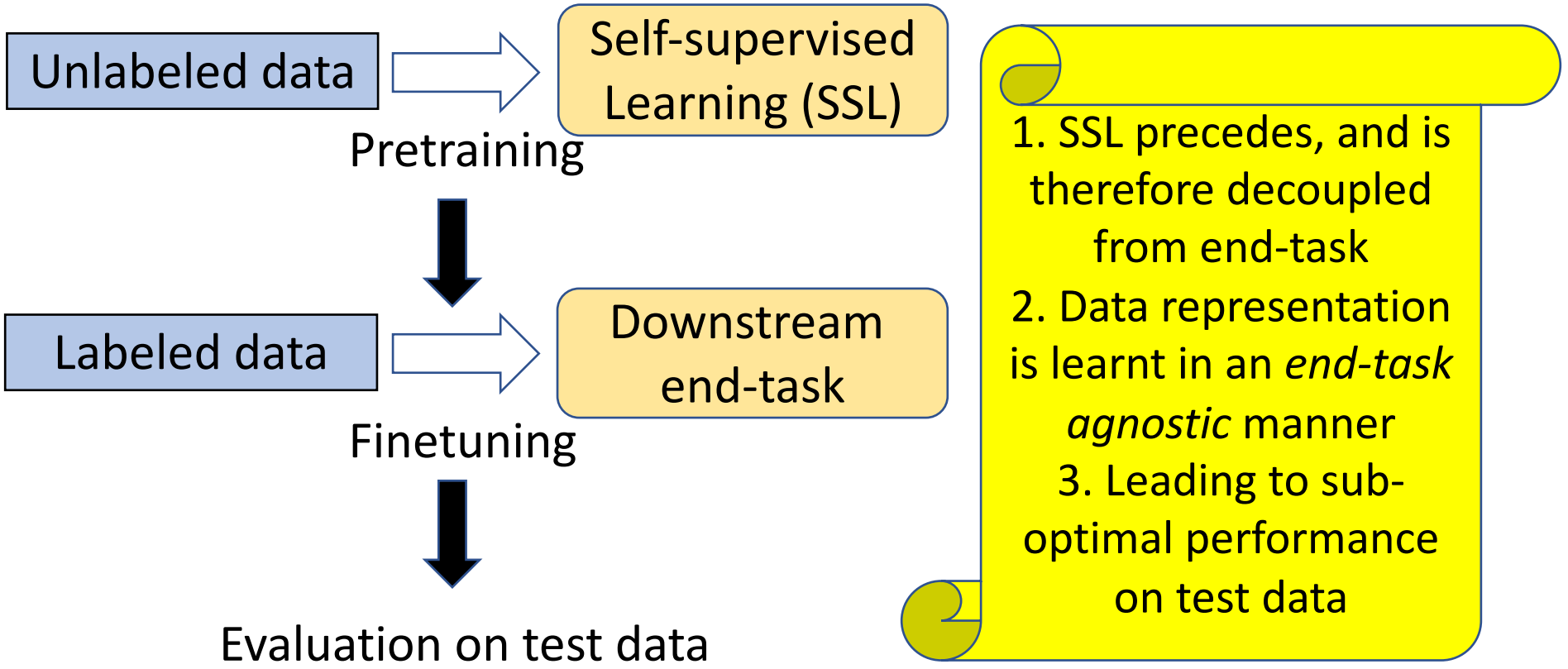
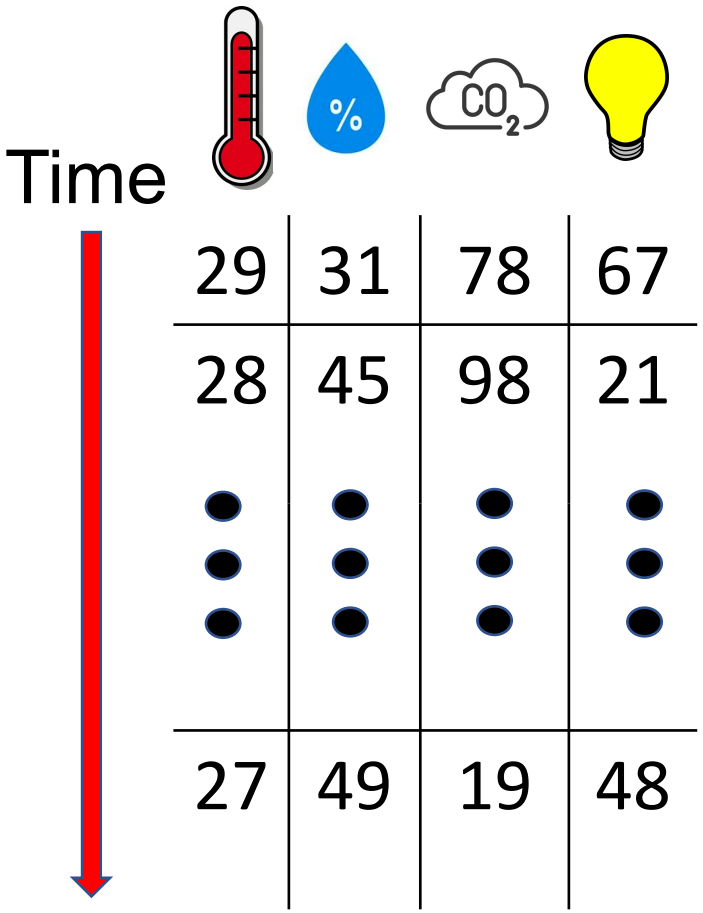
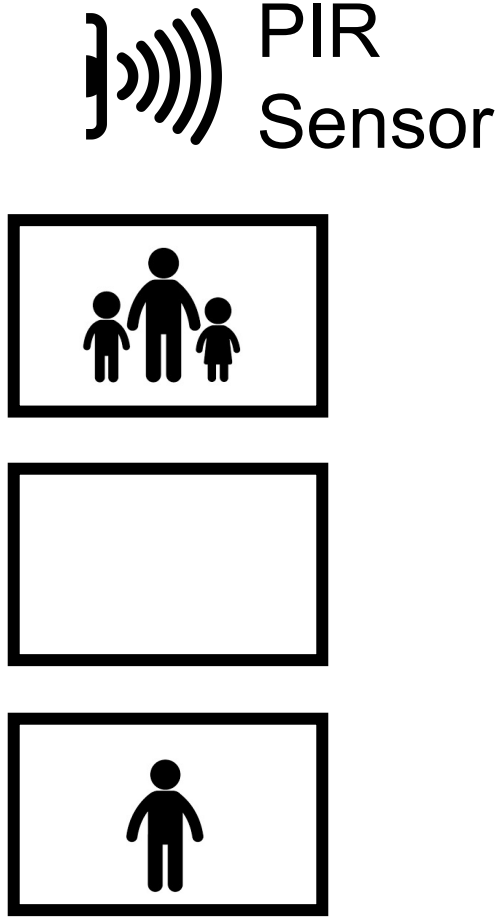

