Pseudo Code for TimesURL

Algorithm 1: TimesURL Algorithm

Input: training set $\mathcal{X}$, the number of training set N, mix rate μ for FTAug, missing rate ρ in reconstruction, encoder model f_θ, reconstruction model f_{θ_r}

Output: encoder model f_θ

$\mathcal{L}_{recon} \leftarrow 0$
$\mathcal{L}_{dual} \leftarrow 0$
for x_i in $\mathcal{X}$ **do**
  x_i, x_i' = FTAug($\mathcal{X}$, x_i, μ)
  Encode x_i and x_i' by f_θ and then obtain the overlapping representations r_i and r_i'
  $h \leftarrow 0$
  $\mathcal{L}^i_{dual} \leftarrow 0$
  while length(r_i) > 1 **do**
    Generate double Universums by Eq. (1) and Eq. (2)
    Calculate contrastive loss ℓ^i_{temp} and ℓ^i_{inst} by Eq. (3) and Eq. (4)
    $\mathcal{L}^i_{dual} \leftarrow \mathcal{L}^i_{dual} + \ell^i_{temp} + \ell^i_{inst}$
    $r_i \leftarrow$ MaxPooling(r_i)
    $r_i' \leftarrow$ MaxPooling(r_i')
    $h \leftarrow h + 1$
  end while
  $\mathcal{L}_{dual} \leftarrow \mathcal{L}_{dual} + \frac{1}{h}\mathcal{L}^i_{dual}$
  Create random mask m with ρ
  Mask samples x_i, x_i' and denote them as x_i^M, $x_i'^M$
  Encode x_i^M and $x_i'^M$ by f_θ to obtain the corresponding representations r_i^M and $r_i'^M$
  Decode r_i^M and $r_i'^M$ by R to $\hat{x}_i$ and $\hat{x}_i'$
  Calculate reconstruction loss $\mathcal{L}^i_{recon}$ by Eq. (6)
  $\mathcal{L}_{recon} \leftarrow \mathcal{L}_{recon} + \mathcal{L}^i_{recon}$
end for
$\mathcal{L} \leftarrow \frac{1}{N}(\mathcal{L}_{recon} + \mathcal{L}_{dual})$

Algorithm 2: FTAug Algorithm for Time Series Data

procedure FTAug($\mathcal{X}, x_i, \mu$)
  Random generate cropping range $[a_1, b_1]$ and $[a_2, b_2]$ with $0 < a_1 \le a_2 \le b_1 \le b_2 \le T$
  Random sample x_j from $\mathcal{X}$ with $i \ne j$
  Extract sub-series x_i^l from x_i within the range $[a_1, b_1]$
  Extract sub-series x_i^r from x_i and x_j^r from x_j within the range $[a_2, b_2]$
  Calculate frequency $q_i^r \leftarrow FFT\left(x_i^r\right)$, $q_j^r \leftarrow FFT\left(x_j^r\right)$
  Create random mask m_1 for q_i^r with μ (no more than 0.5)
  Create inverse mask m_2 for q_j^r with m_1
  Mixed frequency $F \leftarrow m_1 \odot q_i^r + m_2 \odot q_j^r$
  Inverse series from mixed frequency $x_i' \leftarrow iFFT\left(F\right)$
  $x_i \leftarrow x_i^l$
  return x_i, x_i'
end procedure

Experimental Details

Details for Benchmark Datasets

We provide the benchmark dataset descriptions in Table 1 and our experiments are conducted on 165 datasets collected from multiple different sources.

It shows that the length of the experiment benchmarks ranges from 8 to 17984 for classification and from 840 to 74580 for anomaly detection. The consistently good experimental results offer compelling evidence that supports the effectiveness of TimesURL across datasets of varying lengths.

Furthermore, the time series data used in each downstream task is collected from diverse sources, resulting in a wide range of temporal variations and time series properties. These inherent challenges serve to further validate the efficacy of TimesURL in various time series tasks.

Reproduction Details on Baselines

Classification & Transfer Learning For classification tasks, the baseline results primarily rely on TS2Vec (Yue et al. 2022). The results of TS2Vec are directly obtained from (Yue et al. 2022) while other baselines including TNC (Tonekaboni, Eytan, and Goldenberg 2021), TS-TCC (Eldele et al. 2021), TST (Zerveas et al. 2021) are based on the reproduction results in TS2Vec. Since InfoTS follows the same experimental settings as TS2Vec, we also utilize the reported results from the original paper on InfoTS(Luo et al. 2023). The results of T-Loss are directly sourced from (Franceschi, Dieuleveut, and Jaggi 2019). It is important to note that some results for T-Loss, TS-TCC, and TNC are missing for several datasets in both UEA and UCR due to their inability to handle time series data with missing values.

For transfer learning, we adopt the same experimental setting as in the classification tasks. Specifically, we train our model on a single dataset without re-training the pre-trained model for every target dataset and evaluate its performance on several other datasets. This approach allows us to assess the transferability and generalization capabilities of our model across multiple datasets. To evaluate the efficacy of transfer learning, we compare the results obtained from our transfer learning approach with non-transfer TimesURL and supervised InfoTS methods.

