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Unsupervised Time-Series Representation Learning with Iterative Bilinear Temporal-Spectral Fusion

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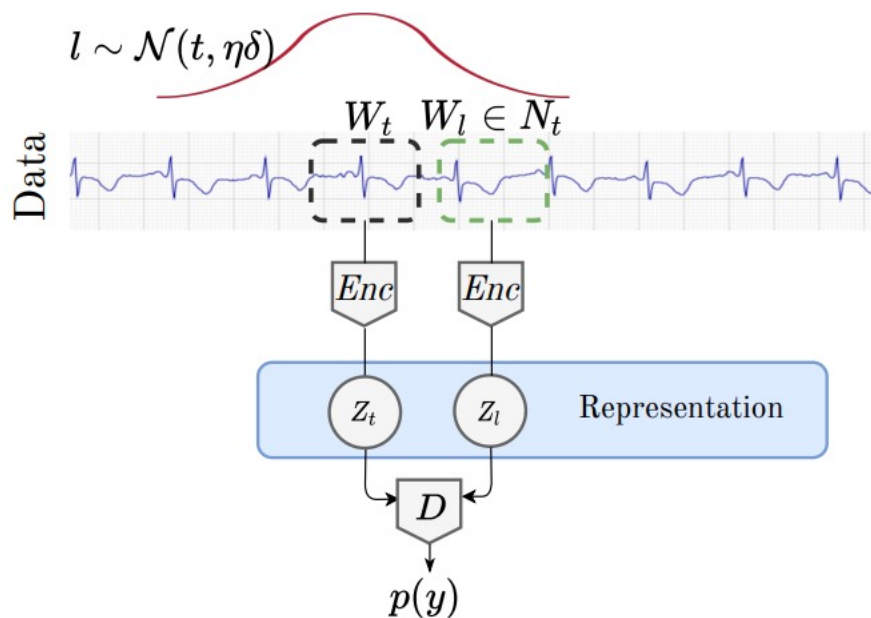
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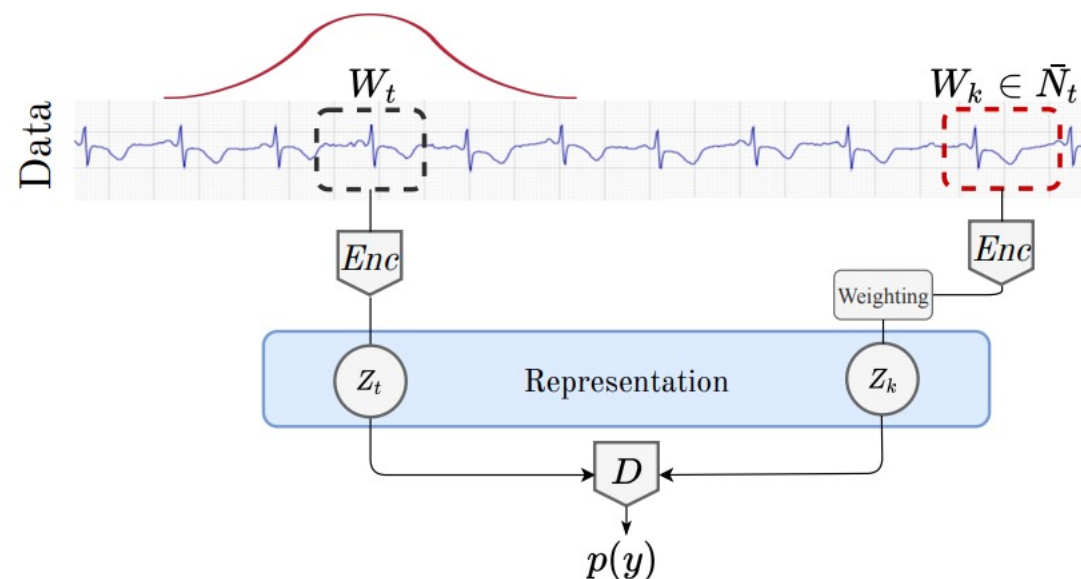
- Related Work and Limitations
- Proposed Method
- Results and Analysis

Related Work

Unsupervised representation learning for time series



(a) Neighborhood samples



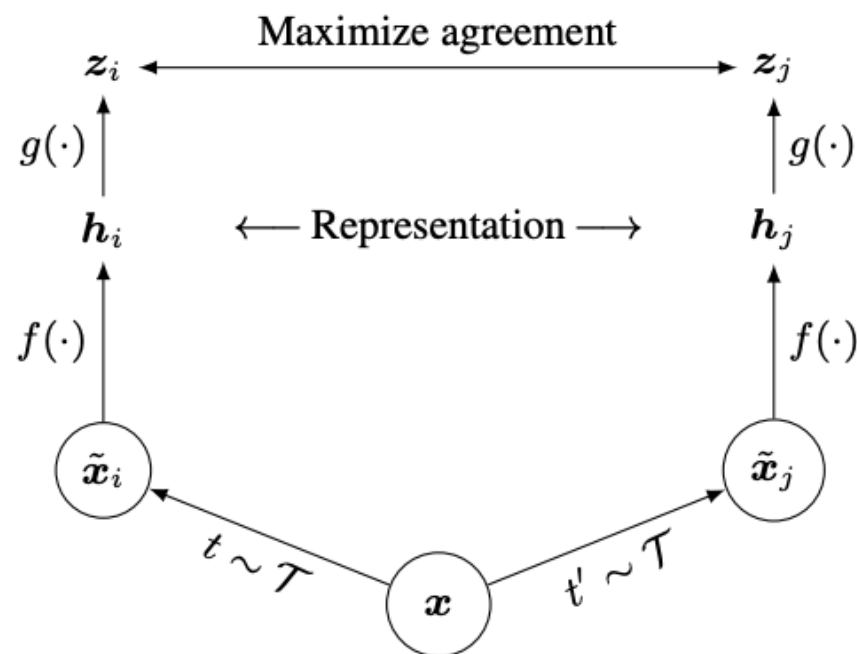
(b) Non-neighboring samples

Tonekaboni S, Eytan D, Goldenberg A. Unsupervised Representation Learning for Time Series with Temporal Neighborhood Coding[C]//International Conference on Learning Representations. 2020.