Unlabeled data
Self-supervised Learning (SSL)
Pretraining
Labeled data
Downstream end-task
Finetuning
Evaluation on test data

Motivation


Unlabeled data
Self-supervised Learning (SSL)
Pretraining
Labeled data
Downstream end-task
Finetuning
Evaluation on test data
1. SSL precedes, and is therefore decoupled from end-task
2. Data representation is learnt in an *end-task agnostic* manner
3. Leading to sub-optimal performance on test data

Motivation





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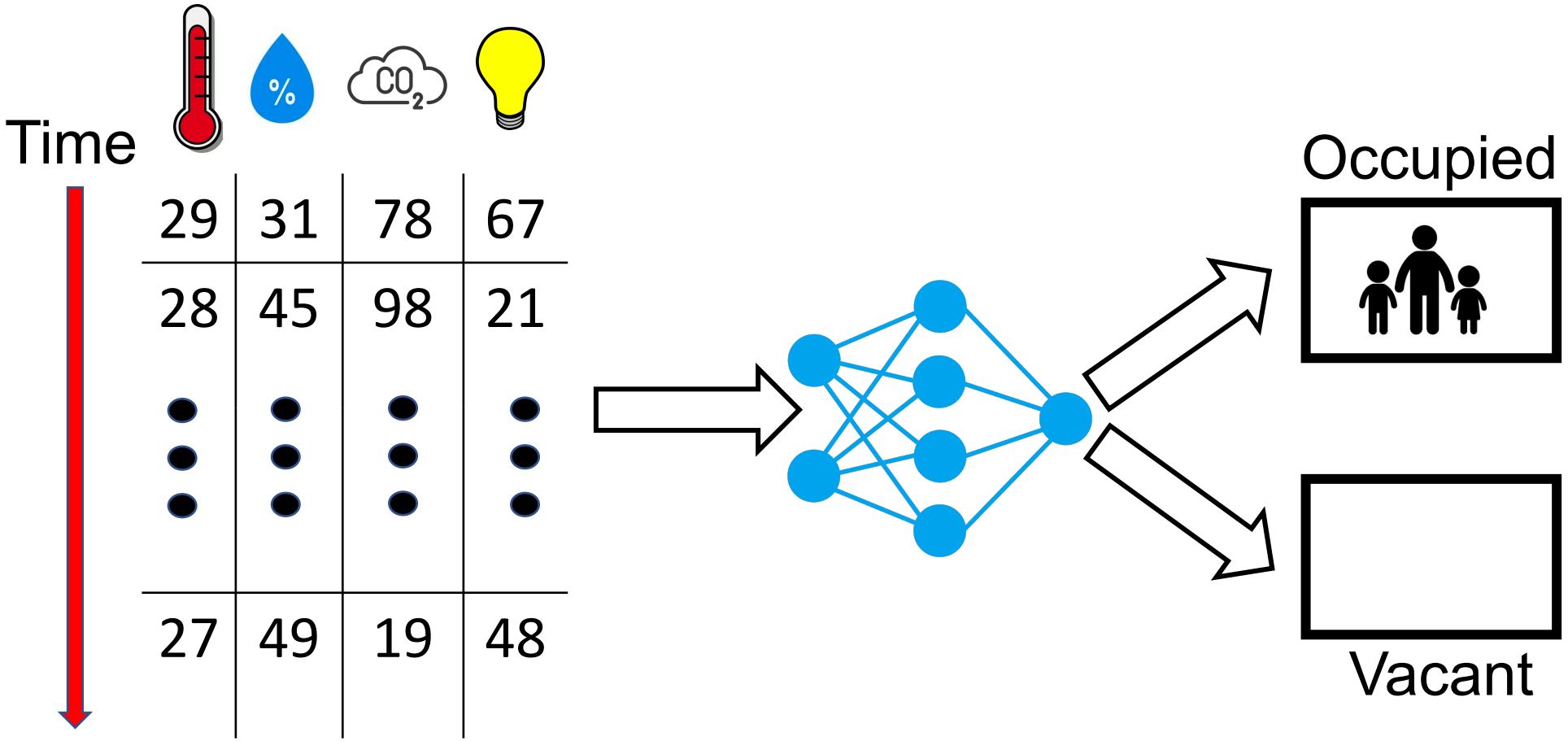

