# Disentangling Domain and General Representations for Time Series Classification

**7237**

## 1 Dataset

- **Battery charging (CHARGE):** The dataset, provided by Huawei, contains charging records of electric cars. Its task is to predict battery anomalies and identify the specific anomaly type. It includes 6 types of abnormal batteries. To safeguard user privacy, three batches of battery charging time series data (CHARGE1, CHARGE2, and CHARGE3) are used within a synthetic environment developed by domain experts. Each batch comprises 10,090 cars, with higher ID batches closely resembling real-world scenarios. Each entry consists of 10 charging records for a car with 96 battery cells, and each batch encompasses thousands of cars.
- **Electricity usage (ELEC):** This dataset, provided by State Grid, aims to identify electricity theft. It includes power consumption records from 179,663 users across 5 cities in Zhejiang Province, averaging 35,932 users per city. The focus is on monthly power usage transitions between these cities.
- **UCIHAR [Reyes-Ortiz *et al.*, 2016]:** This dataset contains six daily activities including walking, sitting, lying, standing, walking upstairs and walking downstairs. Volunteers wear smartphones with built-in accelerometers and gyroscopes to collect data at 50 Hz. There are 1,318,272 samples from 30 users, averaging 343 data pieces per user, with each piece containing 128 time points.
- **WISDM [Kwapisz *et al.*, 2011]:** This dataset also contains six daily activities like UCIHAR. But the accelerometers decreae to 3, The dataset is collected from 29 users, comprising a total of 1,098,207 samples. Each user contributes 295 data pieces, with each piece containing 128 time points.
- **Sleep-EDF [Ragab and Eldele, 2022]:** Sleep stage classification (SSC) problem aims to classify the electroencephalography (EEG) signals into five stages. The dataset is collected from 20 users, with each piece containing 128 data points manually.

## 2 Implementation details

For the battery charging dataset and electricity usage dataset, we treat each batch and city as a domain. For public UCIHAR, WISDM, Sleep-EDF datasets which contain a large number of human domains, we randomly choose 10 pairs of participants for each dataset with the same setting of CoDATS. The hyperparameter is chosen followed the setting of [Gong *et al.*, 2012]. For our method, the hyperparameter $\alpha$ is set to 1, $\beta$ is chosen from $\{0.1, 1\}$, and $\gamma$ is chosen from $\{1, 10, 100\}$. For all baseline methods, we adopt the default network architectures and settings reported in their public papers. For all methods, the batch size is set to $\{32, 64, 128\}$ varying from the size of the dataset. The Adam optimizer is adopted for all methods with the learning rate of 1e-3.

**Algorithm 1** Learning algorithm for CADT

**Input:** Labeled samples from source domain $\{\mathbf{x}_i^s, y_i^s, \}_{i=1}^{n_s}$ , unlabeled samples from target domain $\{\mathbf{x}_i^t\}_{i=1}^{n_t}$, batch iterations $T_1$, $T_2$ and batch size $N$, synthetic data $\{\mathbf{x}_j\}_{j=1}^{\gamma*(n_s+n_t)}$
**Output:** Target label predictions $\{\hat{y}_i\}_{i=1}^{n_t}$
**REPEAT**
**for** $t \leftarrow 1$ **to** $T_1$ **do**
    Randomly sample a minibatch of labeled source data and unlabeled target data of size $N$
    Generate domain-invariant representations $\mathbf{h}_s^v$, $\mathbf{h}_t^v$ and domain-specific representations $\mathbf{h}_s^c$, $\mathbf{h}_t^c$ respectively by forward propagation
    Update $\mathcal{L}_{task}$, $\mathcal{L}_{net}$, $\mathcal{L}_{domain}$ and $\mathcal{L}_{sphere}$
    Randomly sample a minibatch of synthetic data of size $N$
    Generate domain-specific representations $\mathbf{h}^c$ and update $\mathcal{L}_{domain}$
**end for**
**for** $t \leftarrow 1$ **to** $T_2$ **do**
    Optimize the discriminator and update $\mathcal{L}_{dis}$
**end for**
**UNTIL** stopping
Predict target label $\hat{y}_i$ for $i = 1, \ldots, n_t$

### 2.1 Hyper-parameter Analysis

We further study the effect of different settings of the hyperparameters in our proposed CADT. Both $\beta$ and $\gamma$ in the objective play the important role for learning. Specifically, $\beta$ regularizes how indistinguishable the domain-invariant representations are, while $\gamma$ controls the degree of con-