Forecasting For short- and long-Term forecasting tasks, the results of representation learning baselines mainly rely on CoST (Woo et al. 2022). Given that CoST follows a similar setting as TS2Vec, we directly use the results of CoST, TS2Vec and TNC reported in (Woo et al. 2022), which are reproduced results in CoST. Additionally, we extract the results of end-to-end forecasting methods, including Informer (Zhou et al. 2021), LogTrans (Li et al. 2019), N-BEATS (Oreshkin et al. 2019) and TCN (Bai, Kolter, and Koltun 2018) are taken directly from their respective original papers.

Imputation For imputation tasks, none of the existing self-supervised representation learning methods have previously addressed this specific task. To evaluate the effec-

Table 1: Summary of experiment benchmarks.

Tasks	Benchmarks	Metrics	Series Length
Forecasting	**Long-term**: ETT (3 subsets), Electricity, Weather	MSE, MAE	96∼720
	Short-term: ETT (3 subsets), Electricity, Weather	MSE, MAE	24∼48
Imputation	ETT (3 subsets)	MSE, MAE	96
Classification	UEA (30 subsets), UCR(128 subsets)	Accuracy	8∼17984
Anomaly Detection	Yahoo, KPI	Precision, Recall, F1-Socre	840∼74580
Transfer Learning	UCR(10 subsets)	Accuracy	128∼1639

tiveness of TimesURL for imputation, we choose InfoTS and TS2Vec as the comparison models, as they are the only two existing methods capable of handling two types of tasks. Both methods follow their original setting with the randomly masked input time series data in the ratio of $\{12.5\%, 25\%, 37.5\%, 50\%\}$ as well as TimesURL.

Anomaly Detection In anomaly detection tasks, we adhere to the settings proposed in TS2Vec, which recommend using the anomaly score as the dissimilarity between representations computed from masked and unmasked last observations. In line with this approach, we directly utilize the results reported in TS2Vec and (Ren et al. 2019) for our analysis.

Details for Benchmark Tasks

Classification & Transfer Learning For classification and transfer learning tasks in TimesURL, we adhere to the protocol outlined in (Franceschi, Dieuleveut, and Jaggi 2019) that utilizes an SVM classifier with RBF kernel on the top of the learned representations. The penalty C is selected through a grid search conducted via cross-validation on the training set from a search space of $\{10^i | i \in [-4, 4]\} \cup \{\infty\}$.

In the case of classification tasks, the result of DTW on *InsectWingbeat* dataset in the UEA archive is not reported, while T-Loss, TS-TCC and TNC cannot handle *DodgerLoopDay*, *DodgerLoopGame* and *DodgerLoop-Weekend* in UCR archive, because they cannot handle datasets with missingness. Consequently, these unavailable accuracy scores are dismissed when calculating average accuracy and average rank. It is essential to highlight that our TimesURL can operate on all UEA and UCR datasets and we provide the comprehensive results in Table 4 and 5.

Forecasting We employ the linear protocol, which utilizes a ridge regression model on the learned representations to predict future values. The mentioned ridge regression is a linear regression model with L_2 regularization term α selected using a grid search on the validation set from a search space of $\{0.1, 0.2, 0.5, 1, 2, 5, 10, 20, 50, 100, 200, 500, 1000\}$.

All the evaluation results reported in this study pertain to the test set. We assess the forecasting performance using mean squared error (MSE) and mean absolute error (MAE) based on the following metrics.

$$\begin{aligned} MSE &= \frac{1}{HF} \sum_{i=1}^{H} \sum_{j=1}^{F} (x_{t+i}^{(j)} - \hat{x}_{t+i}^{(j)})^2 \\ MAE &= \frac{1}{HF} \sum_{i=1}^{H} \sum_{j=1}^{F} |x_{t+i}^{(j)} - \hat{x}_{t+i}^{(j)}| \end{aligned} \quad (1)$$

where $x_{t+i}^{(j)}$ and $\hat{x}_{t+i}^{(j)}$ are the ground truth and predicted value respectively on variable j at timestamp $t+i$. The overall metrics for a dataset are the average MSE and MAE over all slices and instances.

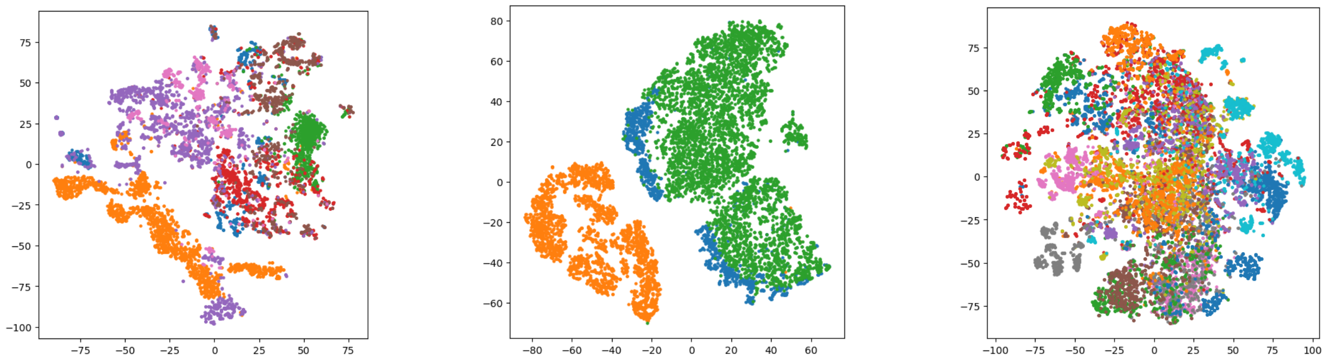
Anomaly Detection In anomaly detection tasks, we follow the settings suggested in TS2Vec that propose the anomaly score as the dissimilarity between the representations computed from masked and unmasked last observation(i.e. x_t) and we denote them as r_t^u and r_t^m, respectively. The anomaly score α_t is measured using L_1 distance:

$$\alpha_t = \|r_t^u - r_t^m\|_1 \quad (2)$$

To mitigate drifting effects, we incorporate local averages, as suggested in (Ren et al. 2019). Specifically, we utilize the preceding Z points, denoted as $\bar{a}t = \frac{1}{Z} \sum i = t - Z^{t-1} \alpha_i$, to adjust the anomaly score. The adjusted anomaly score is computed as $a_t^{adj} = \frac{\alpha_t - \bar{\alpha}_t}{\bar{\alpha}_t}$. During the inference part, if $\alpha_t^{adj} > \mu + \beta\delta$, the timestamp t is an anomaly point, where μ and δ the mean and standard deviation respectively of the historical scores and β is a hyperparameter.

In common anomaly detection tasks, point-wise metrics are often deemed unnecessary since it suffices to trigger an alarm at any point within a continuous anomaly segment, as long as the delay is not excessively long. Consequently, anomalies detected within a certain delay k are considered correct (Ren et al. 2019; Xu et al. 2018). For a fair comparison, we use $k = 7$ in TimesURL for minutely sampled data and $k = 3$ for hourly sampled data as in (Ren et al. 2019; Xu et al. 2018; Yue et al. 2022). Additionally, in the preprocessing stage, we employ difference to mitigate drifting in the raw data. Specifically, we apply differencing d times, where d represents the number of unit roots determined by the Augmented Dickey-Fuller (ADF) test.

Imputation We employ a single-layer perceptron on top of the learned representations obtained from the missing dataset to learn the complete series. The imputation performance is evaluated using MSE and MAE between ground truth and the imputed values.



(a) ElectricDevices. (b) StarLightCurves. (c) Crop.

Figure 1: t-SNE visualizations of the learned representations of TimesURL on the top 3 UCR datasets with the largest number of test samples. Different colors represent different classes.

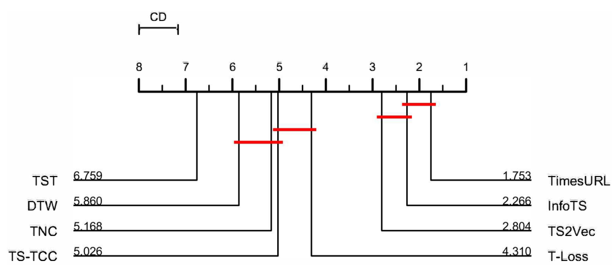


Figure 2: Critical Difference (CD) diagram of representation learning methods on time series classification tasks with a confidence level of 95%.

Full Results

Classification The complete results of TimesURL on 30 UEA and 128 UCR datasets can be found in Tables 4 and 5, respectively. It is clear that when compared to other existing methods of unsupervised representation, TimesURL consistently achieves the highest average accuracy across both datasets.

We employ t-SNE for visualizing the learned time series representations, as depicted in Figure 1. The visualization clearly demonstrates that the representations learned by TimesURL possess the ability to effectively distinguish between different classes within the latent space.

To further analyze the effectiveness of TimesURL, we conduct the significance test on the obtained results. Specifically, we employed the critical difference diagram (Nemenyi 1963; Demšar 2006) for Nemenyi tests across all datasets, including the 30 UEA and 128 UCR datasets.

The significance level α is set 0.05, then the critical value is $q_\alpha = 3.031$, and the critical difference $CD = q_\alpha\sqrt{k(k+1)/6N}(k=8, N=158)$. The results of the significance test are presented in Figure 2, in which classifiers that are not connected by a bold line are significantly different in average ranks. TimesURL achieves an average rank of 1.7532, surpassing all other methods and demonstrating significantly superior performance compared to all methods

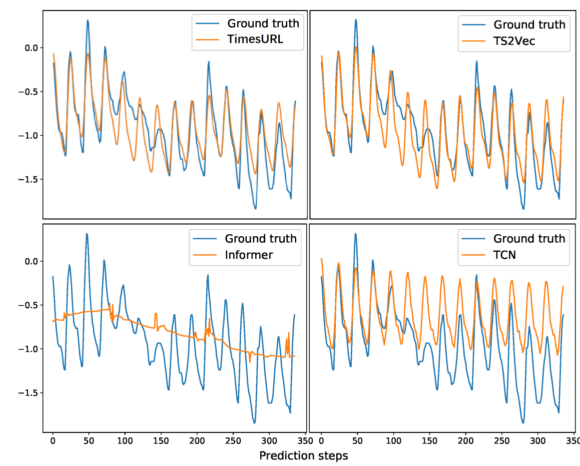


Figure 3: A prediction sline (H=336) on $ETTh_2$.

except InfoTS.

Forecasting For both long-term and short-term forecasting, we expand our comparative analysis to include additional real-world applications, namely Electricity (UCI 2015) and Weather (Wetterstation 2008). Overall, our proposed TimesURL method establishes a new state-of-the-art (SOTA) performance in most cases, as demonstrated in Table 2. It achieves lower average MSE and demonstrates favorable performance across various application domains. Notably, TimesURL outperforms CoST, a representation learning method specifically designed for forecasting, as well as other well-recognized and advanced time series forecasting models including some end-to-end models.