Related Work

Contrastive learning

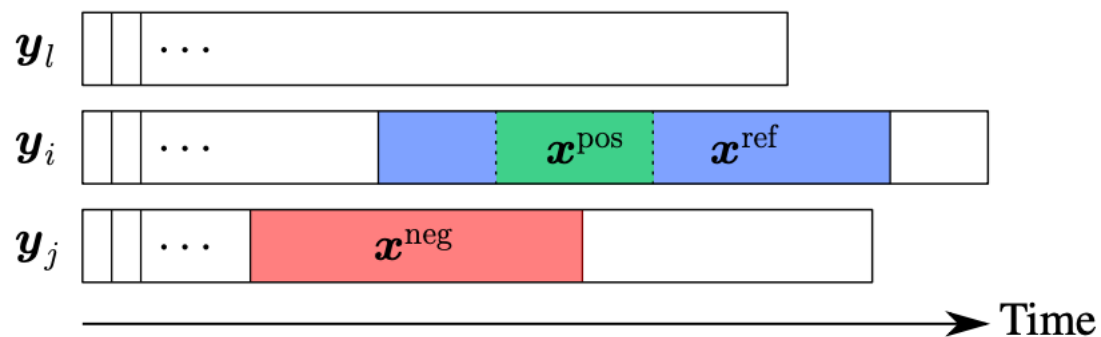


Chen T, Kornblith S, Norouzi M, et al. A simple framework for contrastive learning of visual representations[C]//International conference on machine learning. PMLR, 2020: 1597-1607.



Related Work

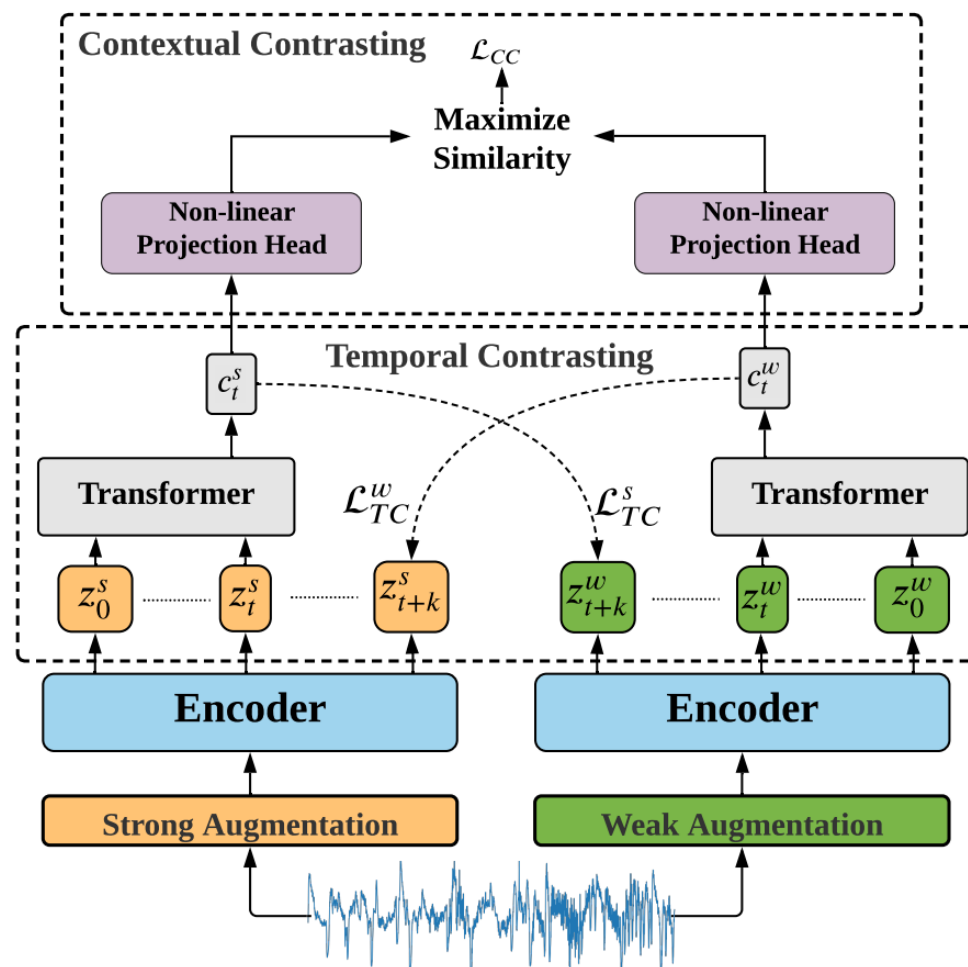
Time series contrastive learning



Franceschi J Y, Dieuleveut A, Jaggi M. Unsupervised scalable representation learning for multivariate time series[J]. Advances in neural information processing systems, 2019, 32.

Related Work

Time series contrastive learning



Eldele E, Ragab M, Chen Z, et al. Time-series representation learning via temporal and contextual contrasting[J]. arXiv preprint arXiv:2106.14112, 2021.