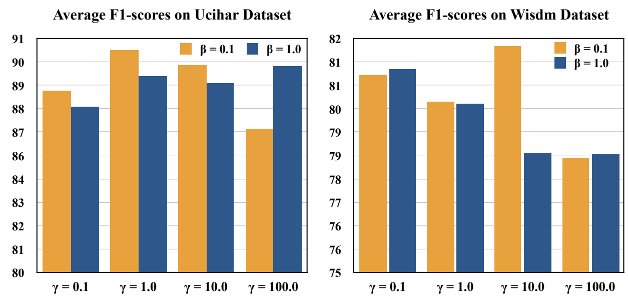


Figure 1: Results with different parameters.

straining the source and target representations in the latent space. Fig. 1 shows our CADT performance with parameter $\beta$ selected from $\{0.1, 1\}$ and parameter $\gamma$ selected from $\{0.1, 1.0, 10.0, 100.0\}$ on two public dataset UCIHAR and WISDM. We notice that CADT is robust to both $\beta$ and $\gamma$ since the gaps of average F1-score between the best and the worst are just $3.5\%$ on Ucihar dataset and $2.9\%$ on Wisdom dataset. The best performance for both datasets is achieved with parameter $\beta = 0.1$. The performance on Ucihar dataset decreases when $\gamma$ is larger than $1.0$. On the contrary, the best F1-score on Wisdm dataset is achieved with $\gamma = 10.0$. It shows that the degree of our class-wise hypersphere constraints should be tuned based on the dataset.

# 3 Recall and F1_score 71

Table 1: Recall and F1_score of different models on CHARGE dataset.S represents source and T represents target

| S | T | CNN | RNN | DDNN | MultiRocket | RDANN | VRADA | SASA | CoDATS | DAF | CADT |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 37.35/33.30 | 40.17/36.40 | 24.81/20.01 | 35.13/28.60 | 25.77/39.68 | 42.99/39.06 | 15.59/6.823 | 43.61/92.45 | 16.66/6.550 | 39.20/35.80 |
| 1 | 3 | 37.01/31.67 | 33.90/28.65 | 22.31/17.31 | 25.39/19.80 | 20.86/32.10 | 52.23/50.55 | 14.69/7.017 | 38.24/98.14 | 14.30/4.866 | 42.53/40.09 |
| 2 | 3 | 48.40/43.10 | 54.20/50.62 | 24.73/17.12 | 41.87/36.47 | 25.06/41.21 | 45.24/39.68 | 13.74/6.838 | 46.08/96.44 | 14.28/4.821 | 56.80/57.18 |
| 2 | 1 | 59.75/59.58 | 59.72/61.25 | 34.36/25.02 | 44.53/47.00 | 25.11/57.54 | 67.47/66.43 | 18.06/7.819 | 56.50/98.88 | 20.0/28.765 | 57.50/59.43 |
| 3 | 2 | 43.36/40.74 | 44.01/43.35 | 24.62/22.44 | 32.12/32.93 | 42.62/43.46 | 44.71/42.41 | 14.73/7.372 | 43.73/93.18 | 16.66/6.548 | 51.23/50.19 |
| 3 | 1 | 27.59/26.12 | 36.67/34.37 | 25.74/20.67 | 34.83/32.00 | 27.08/35.25 | 75.73/76.35 | 18.16/9.296 | 37.76/99.03 | 20.11/9.337 | 48.31/49.99 |

Table 2: Recall and F1_score of different models on ELEC dataset.S represents source and T represents target