Examining the predictive capabilities of different models, as depicted in Figure 3, we observe that Informer excels in capturing long-term trends but struggles with capturing temporal patterns. On the other hand, TCN exhibits potential in capturing periodic patterns but falls short in long-term forecasting. In contrast, both our TimesURL and TS2Vec demonstrate proficiency in capturing temporal properties, resulting in superior predictive performance compared to other methods.

As illustrated in Figure 3, Informer has the ability in capturing long-term trends but fails to capture temporal patterns. While TCN shows potential in capturing periodical patterns but fails in long-term forecasting. Our TimesURL can capture temporal properties well as TS2Vec and show better predictive results than other methods.

Transfer Learning We test the transferability of the learned representations for the first 10 datasets from the UCR. Specifically, we use the encoder trained on one dataset and computed representations on the remaining nine datasets for classification. The transferability results are presented in Table 3, indicating that the transfer version of TimesURL achieves competitive performance compared to the non-transfer version. Furthermore, the classification results obtained through transfer learning are comparable to those achieved using supervised learning, thus highlighting the successful transferability of TimesURL across different datasets.

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Table 2: Short- and Long-Term Forecasting Univariate forecasting results.

Methods		Representation Learning								End-to-end Forecasting							
		TimesURL		CoST		TS2Vec		TNC		Informer		LogTrans		N-BEATS		TCN	
Metrics		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTh1	24	**0.0355**	**0.1423**	0.0400	0.1520	0.0390	0.1510	0.0570	0.1840	0.0980	0.2470	0.1030	0.2590	0.0940	0.2380	0.1040	0.2540
	48	**0.0535**	**0.1460**	0.0600	0.1860	0.0620	0.1890	0.0940	0.2390	0.1580	0.3190	0.1670	0.3280	0.2100	0.3670	0.2060	0.3660
	168	**0.0956**	**0.2327**	0.0970	0.2360	0.1420	0.2910	0.1710	0.3290	0.1830	0.3460	0.2070	0.3750	0.2320	0.3910	0.4620	0.5860
	336	0.1210	0.2672	**0.1120**	**0.2580**	0.1600	0.3160	0.1920	0.3570	0.2220	0.3870	0.2300	0.3980	0.2320	0.3880	0.4220	0.5640
	720	**0.1453**	0.3068	0.1480	**0.3060**	0.1790	0.3450	0.2350	0.4080	0.2690	0.4350	0.2730	0.4630	0.3220	0.4900	0.4380	0.5780
ETTh2	24	0.0834	0.2186	**0.0790**	**0.2070**	0.0910	0.2300	0.0970	0.2380	0.0930	0.2400	0.1020	0.2550	0.1980	0.3450	0.1090	0.2510
	48	**0.1158**	**0.2186**	0.1180	0.2590	0.1240	0.2740	0.1310	0.2810	0.1550	0.3140	0.1690	0.3480	0.2340	0.3860	0.1470	0.3020
	168	**0.1747**	**0.3324**	0.1890	0.3390	0.1980	0.3550	0.1970	0.3540	0.2320	0.3890	0.2460	0.4220	0.3310	0.4530	0.2090	0.3660
	336	**0.1875**	**0.3469**	0.2060	0.3600	0.2050	0.3640	0.2070	0.3660	0.2630	0.4170	0.2670	0.4370	0.4310	0.5080	0.2370	0.3910
	720	**0.1862**	**0.3519**	0.2140	0.3710	0.2080	0.3710	0.2070	0.3700	0.2770	0.4310	0.3030	0.4930	0.4370	0.5170	0.2000	0.3670
ETTm1	24	**0.0128**	**0.0839**	0.0150	0.0880	0.0160	0.0930	0.0190	0.1030	0.0300	0.1370	0.0650	0.2020	0.0540	0.1840	0.0270	0.1270
	48	**0.0242**	0.1765	0.0250	**0.1170**	0.0280	0.1260	0.0360	0.1420	0.0690	0.2030	0.0780	0.2200	0.1900	0.3610	0.0400	0.1540
	96	**0.0366**	**0.1445**	0.0380	0.1470	0.0450	0.1620	0.0540	0.1780	0.1940	0.3720	0.1990	0.3860	0.1830	0.3530	0.0970	0.2460
	288	0.0797	0.2139	**0.0770**	**0.2090**	0.0950	0.2350	0.0980	0.2440	0.4010	0.5540	0.4110	0.5720	0.1860	0.3620	0.3050	0.4550
	672	0.1141	**0.2552**	**0.1130**	0.2570	0.1420	0.2900	0.1360	0.2900	0.5120	0.6440	0.5980	0.7020	0.1970	0.3680	0.4450	0.5760
Electricity	24	0.2450	0.2750	**0.2430**	**0.2640**	0.2600	0.2880	0.2520	0.2780	0.2510	0.2750	0.5280	0.4470	0.4270	0.3300	**0.2430**	0.3670
	48	0.2950	0.3070	0.2920	**0.3000**	0.3130	0.3210	0.3000	0.3080	0.3460	0.3390	0.4090	0.4140	0.5510	0.3920	**0.2830**	0.3970
	168	0.4080	0.3790	0.4050	**0.3750**	0.4290	0.3920	0.4120	0.3840	0.5440	0.4240	0.9590	0.6120	0.8930	0.5380	**0.3570**	0.4490
	336	0.5480	0.4640	0.5600	0.4730	0.5650	0.4780	0.5480	0.4660	0.7130	0.5120	1.0790	0.6390	1.0350	0.6690	**0.3550**	**0.4460**
	720	0.8560	0.6550	0.8890	0.6450	0.8630	0.6510	0.8590	0.6510	1.1820	0.8060	1.0010	0.7140	1.5480	0.8810	**0.3870**	**0.4770**
Weather	24	**0.0933**	**0.2111**	0.0960	0.2130	0.0960	0.2150	0.1020	0.2210	0.1170	0.2510	0.1360	0.2790	-	-	0.1090	0.2170
	48	**0.1312**	**0.2547**	0.1380	0.2620	0.1400	0.2640	0.1390	0.2640	0.1780	0.3180	0.2060	0.3560	-	-	0.1430	0.2690
	168	0.1994	0.3268	0.2070	0.3340	0.2070	0.3350	0.1980	0.3280	0.2660	0.3980	0.3090	0.4390	-	-	**0.1880**	**0.3190**
	336	0.2235	0.3514	0.2300	0.3560	0.2310	0.3600	0.2150	0.3470	0.2970	0.4160	0.3590	0.4840	-	-	**0.1920**	**0.3200**
	720	0.2362	0.3646	0.2420	0.3700	0.2330	0.3650	0.2190	0.3530	0.3590	0.4660	0.3880	0.4990	-	-	**0.1980**	**0.3290**
Avg.		**0.1881**	**0.2810**	0.1933	0.2834	0.2028	0.2984	0.2070	0.3073	0.2964	0.3856	0.3517	0.4297	-	-	0.2361	0.3669