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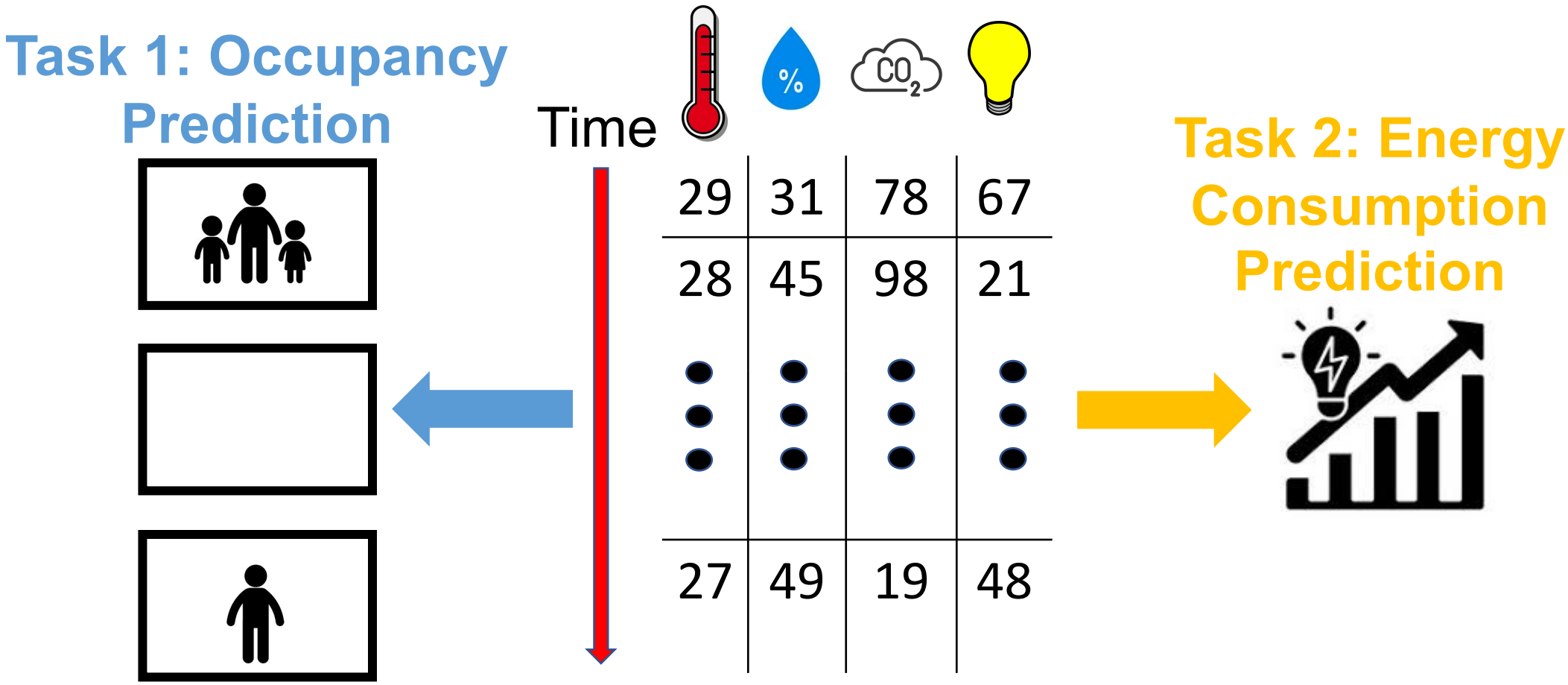
Task 1: Occupancy Prediction
Time
%
CO2
29 31 78 67
28 45 98 21
27 49 19 48
Task 2: Energy Consumption Prediction