| S | T | CNN | RNN | DDNN | MultiRocket | RDANN | VRADA | SASA | CoDATS | DAF | CADT |
|---|---|---|---|---|---|---|---|---|---|---|---|
| E | B | 52.46/20.75 | 50.75/5.960 | 51.63/39.47 | 14.68/10.42 | 50.15/1.803 | 48.95/48.95 | 47.94/34.25 | 61.64/38.77 | 91.05/89.12 | 81.04/79.30 |
| B | A | 56.07/37.52 | 50.97/5.250 | 54.24/46.00 | 14.68/11.28 | 50.43/3.535 | 62.13/62.13 | 62.53/62.47 | 71.54/61.46 | 76.84/70.48 | 82.72/82.70 |
| C | E | 56.37/30.56 | 51.19/5.514 | 53.01/44.05 | 15.29/13.10 | 50.43/2.431 | 85.05/85.05 | 57.63/56.38 | 64.66/45.58 | 83.16/79.10 | 94.10/94.64 |
| C | B | 57.99/37.12 | 50.45/2.992 | 51.09/36.05 | 15.13/11.68 | 50.13/1.264 | 85.29/85.29 | 51.41/38.84 | 61.22/37.26 | 68.81/57.76 | 85.28/84.23 |
| B | E | 57.79/35.28 | 51.56/7.842 | 53.65/45.63 | 14.93/12.01 | 50.52/3.233 | 60.89/60.89 | 56.36/54.63 | 69.78/56.66 | 69.22/60.37 | 85.38/85.98 |
| D | E | 53.51/22.85 | 51.78/8.261 | 52.75/43.73 | 14.50/11.09 | 50.94/4.883 | 50.63/50.63 | 65.95/65.82 | 65.82/48.15 | 88.61/85.87 | 90.42/91.26 |
| A | C | 51.16/8.038 | 51.02/5.607 | 51.26/42.20 | 14.61/11.84 | 50.36/2.528 | 52.86/52.86 | 67.98/68.22 | 55.25/19.64 | 71.65/66.95 | 66.64/67.05 |
| D | C | 51.27/12.92 | 51.29/6.367 | 51.24/42.23 | 14.56/11.95 | 50.32/2.238 | 57.54/57.54 | 62.79/61.68 | 64.59/45.76 | 77.24/72.86 | 91.96/93.17 |
| C | D | 52.48/22.60 | 50.80/4.106 | 50.80/37.46 | 14.79/11.78 | 50.15/1.426 | 75.05/75.05 | 55.11/53.13 | 60.89/36.94 | 74.16/67.96 | 89.55/89.86 |
| D | B | 55.70/32.65 | 50.85/4.764 | 51.78/37.95 | 14.77/10.55 | 50.56/3.658 | 52.82/52.82 | 49.47/42.85 | 65.83/48.75 | 91.03/89.21 | 86.43/85.77 |
| B | D | 53.92/30.17 | 51.32/6.685 | 53.04/44.81 | 14.96/11.65 | 50.77/4.428 | 69.68/69.68 | 61.08/59.08 | 63.28/42.25 | 68.66/59.16 | 79.66/79.76 |
| A | E | 51.28/8.639 | 50.62/3.590 | 52.65/42.95 | 17.39/12.78 | 50.32/2.431 | 51.75/51.75 | 51.15/48.04 | 55.16/19.28 | 81.17/80.17 | 73.44/73.77 |
| E | D | 53.11/19.43 | 50.98/5.789 | 52.25/41.14 | 14.72/11.28 | 50.57/3.388 | 48.28/48.28 | 58.01/57.53 | 56.01/22.81 | 77.65/71.52 | 81.97/82.05 |
| A | B | 50.72/8.136 | 50.38/2.966 | 51.06/35.84 | 14.35/9.397 | 50.06/1.554 | 52.95/52.95 | 54.40/46.87 | 54.91/19.50 | 72.11/64.31 | 74.04/71.89 |
| E | A | 54.00/27.11 | 50.97/6.282 | 53.97/45.60 | 14.55/11.46 | 50.72/4.982 | 50.38/50.38 | 57.02/54.80 | 59.29/33.22 | 88.86/87.39 | 80.57/80.63 |
| D | A | 54.30/29.41 | 51.15/5.879 | 52.21/41.54 | 14.79/11.74 | 50.43/3.080 | 54.24/54.24 | 58.78/57.96 | 66.73/51.79 | 75.11/70.48 | 87.93/88.28 |
| A | D | 50.50/5.873 | 50.70/4.166 | 50.63/36.99 | 15.11/11.12 | 50.34/2.275 | 51.19/51.19 | 63.60/63.85 | 55.87/21.12 | 81.49/79.71 | 68.63/68.16 |
| B | C | 54.85/26.28 | 51.13/6.087 | 51.57/43.47 | 14.73/12.28 | 50.33/2.207 | 66.73/66.73 | 73.69/63.75 | 64.47/45.54 | 72.51/66.97 | 80.83/81.64 |
| C | A | 58.24/40.03 | 51.33/6.219 | 52.91/41.98 | 15.68/13.57 | 50.81/4.584 | 60.16/60.16 | 63.77/61.16 | 63.63/44.56 | 67.80/58.61 | 83.99/84.19 |
| E | C | 54.11/22.45 | 51.04/6.026 | 53.45/47.39 | 15.42/13.66 | 50.40/2.739 | 53.08/53.08 | 70.59/70.43 | 58.99/31.09 | 77.11/72.75 | 85.56/87.46 |