Table 3: Test classification results of transfer learning for partial datasets in UEA and UCR. The number in parentheses represents the length of the time series. CC is the abbreviation of ChlorineConcentration.

Test \ Training	Adiac (176)	ArrowHead (251)	Beef (470)	BeetleFly (512)	BirdChicken (512)	Car (577)	CBF (128)	CC (166)	CinCECGTorso (1639)	Coffee (286)	InfoTS Supervised
Adiac	***0.818***	0.780	0.785	0.775	0.785	0.785	0.790	0.765	0.780	0.770	0.795
ArrowHead	0.817	***0.897***	0.863	0.846	0.869	0.851	0.823	0.817	0.874	0.846	0.874
Beef	0.800	0.800	***0.867***	0.867	0.767	0.800	0.867	0.800	0.867	0.800	0.900
BeetleFly	0.900	0.900	0.900	***1.000***	0.900	0.950	0.950	0.950	0.900	0.950	0.950
BirdChicken	0.800	0.800	0.800	0.800	***0.900***	0.800	0.800	0.800	0.850	0.800	0.850
Car	0.883	0.833	0.867	0.867	0.850	***0.950***	0.917	0.833	0.917	0.817	0.900
CBF	0.991	0.991	0.987	0.988	0.987	0.987	***0.998***	0.998	0.993	0.996	1.000
CC	0.819	0.837	0.819	0.786	0.790	0.802	0.824	***0.783***	0.871	0.799	0.825
CinCECGTorso	0.747	0.701	0.891	0.933	0.907	0.741	0.805	0.730	***0.909***	0.699	0.896
Coffee	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	***1.000***	1.000

Table 4: Full results of multivariate time series classification on 30 UEA datasets.