Limitations of Existing Approaches

1. Inconsistency between temporal and spectral representations
2. Severely based on the nearest principle when choosing positive and negative samples

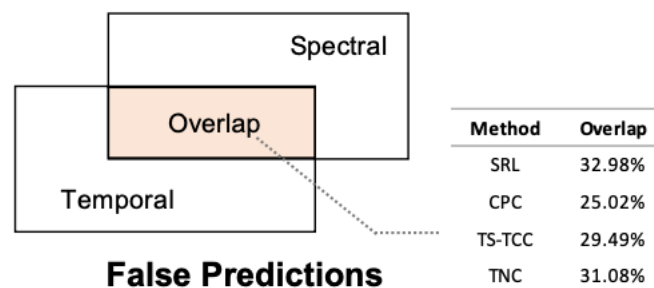


Figure 1. Statistics about false predictions of randomly selected evaluation samples.



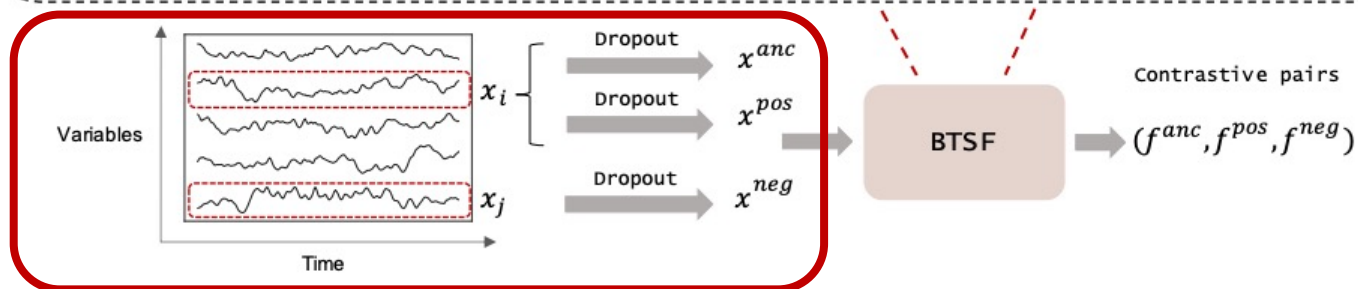
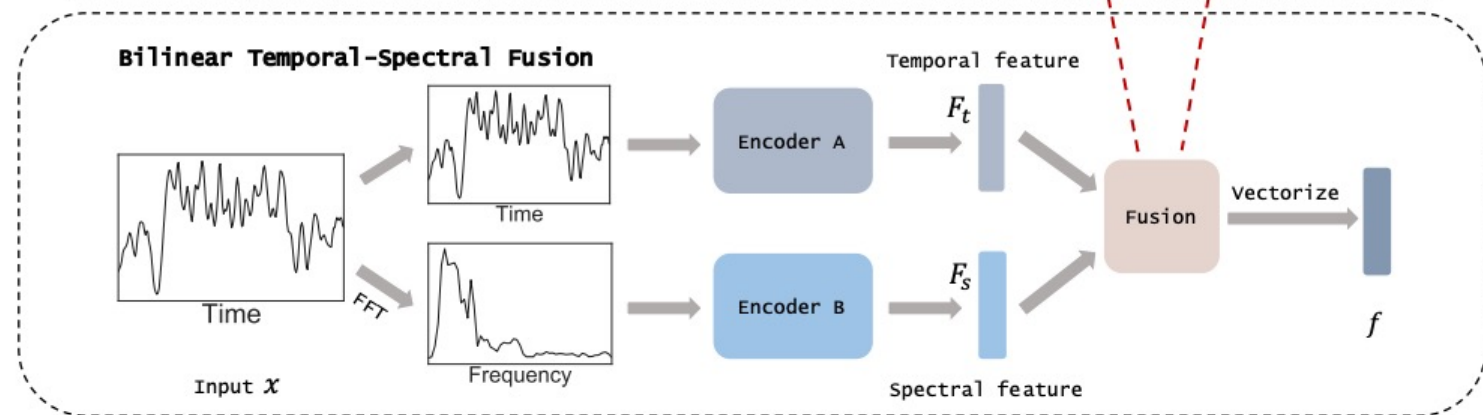
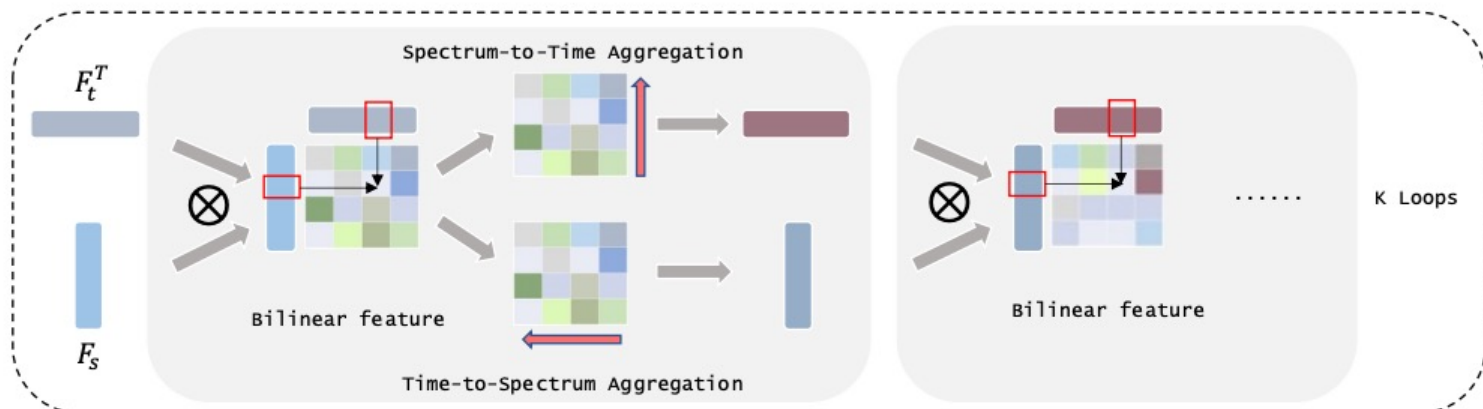
Our Proposed Framework