Table 3: Recall and F1_score of different models using UCIHAR dataset.S represents source and T represents target

| S | T | CNN | RNN | DDNN | MultiRocket | RDANN | VRADA | SASA | CoDATS | DAF | CADT |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | 4 | 51.33/48.60 | 46.90/45.86 | 54.85/46.57 | 39.34/39.08 | 38.29/35.93 | 44.44/35.07 | 51.78/44.95 | 76.95/75.90 | 27.30/19.42 | 87.74/87.41 |
| 26 | 3 | 45.48/43.60 | 45.10/43.91 | 59.52/52.77 | 21.40/9.034 | 37.68/34.33 | 51.72/44.47 | 46.72/42.19 | 74.56/74.71 | 27.06/21.78 | 84.24/83.83 |
| 7 | 25 | 37.11/31.94 | 33.71/32.19 | 62.12/54.96 | 27.02/23.46 | 27.40/20.33 | 39.23/31.76 | 53.63/49.06 | 57.08/54.31 | 27.59/20.59 | 82.33/80.73 |
| 16 | 9 | 48.99/47.35 | 56.84/56.52 | 53.39/47.23 | 68.34/68.95 | 38.72/34.23 | 39.93/30.26 | 50.07/49.23 | 78.33/78.12 | 27.86/22.61 | 82.79/81.67 |
| 6 | 23 | 50.60/47.23 | 46.55/45.85 | 71.90/66.75 | 39.50/38.84 | 37.24/34.05 | 46.83/38.58 | 57.47/56.19 | 71.23/69.60 | 30.83/21.12 | 91.67/91.46 |
| 7 | 8 | 53.30/48.55 | 58.26/57.73 | 73.32/70.52 | 13.84/10.44 | 45.94/44.22 | 43.40/33.18 | 64.86/63.24 | 79.79/78.58 | 38.15/35.64 | 85.07/83.74 |
| 13 | 7 | 65.76/63.23 | 69.41/68.73 | 77.92/73.93 | 28.47/28.30 | 68.75/67.78 | 47.81/37.90 | 72.02/70.88 | 88.11/87.99 | 42.46/39.13 | 90.73/90.32 |
| 16 | 10 | 34.83/31.58 | 28.35/27.19 | 44.58/38.45 | 58.53/55.38 | 23.72/18.78 | 33.79/24.67 | 36.24/35.89 | 46.00/44.75 | 24.90/19.61 | 72.80/72.65 |
| 29 | 14 | 44.00/38.81 | 42.13/37.80 | 63.01/57.69 | 33.21/29.22 | 33.47/26.88 | 39.79/29.53 | 37.22/34.55 | 56.52/51.85 | 29.46/21.80 | 83.76/82.85 |
| 13 | 29 | 53.15/49.32 | 57.46/57.02 | 68.29/62.19 | 14.90/13.03 | 47.45/44.56 | 46.85/38.75 | 61.45/58.09 | 83.68/83.32 | 38.51/34.44 | 88.79/87.58 |

Table 4: Recall and F1_score of different models using WISDM dataset.S represents source and T represents target

| S | T | CNN | RNN | DDNN | MultiRocket | RDANN | VRADA | SASA | CoDATS | DAF | CADT |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 9 | 18 | 32.25/25.32 | 41.24/37.45 | 34.44/28.35 | 74.07/71.73 | 31.17/25.08 | 21.38/15.36 | 21.23/16.07 | 67.93/62.75 | 16.93/8.952 | 54.55/51.30 |
| 31 | 11 | 31.42/22.86 | 22.51/16.10 | 41.38/33.51 | 40.83/33.47 | 19.64/15.61 | 28.69/19.88 | 26.71/21.28 | 32.01/29.26 | 25.0/013.81 | 41.80/35.93 |
| 2 | 6 | 33.77/28.30 | 31.88/22.95 | 40.42/36.29 | 48.00/42.64 | 31.25/26.00 | 37.45/31.84 | 29.71/25.41 | 70.38/67.64 | 21.80/16.58 | 65.54/63.83 |
| 7 | 25 | 24.73/18.85 | 40.08/37.15 | 32.73/26.30 | 28.13/23.52 | 30.92/27.56 | 25.42/20.03 | 17.42/9.946 | 54.96/46.38 | 22.66/16.40 | 67.55/63.84 |
| 3 | 27 | 25.46/20.00 | 41.55/40.58 | 33.38/26.38 | 39.66/35.96 | 35.08/33.04 | 26.19/21.03 | 25.61/24.58 | 60.93/59.06 | 17.45/10.18 | 52.54/50.64 |
| 22 | 8 | 47.88/42.49 | 26.81/20.91 | 41.22/35.48 | 26.29/16.83 | 26.72/18.82 | 32.01/25.36 | 34.17/34.35 | 37.25/33.11 | 28.47/20.49 | 76.41/76.18 |
| 6 | 23 | 28.86/24.05 | 29.54/27.48 | 35.36/30.45 | 38.31/37.63 | 30.67/26.63 | 31.84/26.67 | 29.65/28.58 | 44.36/41.51 | 24.53/18.92 | 62.89/59.70 |
| 27 | 20 | 40.78/33.70 | 37.53/34.90 | 45.96/38.42 | 38.12/33.11 | 31.57/27.11 | 37.52/30.74 | 28.29/28.00 | 74.37/70.32 | 34.82/25.65 | 91.25/92.05 |
| 15 | 19 | 29.51/20.75 | 25.44/18.20 | 45.89/36.82 | 12.58/14.30 | 28.19/20.91 | 38.61/28.40 | 8.823/9.098 | 27.08/20.17 | 29.73/20.45 | 41.87/33.40 |
| 16 | 7 | 35.12/29.73 | 32.73/30.08 | 39.66/34.54 | 36.89/35.86 | 29.05/25.46 | 26.05/20.82 | 29.78/28.98 | 39.89/34.67 | 26.44/20.07 | 60.31/60.41 |