Dataset	TimesURL	InfoTS	TS2Vec	T-Loss	TNC	TS-TCC	TST	DTW
ArticularyWordRecognition	**0.990**	0.987	0.987	0.943	0.973	0.953	0.977	0.987
AtrialFibrillation	**0.400**	0.200	0.200	0.133	0.133	0.267	0.067	0.200
BasicMotions	**1.000**	0.975	0.975	**1.000**	0.975	**1.000**	0.975	0.975
CharacterTrajectories	0.990	0.974	**0.995**	0.993	0.967	0.985	0.975	0.989
Cricket	**1.000**	0.986	0.972	0.972	0.958	0.917	**1.000**	**1.000**
DuckDuckGeese	**0.720**	0.540	0.680	0.650	0.460	0.380	0.620	0.600
EigenWorms	**0.870**	0.733	0.847	0.840	0.840	0.779	0.748	0.618
Epilepsy	**0.978**	0.971	0.964	0.971	0.957	0.957	0.949	0.964
ERing	**0.985**	0.949	0.874	0.133	0.852	0.904	0.874	0.133
EthanolConcentration	0.304	0.281	0.308	0.205	0.297	0.285	0.262	**0.323**
FaceDetection	**0.608**	0.534	0.501	0.513	0.536	0.544	0.534	0.529
FingerMovements	**0.660**	0.630	0.480	0.580	0.470	0.460	0.560	0.530
HandMovementDirection	**0.432**	0.392	0.338	0.351	0.324	0.243	0.243	0.231
Handwriting	0.462	0.452	**0.515**	0.451	0.249	0.498	0.225	0.286
Heartbeat	0.746	0.722	0.683	0.741	0.746	**0.751**	0.746	0.717
JapaneseVowels	**0.989**	0.984	0.984	**0.989**	0.978	0.930	0.978	0.949
Libras	**0.922**	0.883	0.867	0.883	0.817	0.822	0.656	0.870
LSST	**0.602**	0.591	0.537	0.509	0.595	0.474	0.408	0.551
MotorImagery	**0.680**	0.630	0.510	0.580	0.500	0.610	0.500	0.500
NATOPS	**0.961**	0.933	0.928	0.917	0.911	0.822	0.850	0.883
PEMS-SF	**0.821**	0.751	0.682	0.676	0.699	0.734	0.740	0.711
PenDigits	0.989	**0.990**	0.989	0.981	0.979	0.974	0.560	0.977
PhonemeSpectra	0.237	0.249	0.233	0.222	0.207	**0.252**	0.085	0.151
RacketSports	**0.862**	0.855	0.855	0.855	0.776	0.816	0.809	0.803
SelfRegulationSCP1	**0.908**	0.874	0.812	0.843	0.799	0.823	0.754	0.775
SelfRegulationSCP2	**0.600**	0.578	0.578	0.539	0.550	0.533	0.550	0.539
SpokenArabicDigits	0.985	0.947	**0.988**	0.905	0.934	0.970	0.923	0.963
StandWalkJump	**0.467**	**0.467**	**0.467**	0.333	0.400	0.333	0.267	0.200
UWaveGestureLibrary	**0.919**	0.884	0.906	0.875	0.759	0.753	0.575	0.903
InsectWingbeat	**0.473**	0.470	0.466	0.156	0.469	0.264	0.105	–
Avg. ACC	**0.752**	0.714	0.704	0.658	0.670	0.668	0.617	0.629
Avg. Rank	**1.367**	3.200	3.567	4.567	5.333	5.000	5.900	5.207

Table 5: Full results of univariate time series classification on 128 UCR datasets.