Main Contributions:

1. Instance-level augmentation technique
2. A novel iterative bilinear temporal-spectral fusion
3. Sufficient assessments including alignment and uniformity
4. Significantly outperforms previous works in downstream classification, forecasting and anomaly detection tasks



Our Proposed Framework — BTSF



Instance-level augmentation technique

$$\mathbf{x}^{anc} = Dropout(\mathbf{x}), \quad \mathbf{x}^{pos} = Dropout(\mathbf{x}).$$



Our Proposed Framework — BTSF

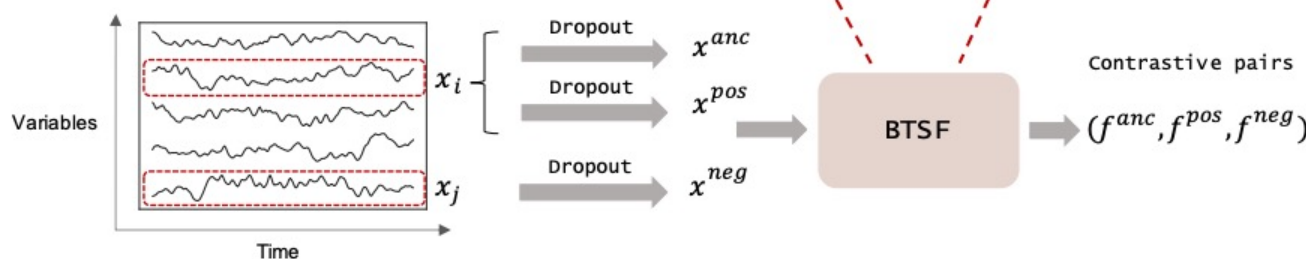
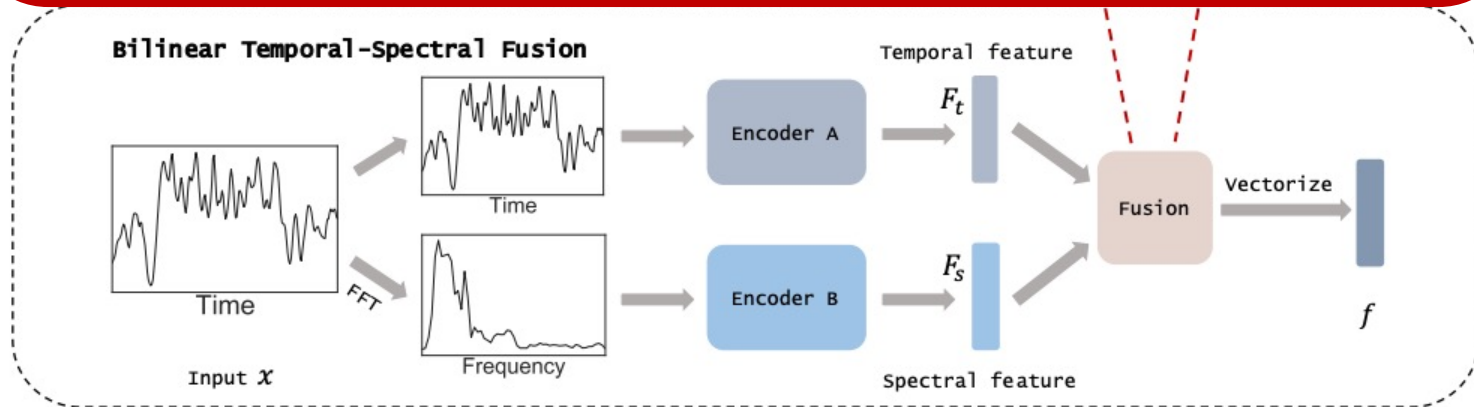
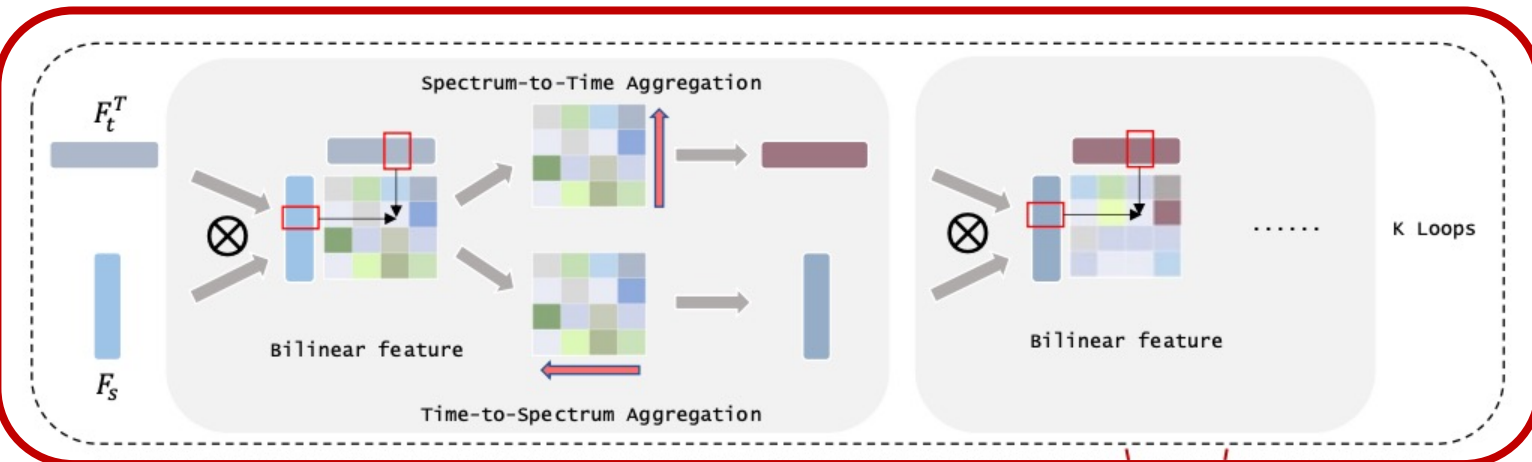
Iterative bilinear temporal-spectral fusion