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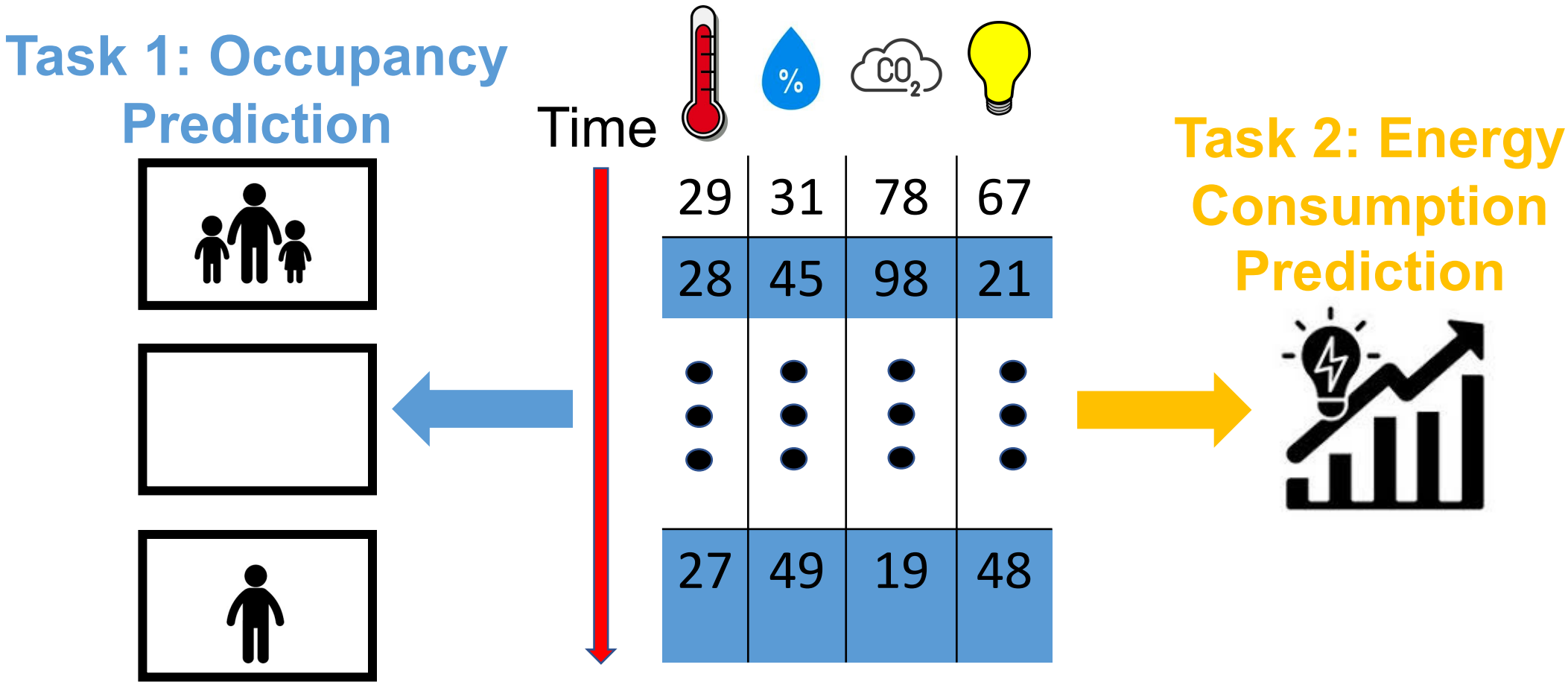
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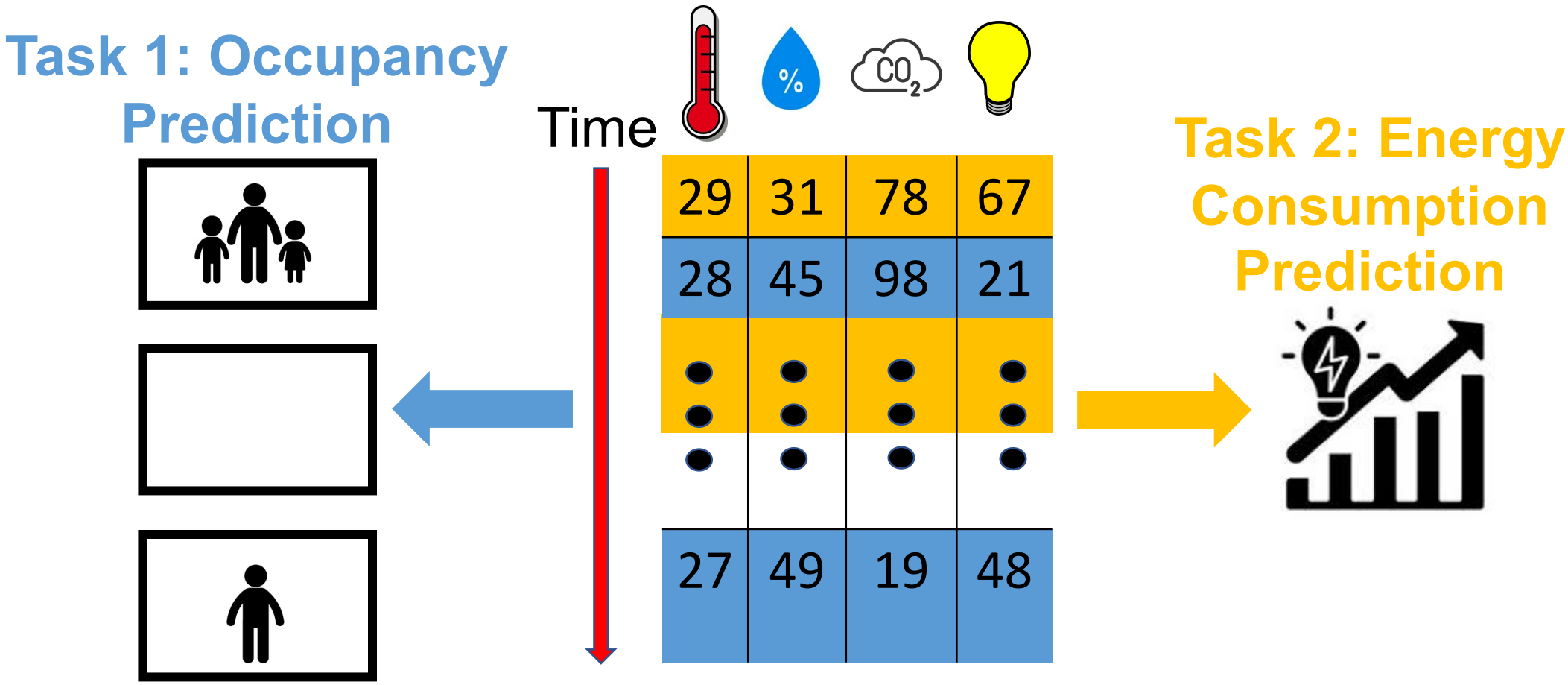
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Motivation