	TimesURL	InfoTS	TS2Vec	T-Loss	TNC	TS-TCC	TST	DTW
Adiac	**0.818**	0.788	0.775	0.675	0.726	0.767	0.550	0.604
ArrowHead	**0.897**	**0.874**	0.857	0.766	0.703	0.737	0.771	0.703
Beef	**0.867**	0.833	0.767	0.667	0.733	0.600	0.500	0.633
BeetleFly	**1.000**	0.950	0.900	0.800	0.850	0.800	**1.000**	0.700
BirdChicken	**0.900**	**0.900**	0.800	0.850	0.750	0.650	0.650	0.750
Car	**0.950**	0.883	0.883	0.833	0.683	0.583	0.550	0.733
CBF	0.998	0.999	**1.000**	0.983	0.983	0.998	0.898	0.997
ChlorineConcentration	0.783	0.822	**0.832**	0.749	0.760	0.753	0.562	0.648
CinCECGTorso	0.909	**0.928**	0.827	0.713	0.669	0.671	0.508	0.651
Coffee	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.821	**1.000**
Computers	0.736	**0.748**	0.660	0.664	0.684	0.704	0.696	0.700
CricketX	0.733	0.774	**0.805**	0.713	0.623	0.731	0.385	0.754
CricketY	0.736	**0.774**	0.769	0.728	0.597	0.718	0.467	0.744
CricketZ	0.746	0.787	**0.792**	0.708	0.682	0.713	0.403	0.754
DiatomSizeReduction	0.993	**0.997**	0.987	0.984	0.993	0.977	0.961	0.967
DistalPhalanxOutlineCorrect	0.790	**0.801**	0.775	0.775	0.754	0.754	0.728	0.717
DistalPhalanxOutlineAgeGroup	**0.784**	0.763	0.727	0.727	0.741	0.755	0.741	0.770
DistalPhalanxTW	0.712	**0.727**	0.698	0.676	0.669	0.676	0.568	0.590
Earthquakes	0.820	**0.821**	0.748	0.748	0.748	0.748	0.748	0.719
ECG200	0.930	0.930	0.920	**0.940**	0.830	0.880	0.830	0.770
ECG5000	0.943	**0.945**	0.935	0.933	0.937	0.941	0.928	0.924
ECGFiveDays	**1.000**	**1.000**	**1.000**	**1.000**	0.999	0.878	0.763	0.768
ElectricDevices	**0.727**	0.702	0.721	0.707	0.700	0.686	0.676	0.602
FaceAll	**0.928**	0.929	0.805	0.786	0.766	0.813	0.504	0.808
FaceFour	**0.943**	0.818	0.932	0.920	0.659	0.773	0.511	0.830
FacesUCR	0.929	0.913	**0.930**	0.884	0.789	0.863	0.543	0.905
FiftyWords	**0.802**	0.793	0.774	0.732	0.653	0.653	0.525	0.690
Fish	**0.954**	0.937	0.937	0.891	0.817	0.817	0.720	0.920
FordA	0.925	0.915	**0.948**	0.928	0.902	0.930	0.568	0.555
FordB	0.775	0.785	0.807	0.793	0.733	**0.815**	0.507	0.620
GunPoint	**1.000**	**1.000**	0.987	0.980	0.967	0.993	0.827	0.907
Ham	**0.819**	0.838	0.724	0.724	0.752	0.743	0.524	0.467
HandOutlines	**0.949**	0.946	0.930	0.922	0.930	0.724	0.735	0.881
Haptics	**0.549**	0.546	0.536	0.490	0.474	0.396	0.357	0.377
Herring	**0.703**	0.656	0.641	0.594	0.594	0.594	0.594	0.531
InlineSkate	0.444	0.424	0.415	0.371	0.378	0.347	0.287	0.384
InsectWingbeatSound	**0.642**	0.639	0.630	0.597	0.549	0.415	0.266	0.355
ItalyPowerDemand	**0.970**	0.966	0.961	0.954	0.928	0.955	0.845	0.950
LargeKitchenAppliances	**0.883**	0.853	0.875	0.789	0.776	0.848	0.595	0.795
Lightning2	**0.951**	0.934	0.869	0.869	0.869	0.836	0.705	0.869
Lightning7	**0.877**	**0.877**	0.863	0.795	0.767	0.685	0.411	0.726
Mallat	**0.974**	**0.974**	0.915	0.951	0.871	0.922	0.713	0.934
Meat	**0.967**	**0.967**	**0.967**	0.950	0.917	0.883	0.900	0.933
MedicalImages	0.793	**0.820**	0.793	0.750	0.754	0.747	0.632	0.737
MiddlePhalanxOutlineCorrect	0.856	**0.859**	0.838	0.825	0.818	0.818	0.753	0.698
MiddlePhalanxOutlineAgeGroup	**0.669**	0.662	0.636	0.656	0.643	0.630	0.617	0.500
MiddlePhalanxTW	0.604	**0.617**	0.591	0.591	0.571	0.610	0.506	0.506
MoteStrain	0.865	**0.873**	0.863	0.851	0.825	0.843	0.768	0.835
NonInvasiveFetalECGThorax1	**0.951**	0.941	0.930	0.878	0.898	0.898	0.471	0.790
NonInvasiveFetalECGThorax2	**0.954**	0.944	0.940	0.919	0.912	0.913	0.832	0.865
OliveOil	**0.933**	**0.933**	0.900	0.867	0.833	0.800	0.800	0.833
OSULeaf	0.860	0.760	**0.876**	0.760	0.723	0.723	0.545	0.591
PhalangesOutlinesCorrect	**0.839**	0.826	0.823	0.784	0.787	0.804	0.773	0.728
Phoneme	0.285	0.281	**0.312**	0.276	0.180	0.242	0.139	0.228
Plane	**1.000**	**1.000**	**1.000**	0.990	**1.000**	**1.000**	0.933	**1.000**
ProximalPhalanxOutlineCorrect	0.914	**0.927**	0.900	0.859	0.866	0.873	0.770	0.784
ProximalPhalanxOutlineAgeGroup	0.873	**0.883**	0.844	0.844	0.854	0.839	0.854	0.805
ProximalPhalanxTW	0.829	**0.844**	0.824	0.771	0.810	0.800	0.780	0.761
RefrigerationDevices	0.621	**0.624**	0.589	0.515	0.565	0.563	0.483	0.464
ScreenType	**0.533**	0.493	0.411	0.416	0.509	0.419	0.419	0.397
ShapeletSim	0.894	0.856	**1.000**	0.672	0.589	0.683	0.489	0.650
ShapesAll	0.8775	0.852	**0.905**	0.848	0.788	0.773	0.733	0.768
SmallKitchenAppliances	0.767	**0.773**	0.733	0.677	0.725	0.691	0.592	0.643
SonyAIBORobotSurface1	**0.935**	0.927	0.903	0.902	0.804	0.899	0.724	0.725
SonyAIBORobotSurface2	0.925	**0.953**	0.890	0.889	0.834	0.907	0.745	0.831

Table 5: Full results of univariate time series classification on 128 UCR datasets.