$$\begin{aligned}
 \mathbf{F}_{bilinear} &= \mathbf{F}_t^T \times \mathbf{F}_s = \sum_{i=1}^m \sum_{j=1}^n \mathbf{F}(i, j) \\
 &= \sum_{i=1}^m \sum_{j=1}^n \mathbf{F}_t(i)^T \mathbf{F}_s(j)
 \end{aligned}$$

$$\begin{aligned}
 \mathbf{F}_{bilinear} &= \mathbf{F}_t^T \times \mathbf{U} \times \mathbf{V}^T \times \mathbf{F}_s \\
 &= (\mathbf{U}^T \times \mathbf{F}_t) \circ (\mathbf{V}^T \times \mathbf{F}_s)
 \end{aligned}$$

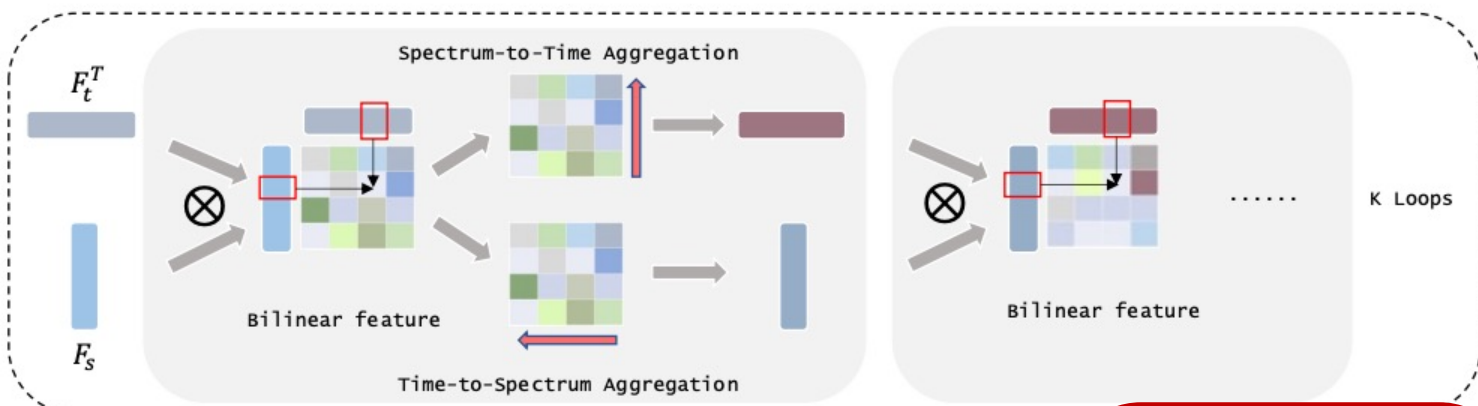
$$S2T: \mathbf{F}_t = BiCasual(Conv(\mathbf{F}_{bilinear}))$$

$$T2S: \mathbf{F}_s = Conv(BiCasual(\mathbf{F}_{bilinear}))$$



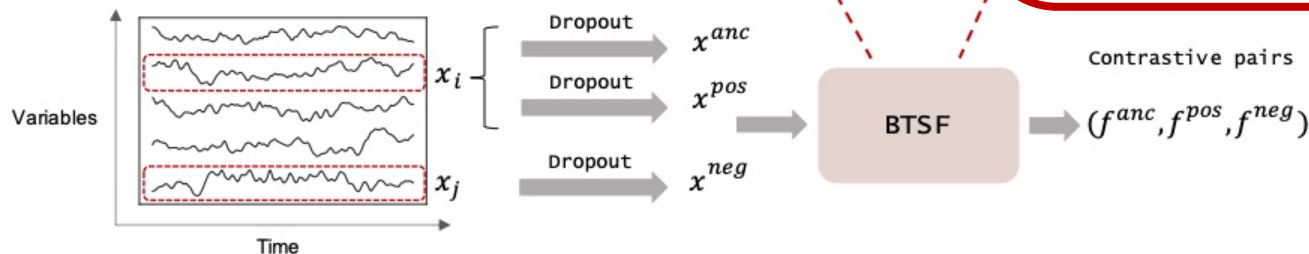
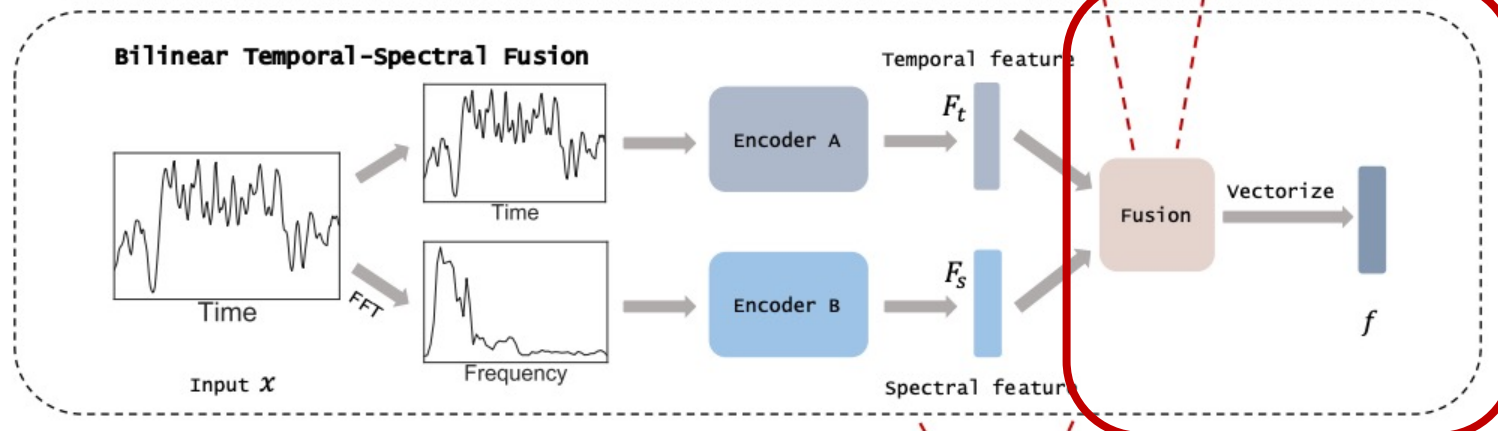