- **Goal:** How can we learn a more *task-aware* data representation through SSL?
- **Hypothesis**: Using end-task specific knowledge to customize the learnt representation towards the end task may improve performance on end-task

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Related Work

- Statistical Methods: Distance-based[1], Shapelets[2], ROCKET[3]

[1] Abhilash Dorle, Fangyu Li, Wenzhan Song, and Sheng Li. 2020. Learning Discriminative Virtual Sequences for Time Series Classification. In CIKM. 2001–2004.
[2] Lexiang Ye and Eamonn Keogh. 2009. Time series shapelets: a new primitive for data mining. In KDD. 947–956.
[3] Angus Dempster, François Petitjean, and Geoffrey I Webb. 2020. ROCKET: exceptionally fast and accurate time series classification using random convolutional kernels. Data Mining and Knowledge Discovery 34, 5 (2020), 1454–1495.

Related Work

- Statistical Methods: Distance-based, Shapelets, ROCKET
- Deep Learning Methods:
  - Using labeled data: CNN[1], LSTM[2], Attention[3]

[1] Fazle Karim, Somshubra Majumdar, Houshang Darabi, and Samuel Harford. 2019. Multivariate LSTM-FCNs for time series classification. Neural Networks 116 (2019), 237–245.
[2] Yi Zheng, Qi Liu, Enhong Chen, Yong Ge, and J Leon Zhao. 2014. Time series classification using multi-channels deep convolutional neural networks. In International conference on web-age information management. Springer, 298–310.
[3] Xuchao Zhang, Yifeng Gao, Jessica Lin, and Chang-Tien Lu. 2020. Tapnet: Multivariate time series classification with attentional prototypical network. In AAAI.

Related Work

- Statistical Methods: Distance-based, Shapelets, ROCKET
- Deep Learning Methods:
  - Using labeled data: CNN, LSTM, Attention
  - Using both unlabeled and labeled data: Negative Sampling[1], Contrastive Loss[2], Data Reconstruction[3]

[1] Jean-Yves Franceschi, Aymeric Dieuleveut, and Martin Jaggi. 2019. Unsupervised scalable representation learning for multivariate time series. arXiv preprint arXiv:1901.10738 (2019).
[2] Zhihan Yue, Yujing Wang, Juanyong Duan, Tianmeng Yang, Congrui Huang, and Bixiong Xu. 2021. Learning Timestamp-Level Representations for Time Series with Hierarchical Contrastive Loss. arXiv preprint arXiv:2106.10466 (2021).
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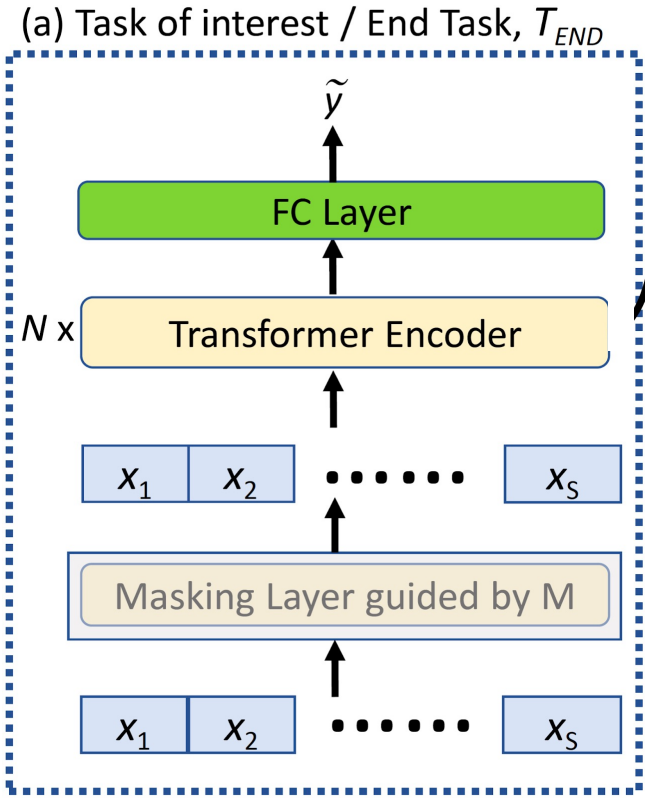
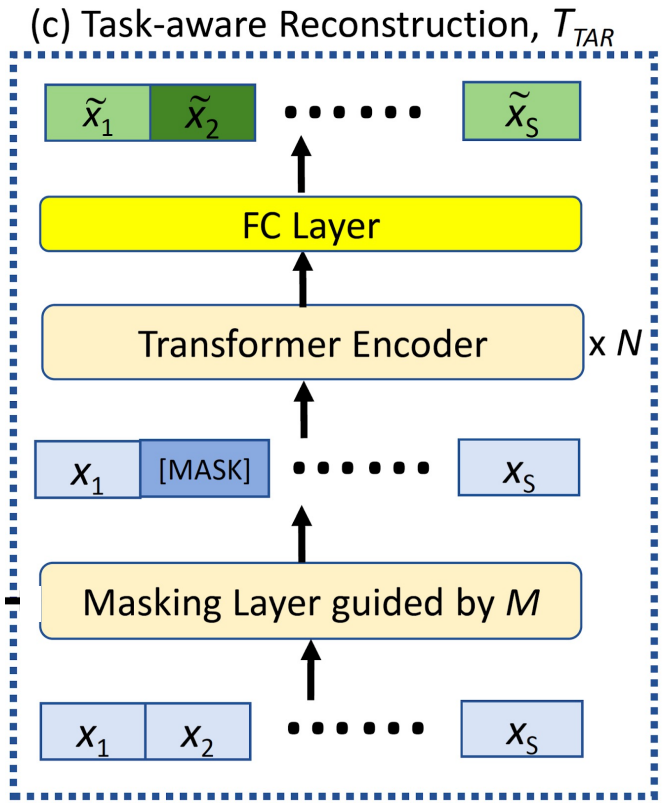
Proposed Method

