

Re-framing Time Series Augmentation Through the Lens of Generative Models

10th Workshop on Advanced Analytics and Learning on Temporal Data -
ECML-PKDD 2025

Ali Ismail-Fawaz¹, Maxime Devanne¹, Stefano Berretti², Jonathan
Weber¹, Germain Forestier^{1,3}

¹IRIMAS, Université Haute-Alsace, Mulhouse, France

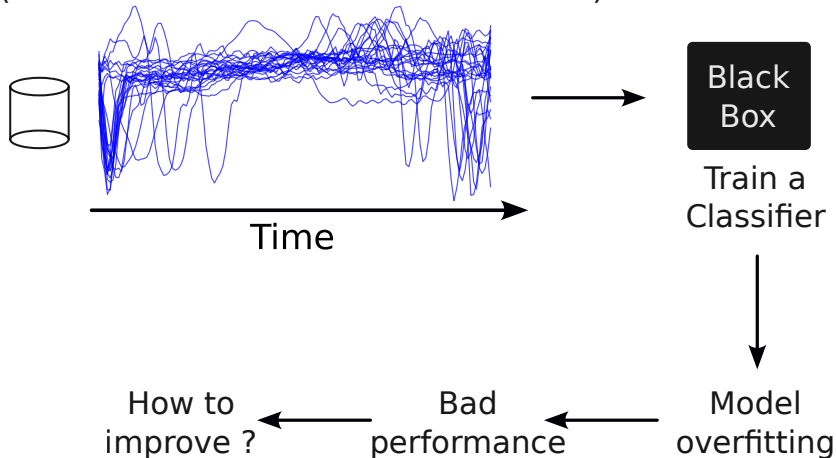
²MICC, University of Florence, Florence, Italy

³DSAI, Monash University, Melbourne Australia

September 19, 2025

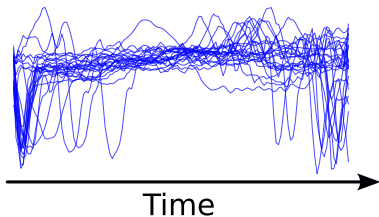
Time Series Classification on Small Datasets

Time Series Classification Dataset
(small ECG5000 Dataset from the UCR)



Synthetic Data Creation / Data Augmentation

Given a set of time series

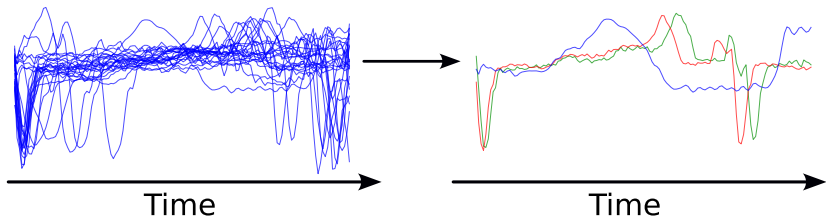


-  Dau, H.A., Bagnall, A., Kamgar, K., Yeh, C.C.M., Zhu, Y., Gharghabi, S., Ratanamahatana, C.A. and Keogh, E., 2019. The UCR time series archive. *IEEE/CAA Journal of Automatica Sinica*, 6(6), pp.1293-1305.

Synthetic Data Creation / Data Augmentation

Given a set of time series

Create synthetic **realistic** series ?

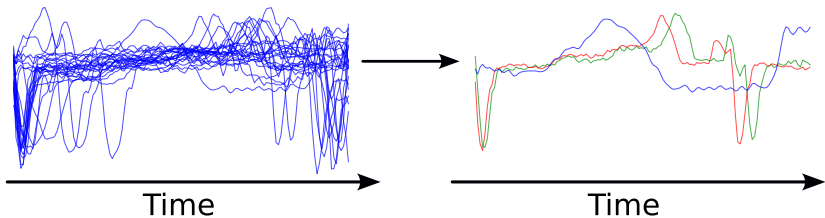


 Dau, H.A., Bagnall, A., Kamgar, K., Yeh, C.C.M., Zhu, Y., Gharghabi, S., Ratanamahatana, C.A. and Keogh, E., 2019. The UCR time series archive. *IEEE/CAA Journal of Automatica Sinica*, 6(6), pp.1293-1305.

Synthetic Data Creation / Data Augmentation

Given a set of time series

Create synthetic **realistic** series ?



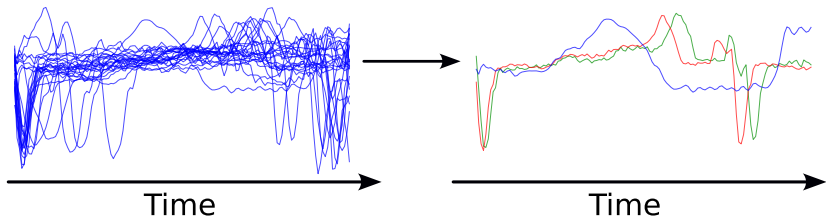
- What makes a synthetic time series realistic ?