Our Proposed Framework — BTSF



Output and Loss Function

$$f = \sigma(W_t^T \times F_t + W_s^T \times F_s + F_t^T \times W \times F_s)$$



$$\mathcal{L} = \mathbb{E}_{\mathbf{X} \sim P_{data}} [-\log(\text{sim}(\mathbf{f}^{anc}, \mathbf{f}^{pos})/\tau)] + \mathbb{E}_{\mathbf{x}^{neg} \sim \mathbf{X}} [\log(\text{sim}(\mathbf{f}^{anc}, \mathbf{f}^{neg})/\tau)]$$



Our Proposed Framework — BTSF

Effectiveness of the Proposed BTSF

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial \mathbf{F}_t} &= \frac{\partial \mathcal{L}}{\partial \mathbf{f}} \mathbf{W}_t + \frac{\partial \mathcal{L}}{\partial \mathbf{f}} \mathbf{W} \times \mathbf{F}_s, \\ \frac{\partial \mathcal{L}}{\partial \mathbf{F}_s} &= \frac{\partial \mathcal{L}}{\partial \mathbf{f}} \mathbf{W}_s + \frac{\partial \mathcal{L}}{\partial \mathbf{f}} \mathbf{W}^T \times \mathbf{F}_t\end{aligned}\tag{12}$$

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial \mathbf{W}_t} &= \frac{\partial \mathcal{L}}{\partial \mathbf{f}} \mathbf{F}_t, \\ \frac{\partial \mathcal{L}}{\partial \mathbf{W}_s} &= \frac{\partial \mathcal{L}}{\partial \mathbf{f}} \mathbf{F}_s, \\ \frac{\partial \mathcal{L}}{\partial \mathbf{W}} &= \frac{\partial \mathcal{L}}{\partial \mathbf{f}} \mathbf{F}_t \times \mathbf{F}_s^T\end{aligned}\tag{13}$$

$$\begin{aligned}\frac{\partial \mathcal{L}}{\partial \theta_t} &= \frac{\partial \mathcal{L}}{\partial \mathbf{f}} \frac{\partial \mathbf{f}}{\partial \mathbf{F}_t} \mathbf{W}_t + \frac{\partial \mathcal{L}}{\partial \mathbf{f}} \frac{\partial \mathbf{f}}{\partial \mathbf{F}_t} \mathbf{W} \times \mathbf{F}_s, \\ \frac{\partial \mathcal{L}}{\partial \theta_s} &= \frac{\partial \mathcal{L}}{\partial \mathbf{f}} \frac{\partial \mathbf{f}}{\partial \mathbf{F}_s} \mathbf{W}_s + \frac{\partial \mathcal{L}}{\partial \mathbf{f}} \frac{\partial \mathbf{f}}{\partial \mathbf{F}_s} \mathbf{W}^T \times \mathbf{F}_t\end{aligned}\tag{14}$$



Results and Analysis

Time-Series Classification

Table 1. Comparisons of classification results.

Methods	HAR		Sleep-EDF		ECG Waveform	
	Accuracy	AUPRC	Accuracy	AUPRC	Accuracy	AUPRC
Supervised	92.03±2.48	0.98±0.00	83.41±1.44	0.78±0.52	84.81±0.28	0.67±0.01
KNN	84.85±0.84	0.75±0.01	64.87±1.73	0.75±2.88	54.76±5.46	0.38±0.06
SRL	63.60±3.37	0.71±0.01	78.32±1.45	0.71±2.83	75.51±1.26	0.47±0.00
CPC	86.43±1.41	0.93±0.01	82.82±1.68	0.73±2.15	68.64±0.49	0.42±0.01
TS-TCC	88.04±2.46	0.92±0.02	83.00±0.71	0.74±2.63	74.81±1.10	0.53±0.02
TNC	88.32±0.12	0.94±0.01	82.97±0.94	0.76±1.73	77.79±0.84	0.55±0.01
BTSF	94.63±0.14	0.99±0.01	87.45±0.54	0.79±0.74	85.14±0.38	0.68±0.01



Results and Analysis

Time-Series Forecasting

Table 2. Comparisons of multivariate forecasting results.