- Input: Uni-/multi-variate time-series *X*, Output: label *y*
- We use Transformer Encoder as the backbone model
- 3 modules
  a) End-task, T_{END}
  b) Data-driven Masking Strategy, M
  c) Task-aware Data Reconstruction, T_{TAR}

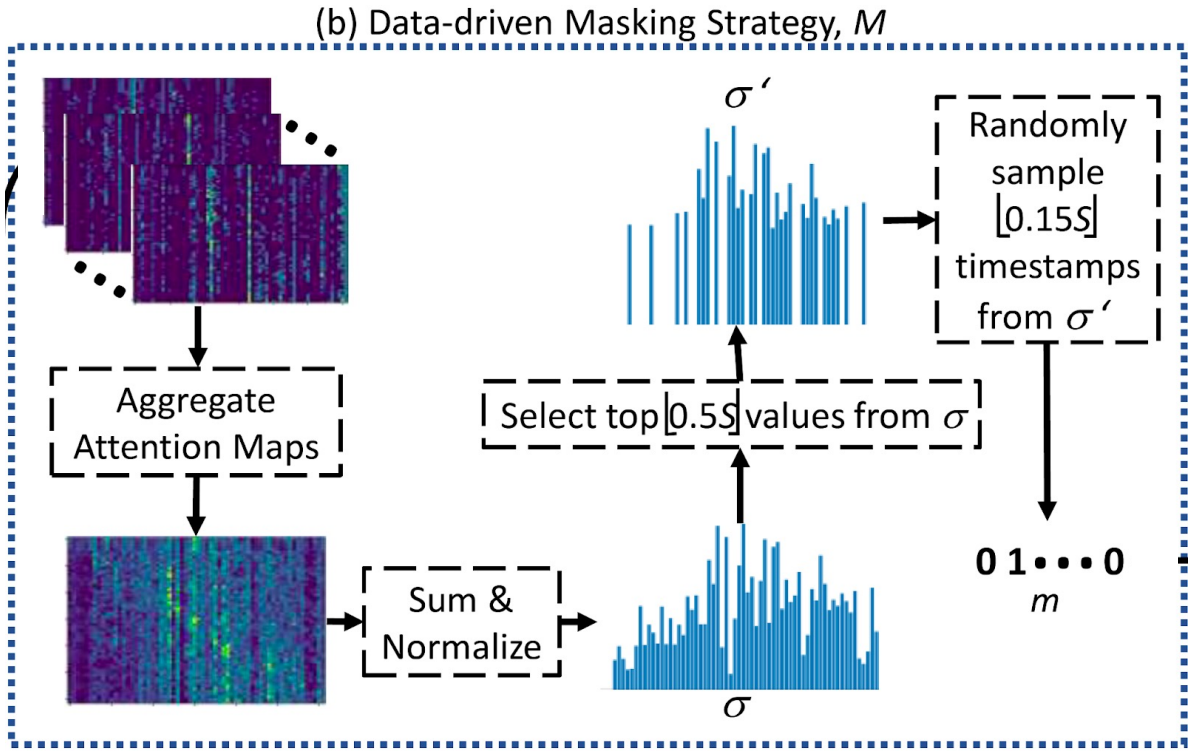
Proposed Method - T_{END}



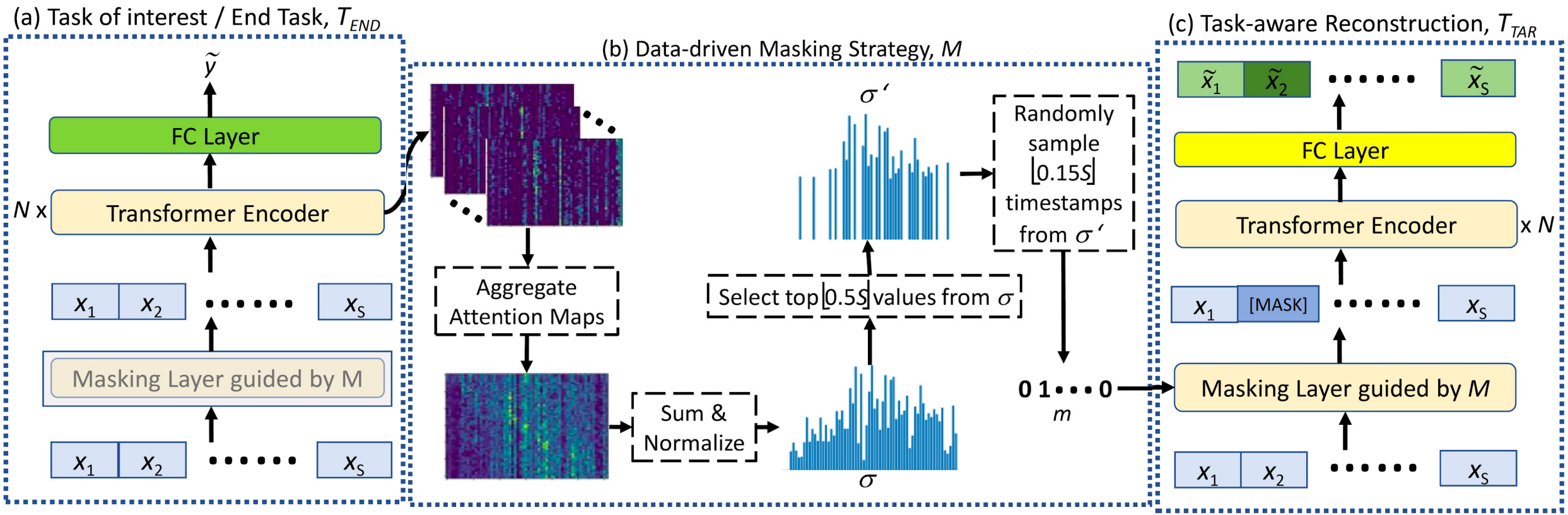
Proposed Method - T_{TAR}



Proposed Method - *M*



Proposed Method



Proposed Method

- T_{END} generates attention scores that is fed to M
- M selects a set of most important timestamps, and randomly samples a subset of those times to produce m
- Generated mask m decides which timestamps to mask during reconstruction, T_{TAR}

$$\mathcal{L}_{Total} = \eta \mathcal{L}_{TAR} + (1 - \eta)\mathcal{L}_{END}$$

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Experimental Results - Classification

- Evaluated 34 classification datasets[1] across 14 baselines
- 2.7% higher average accuracy,
- 1.74-point lower average rank, and
- best results on 17 datasets compared to 7,
- by 2nd best baseline TST[2]