 Dau, H.A., Bagnall, A., Kamgar, K., Yeh, C.C.M., Zhu, Y., Gharghabi, S., Ratanamahatana, C.A. and Keogh, E., 2019. The UCR time series archive. *IEEE/CAA Journal of Automatica Sinica*, 6(6), pp.1293-1305.

Synthetic Data Creation / Data Augmentation

Given a set of time series

Create synthetic **realistic** series ?

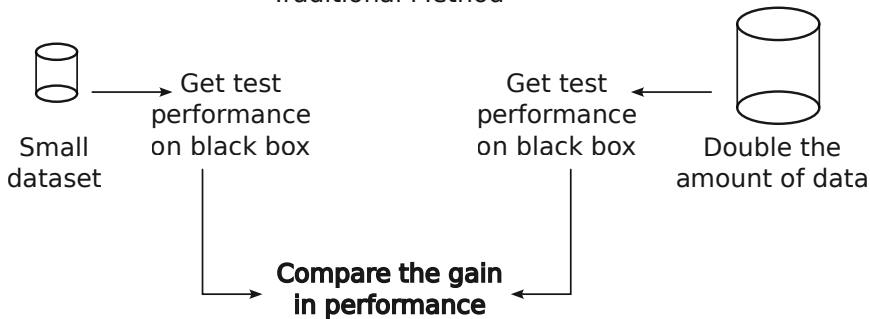


- What makes a synthetic time series realistic ?
- Bigger question: How to evaluate data augmentation ?

 Dau, H.A., Bagnall, A., Kamgar, K., Yeh, C.C.M., Zhu, Y., Gharghabi, S., Ratanamahatana, C.A. and Keogh, E., 2019. The UCR time series archive. *IEEE/CAA Journal of Automatica Sinica*, 6(6), pp.1293-1305.

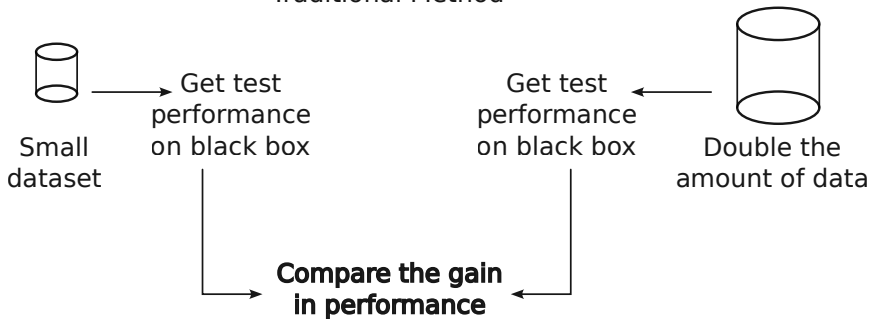
Data Augmentation Evaluation

Traditional Method



Data Augmentation Evaluation

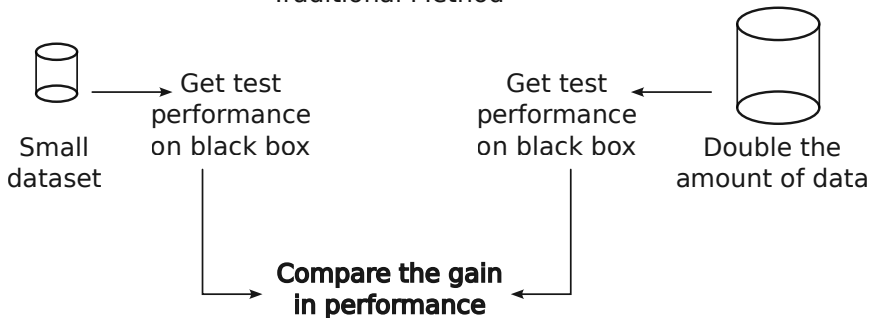
Traditional Method



- Computationally incompressive

Data Augmentation Evaluation

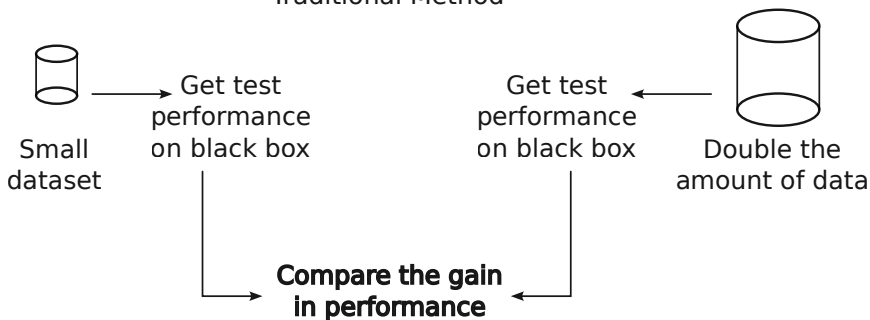
Traditional Method



- Computationally incompressive
- Why not look at data augmentation as a Generative Model ?