Datasets	Length	Supervised		SRL		CPC		TS-TCC		TNC		BTSF	
		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
ETTh1	24	0.577	0.549	0.698	0.661	0.687	0.634	0.653	0.610	0.632	0.596	0.541	0.519
	48	0.685	0.625	0.758	0.711	0.779	0.768	0.720	0.693	0.705	0.688	0.613	0.524
	168	0.931	0.752	1.341	1.178	1.282	1.083	1.129	1.044	1.097	0.993	0.640	0.532
	336	1.128	0.873	1.578	1.276	1.641	1.201	1.492	1.076	1.454	0.919	0.864	0.689
	720	1.215	0.896	1.892	1.566	1.803	1.761	1.603	1.206	1.604	1.118	0.993	0.712
ETTh2	24	0.720	0.665	1.034	0.901	0.981	0.869	0.883	0.747	0.830	0.756	0.663	0.557
	48	1.451	1.001	1.854	1.542	1.732	1.440	1.701	1.378	1.689	1.311	1.245	0.897
	168	3.389	1.515	5.062	2.167	4.591	3.126	3.956	2.301	3.792	2.029	2.669	1.393
	336	2.723	1.340	4.921	3.012	4.772	3.581	3.992	2.852	3.516	2.812	1.954	1.093
	720	3.467	1.473	5.301	3.207	5.191	2.781	4.732	2.345	4.501	2.410	2.566	1.276
ETTm1	24	0.323	0.369	0.561	0.603	0.540	0.513	0.473	0.490	0.429	0.455	0.302	0.342
	48	0.494	0.503	0.701	0.697	0.727	0.706	0.671	0.665	0.623	0.602	0.395	0.387
	96	0.678	0.614	0.901	0.836	0.851	0.793	0.803	0.724	0.749	0.731	0.438	0.399
	288	1.056	0.786	2.471	1.927	2.066	1.634	1.958	1.429	1.791	1.356	0.675	0.429
	672	1.192	0.926	2.042	1.803	1.962	1.797	1.838	1.601	1.822	1.692	0.721	0.643
Weather	24	0.335	0.381	0.688	0.701	0.647	0.652	0.572	0.603	0.484	0.513	0.324	0.369
	48	0.395	0.459	0.751	0.883	0.720	0.761	0.647	0.691	0.608	0.626	0.366	0.427
	168	0.608	0.567	1.204	1.032	1.351	1.067	1.117	0.962	1.081	0.970	0.543	0.477
	336	0.702	0.620	2.164	1.982	2.019	1.832	1.783	1.370	1.654	1.290	0.568	0.487
	720	0.831	0.731	2.281	1.994	2.109	1.861	1.850	1.566	1.401	1.193	0.601	0.522



Results and Analysis

Time-Series Anomaly Detection

Table 3. Comparisons of multivariate anomaly detection.

Datasets	Metric	Supervised	SRL	CPC	TS-TCC	TNC	BTSF
SAaT	F1	0.901	0.710	0.738	0.775	0.799	0.914
WADI	F1	0.649	0.340	0.382	0.427	0.440	0.653
SMD	F1	0.958	0.768	0.732	0.794	0.817	0.972
SMAP	F1	0.842	0.598	0.620	0.679	0.693	0.863
MSL	F1	0.945	0.788	0.813	0.795	0.833	0.957

Results and Analysis

Alignment and Uniformity

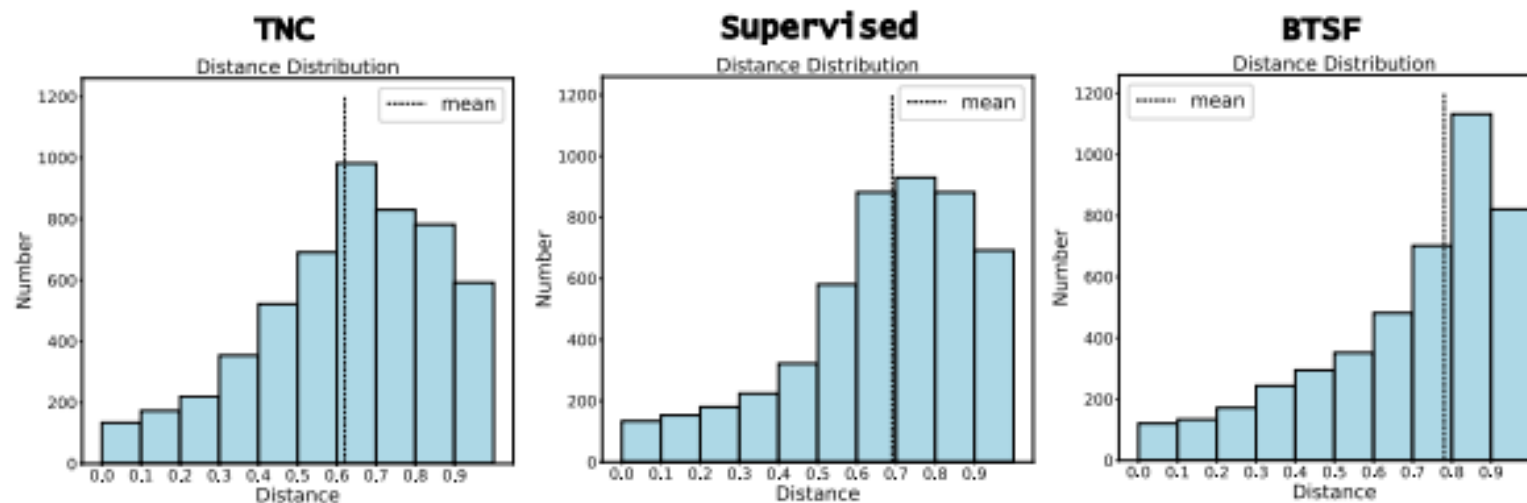


Figure 6. Distance distribution of positive pairs for assessing alignment. Our BTSF is well aligned.