[1] Anthony Bagnall, Hoang Anh Dau, Jason Lines, Michael Flynn, James Large, Aaron Bostrom, Paul Southam, and Eamonn Keogh. 2018. The UEA multivariate time series classification archive, 2018. arXiv preprint arXiv:1811.00075 (2018).
[2] George Zerveas, Srideepika Jayaraman, Dhaval Patel, Anuradha Bhamidipaty, and Carsten Eickhoff. [n. d.]. A Transformer-based Framework for Multivariate Time Series Representation Learning. In KDD, pages=2114–2124, year=2021.

Experimental Results - Regression

- Evaluated 6 regression datasets[1] across 12 baselines
- 0.67-point lower average rank, and
- best results on 3 datasets compared to 2,
- by 2nd best baseline TST[2]

[1] Chang Wei Tan, Christoph Bergmeir, Francois Petitjean, and Geoffrey I Webb. 2020. Monash university, uea, ucr time series regression archive. arXiv e-prints (2020), arXiv–2006.
[2] George Zerveas, Srideepika Jayaraman, Dhaval Patel, Anuradha Bhamidipaty, and Carsten Eickhoff. [n. d.]. A Transformer-based Framework for Multivariate Time Series Representation Learning. In KDD, pages=2114–2124, year=2021.

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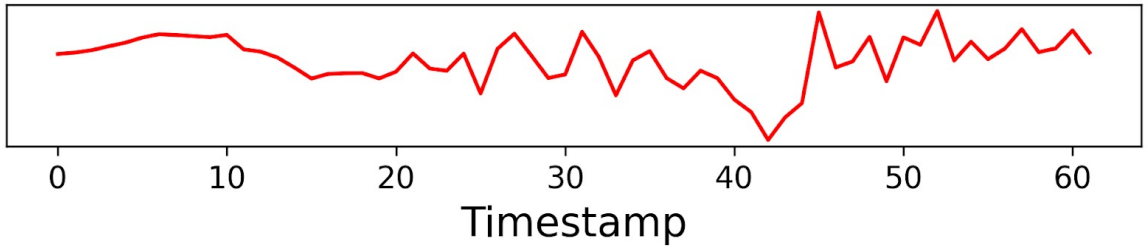
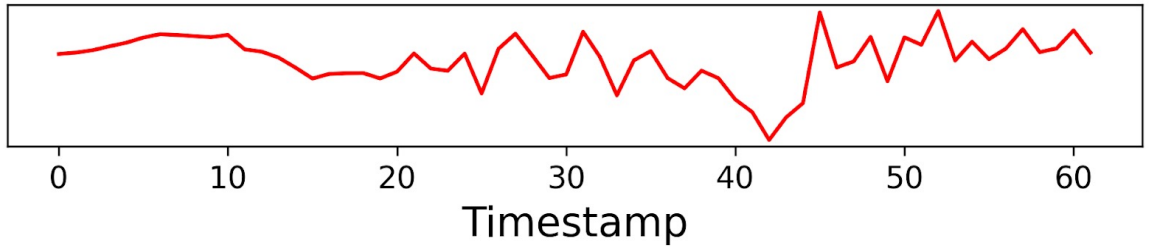
Case Study – Face Detection