	TimesURL	InfoTS	TS2Vec	T-Loss	TNC	TS-TCC	TST	DTW
StarLightCurves	**0.977**	0.973	0.971	0.964	0.968	0.967	0.949	0.907
Strawberry	**0.978**	**0.978**	0.965	0.954	0.951	0.965	0.916	0.941
SwedishLeaf	**0.957**	0.950	0.942	0.914	0.880	0.923	0.738	0.792
Symbols	0.963	**0.979**	0.976	0.963	0.885	0.916	0.786	0.950
SyntheticControl	**1.000**	**1.000**	0.997	0.987	**1.000**	0.990	0.490	0.993
ToeSegmentation1	0.934	0.934	**0.947**	0.939	0.864	0.930	0.807	0.772
ToeSegmentation2	0.869	**0.915**	**0.915**	0.900	0.831	0.877	0.615	0.838
Trace	**1.000**	**1.000**	**1.000**	0.990	**1.000**	**1.000**	**1.000**	**1.000**
TwoLeadECG	**0.999**	0.998	0.987	**0.999**	0.993	0.976	0.871	0.905
TwoPatterns	**1.000**	**1.000**	**1.000**	0.999	**1.000**	0.999	0.466	**1.000**
UWaveGestureLibraryX	0.808	**0.819**	0.810	0.785	0.781	0.733	0.569	0.728
UWaveGestureLibraryY	**0.743**	0.736	0.729	0.710	0.697	0.641	0.348	0.634
UWaveGestureLibraryZ	0.753	0.768	**0.770**	0.757	0.721	0.690	0.655	0.658
UWaveGestureLibraryAll	0.961	**0.967**	0.934	0.896	0.903	0.692	0.475	0.892
Wafer	**0.998**	**0.998**	**0.998**	0.992	0.994	0.994	0.991	0.980
Wine	0.926	**0.963**	0.889	0.815	0.759	0.778	0.500	0.574
WordSynonyms	0.683	**0.704**	**0.704**	0.691	0.630	0.531	0.422	0.649
Worms	**0.818**	0.753	0.701	0.727	0.623	0.753	0.455	0.584
WormsTwoClass	0.831	**0.857**	0.805	0.792	0.727	0.753	0.584	0.623
Yoga	0.867	0.869	**0.887**	0.837	0.812	0.791	0.830	0.837
ACSF1	0.860	0.850	**0.910**	0.900	0.730	0.730	0.760	0.640
AllGestureWiimoteX	0.736	0.630	**0.777**	0.763	0.703	0.697	0.259	0.716
AllGestureWiimoteY	0.744	0.686	**0.793**	0.726	0.699	0.741	0.423	0.729
AllGestureWiimoteZ	0.727	0.629	**0.770**	0.723	0.646	0.689	0.447	0.643
BME	**1.000**	**1.000**	0.993	0.993	0.973	0.933	0.760	0.900
Chinatown	**0.988**	**0.988**	0.968	0.951	0.977	0.983	0.936	0.957
Crop	0.749	**0.766**	0.756	0.722	0.738	0.742	0.710	0.665
EOGHorizontalSignal	**0.619**	0.572	0.544	0.605	0.442	0.401	0.373	0.503
EOGVerticalSignal	0.497	0.459	**0.503**	0.434	0.392	0.376	0.298	0.448
EthanolLevel	0.634	**0.712**	0.484	0.382	0.424	0.486	0.260	0.276
FreezerRegularTrain	**0.998**	0.996	0.986	0.956	0.991	0.989	0.922	0.899
FreezerSmallTrain	0.986	**0.988**	0.894	0.933	0.982	0.979	0.920	0.753
Fungi	**1.000**	0.946	0.962	**1.000**	0.527	0.753	0.366	0.839
GestureMidAirD1	**0.631**	0.592	**0.631**	0.608	0.431	0.369	0.208	0.569
GestureMidAirD2	**0.631**	0.492	0.515	0.546	0.362	0.254	0.138	0.608
GestureMidAirD3	**0.377**	0.315	0.346	0.285	0.292	0.177	0.154	0.323
GesturePebbleZ1	0.698	0.802	**0.930**	0.919	0.378	0.395	0.500	0.791
GesturePebbleZ2	0.696	0.842	0.873	**0.899**	0.316	0.430	0.380	0.671
GunPointAgeSpan	0.997	**1.000**	0.994	0.994	0.984	0.994	0.991	0.918
GunPointMaleVersusFemale	**1.000**	**1.000**	**1.000**	0.997	0.994	0.997	**1.000**	0.997
GunPointOldVersusYoung	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.838
HouseTwenty	**0.950**	0.924	**0.941**	0.933	0.782	0.790	0.815	0.924
InsectEPGRegularTrain	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.872
InsectEPGSmallTrain	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	**1.000**	0.735
MelbournePedestrian	0.953	**0.962**	0.959	0.944	0.942	0.949	0.741	0.791
MixedShapesRegularTrain	**0.958**	0.935	0.922	0.905	0.911	0.855	0.879	0.842
MixedShapesSmallTrain	**0.916**	0.887	0.881	0.860	0.813	0.735	0.828	0.780
PickupGestureWiimoteZ	**0.880**	**0.820**	**0.820**	0.740	0.620	0.600	0.240	0.660
PigAirwayPressure	0.389	0.432	**0.683**	0.510	0.413	0.380	0.120	0.106
PigArtPressure	0.817	0.830	**0.966**	0.928	0.808	0.524	0.774	0.245
PigCVP	0.688	0.653	**0.870**	0.788	0.649	0.615	0.596	0.154
PLAID	0.564	0.355	0.561	0.555	0.495	0.445	0.419	**0.840**
PowerCons	**1.000**	**1.000**	0.972	0.900	0.933	0.961	0.911	0.878
Rock	**0.780**	0.760	0.700	0.580	0.580	0.600	0.680	0.600
SemgHandGenderCh2	0.940	0.944	**0.963**	0.890	0.882	0.837	0.725	0.802
SemgHandMovementCh2	0.773	0.836	**0.893**	0.789	0.593	0.613	0.420	0.584
SemgHandSubjectCh2	0.878	0.924	**0.951**	0.853	0.771	0.753	0.484	0.727
ShakeGestureWiimoteZ	**0.940**	0.920	**0.940**	0.920	0.820	0.860	0.760	0.860
SmoothSubspace	**1.000**	**1.000**	0.993	0.960	0.913	0.953	0.827	0.827
UMD	**1.000**	**1.000**	**1.000**	0.993	0.993	0.986	0.910	0.993
DodgerLoopDay	0.613	**0.675**	0.562	–	–	–	0.200	0.500
DodgerLoopGame	0.920	**0.942**	0.841	–	–	–	0.696	0.877
DodgerLoopWeekend	0.971	**0.986**	0.964	–	–	–	0.732	0.949
Avg.ACC	**0.845**	0.838	0.836	0.806	0.761	0.757	0.639	0.729
Avg.Rank	**1.844**	2.047	2.625	4.248	5.128	5.032	6.961	6.008