Results and Analysis

Alignment and Uniformity

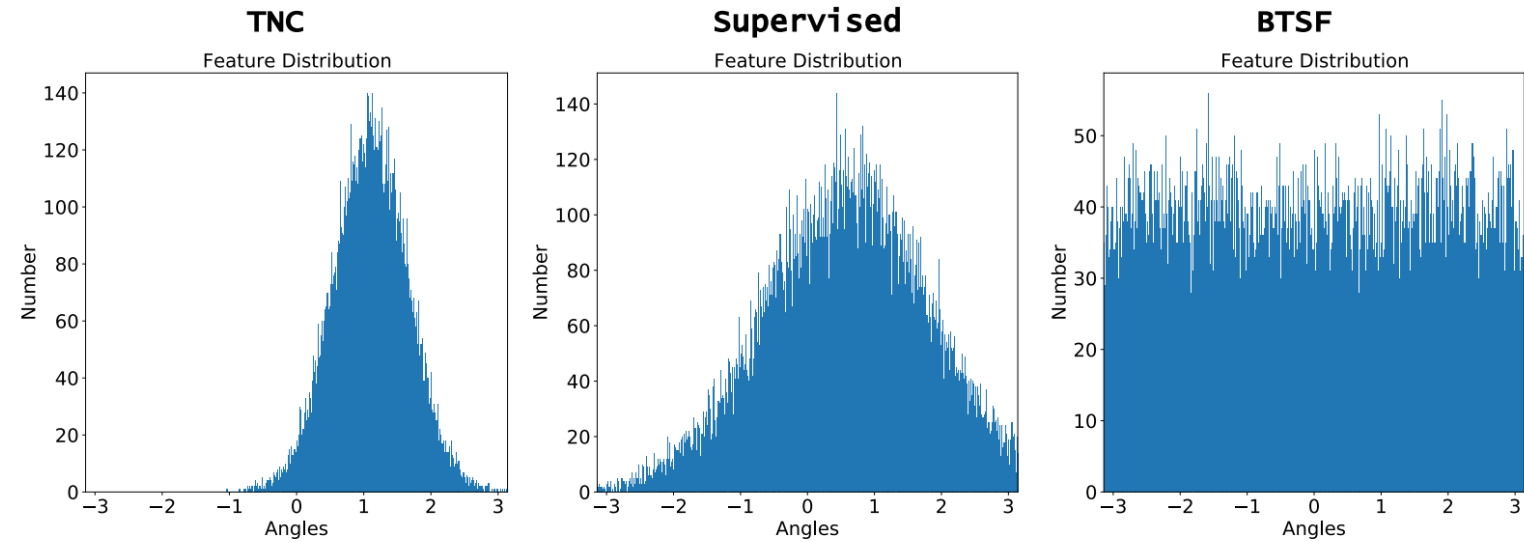


Figure 7. Feature distribution of samples in different classes on the normalized surface area for assessing uniformity. Features extracted by BTSF are evenly distributed.



Results and Analysis

Visualization of Learned Representations

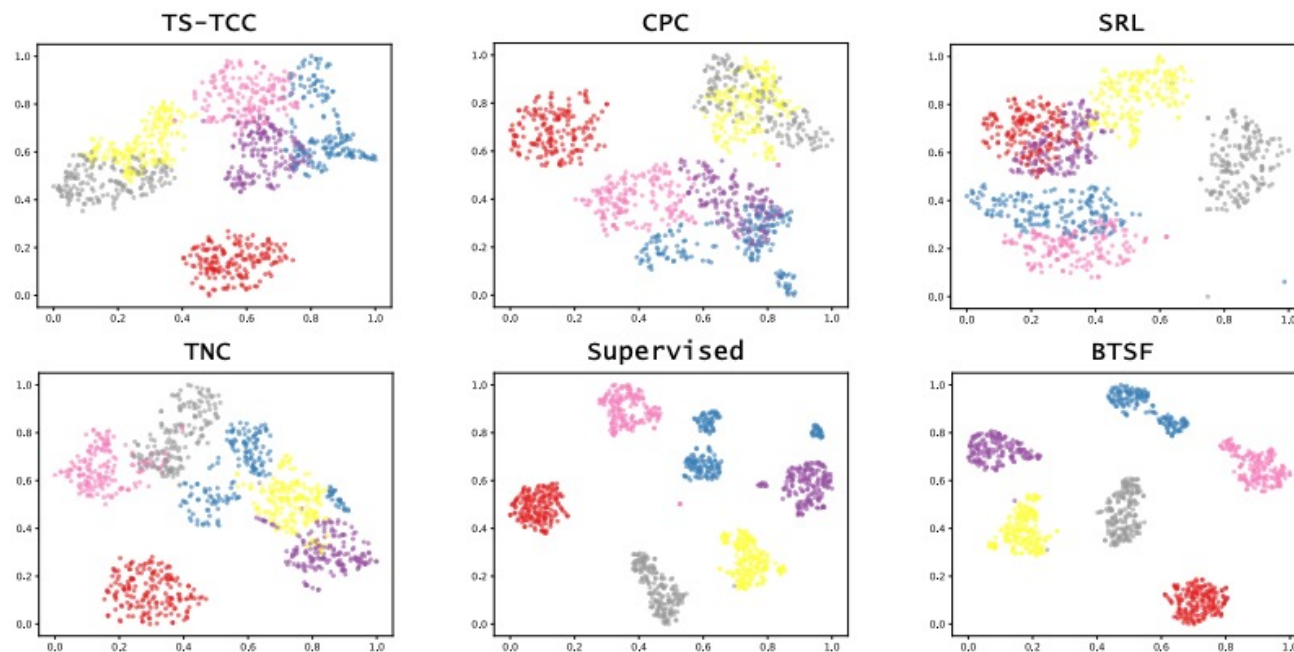


Figure 4. T-SNE visualization of signal representations for HAR dataset.



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Thank You!