Time Series Data

Case Study – Face Detection



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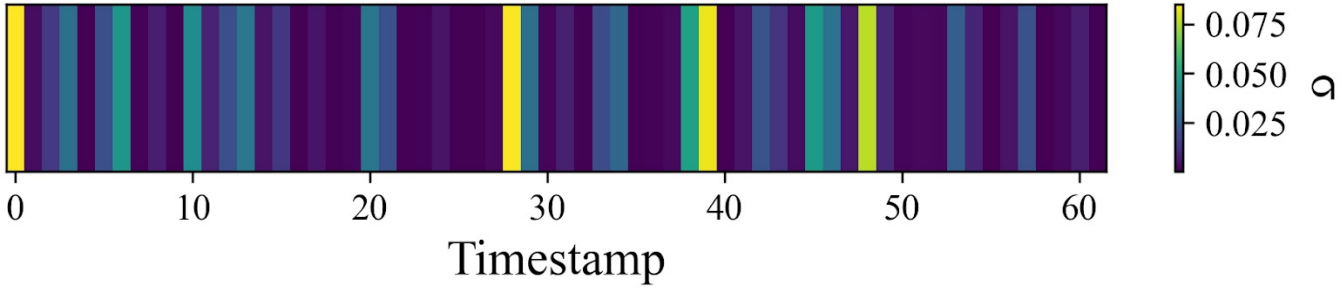
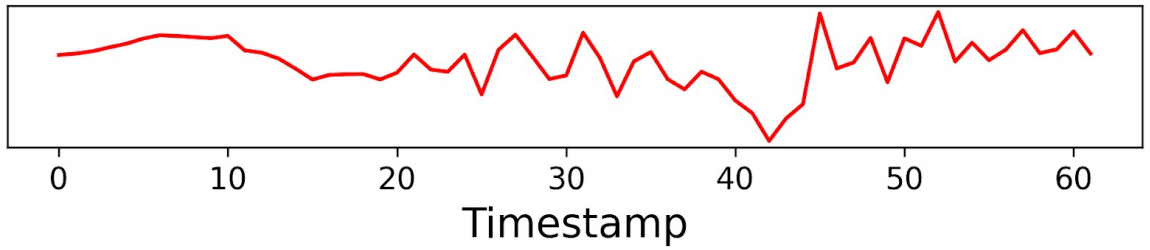
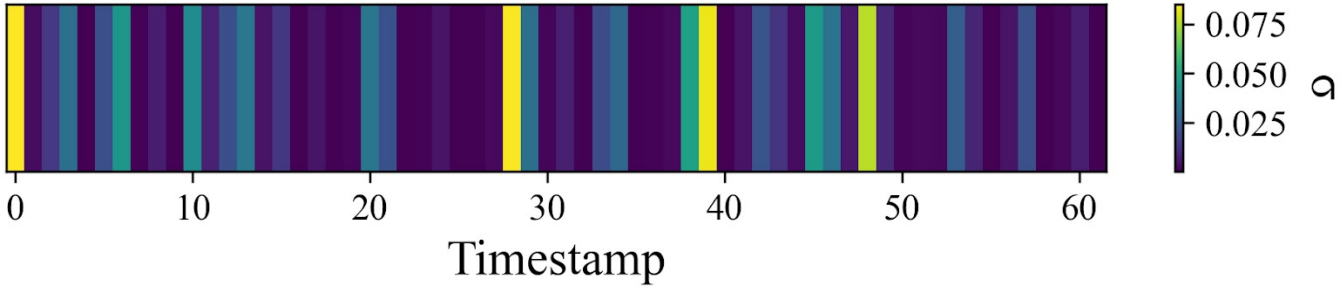


Random Data Reconstruction

Case Study – Face Detection



Time Series Data



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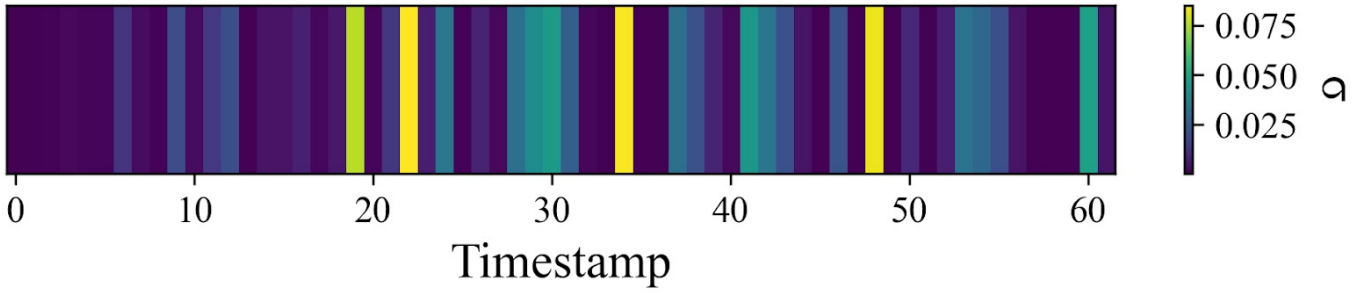

Task-aware Data Reconstruction

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Conclusion

- Task-agnostic SSL may produce sub-optimal performance
- Learn *task-aware* data representation customized to the end-task
- End-task and reconstruction task trained alternately
- Data-driven masking strategy uses attention scores to find timestamps deemed important by end-task and mask them for reconstruction
- TARNet outperforms 26 baselines on 40 datasets
- Case study shows task-aware method captures domain-specific inherent properties from data