Table 5: The performance of not using domain adaptation (CNN), not using coupled interactive networks (w/o CIN), class-wise hyperspheres (w/o CH).

| Dataset | Source | Target | CNN | w/o CH | w/o CIN | CADT |
|---|---|---|---|---|---|---|
| CHARGE | 1 | 2 | 44.46±4.719 | 41.60±3.504 | 46.43±2.397 | 44.70±2.253 |
| | 1 | 3 | 42.43±3.919 | 39.62±3.398 | 48.13±3.015 | 49.72±2.964 |
| | 2 | 3 | 52.27±3.596 | 52.53±5.687 | 64.43±1.491 | 60.86±6.784 |
| | 2 | 1 | 65.56±13.64 | 59.96±7.196 | 69.31±2.633 | 70.44±4.136 |
| | 3 | 2 | 54.70±3.941 | 53.28±1.653 | 55.88±1.126 | 54.77±2.191 |
| | 3 | 1 | 34.84±21.93 | 50.64±2.761 | 57.59±1.779 | 58.49±2.355 |
| UCIHAR | 2 | 4 | 53.08±5.009 | 82.96±2.876 | 87.81±1.510 | 88.67±1.104 |
| | 26 | 3 | 45.65±7.630 | 74.87±4.955 | 83.75±0.684 | 84.31±1.159 |
| | 7 | 25 | 37.73±6.472 | 67.18±5.568 | 81.87±0.650 | 82.23±2.059 |
| | 16 | 9 | 49.21±7.000 | 75.62±1.842 | 81.79±3.437 | 82.65±3.568 |
| | 6 | 23 | 51.0±5.526 | 80.31±2.460 | 91.18±1.610 | 90.93±2.857 |
| | 7 | 8 | 53.86±7.023 | 80.31±4.011 | 87.03±4.039 | 85.39±3.428 |
| | 13 | 7 | 66.56±7.434 | 90.15±0.904 | 92.03±1.174 | 91.40±2.407 |
| | 16 | 10 | 35.27±7.841 | 66.48±3.039 | 74.45±3.652 | 73.98±4.409 |
| | 29 | 14 | 44.59±3.217 | 68.31±7.217 | 82.37±12.70 | 83.56±9.197 |
| | 13 | 29 | 51.34±7.241 | 81.87±0.861 | 88.12±5.929 | 88.62±5.125 |
| WISDM | 9 | 18 | 61.99±3.463 | 71.87±2.237 | 72.57±2.361 | 72.65±2.250 |
| | 31 | 11 | 45.82±11.51 | 72.5±1.494 | 72.26±1.397 | 73.28±0.312 |
| | 2 | 6 | 66.53±1.197 | 78.49±4.277 | 75.87±3.146 | 81.81±5.166 |
| | 7 | 25 | 49.72±12.26 | 67.26±11.64 | 85.07±4.517 | 89.53±1.220 |
| | 3 | 27 | 55.68±12.93 | 66.12±5.754 | 76.56±4.419 | 70.87±7.731 |
| | 22 | 8 | 75.57±5.514 | 77.70±3.747 | 88.02±1.358 | 87.29±1.301 |
| | 6 | 23 | 61.05±3.831 | 72.34±5.196 | 75.31±9.547 | 78.90±7.316 |
| | 27 | 20 | 62.23±7.961 | 80.0±11.03 | 92.70±4.320 | 95.72±1.450 |
| | 15 | 19 | 40.15±7.884 | 47.5±11.06 | 46.87±10.02 | 50.31±9.639 |
| | 16 | 7 | 61.75±3.068 | 77.26±5.053 | 84.76±0.741 | 85.54±1.235 |

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