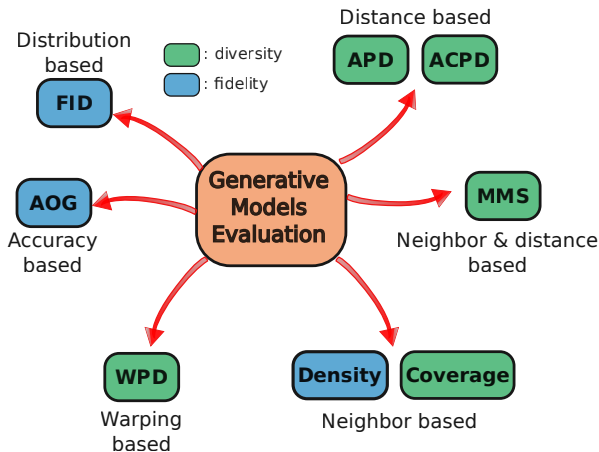
Data Augmentation Evaluation

Traditional Method



- Computationally incompressive
- Why not look at data augmentation as a Generative Model ?
- But how to evaluation Generative Models without relying on performance gain ?

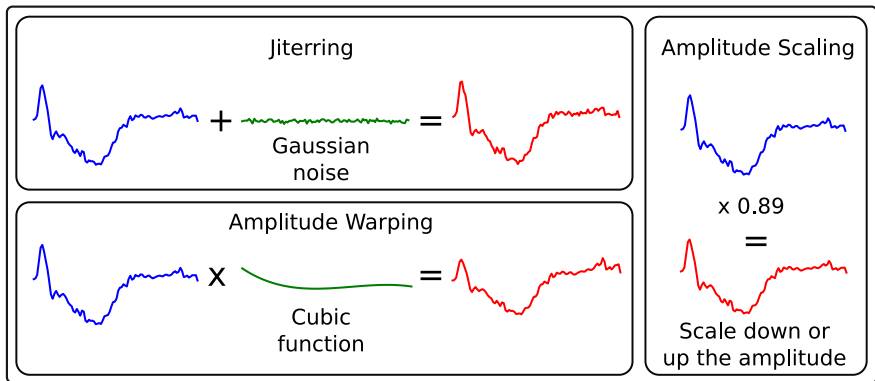
Generative Models Evaluation Measures



Ismail-Fawaz, A., Devanne, M., Berretti, S., Weber, J. and Forestier, G., 2025. Establishing a unified evaluation framework for human motion generation: A comparative analysis of metrics. *Computer Vision and Image Understanding*, 254, p.104337.

Data Augmentation for Time Series Classification

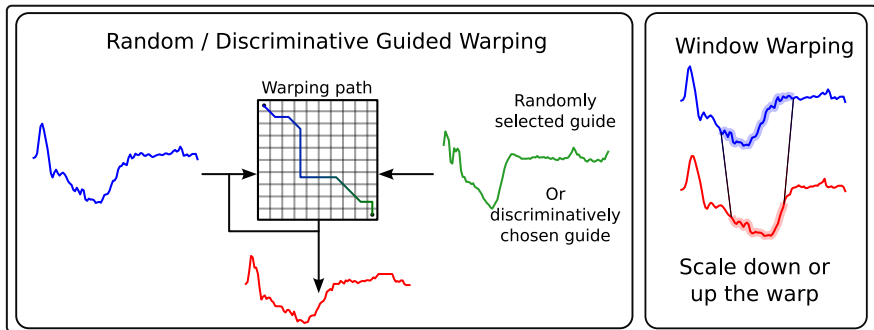
Simple methods



Um, T.T., Pfister, F.M., Pichler, D., Endo, S., Lang, M., Hirche, S., Fietzek, U. and Kulić, D., 2017, November. Data augmentation of wearable sensor data for parkinson's disease monitoring using convolutional neural networks. In Proceedings of the 19th ACM international conference on multimodal interaction (pp. 216-220).

Data Augmentation for Time Series Classification

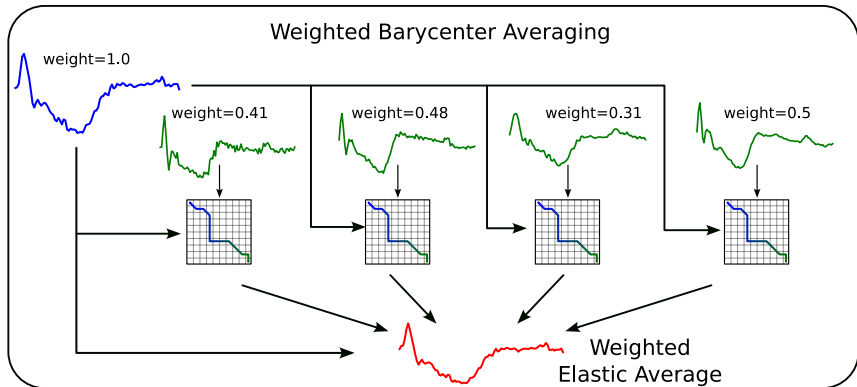
Warping methods



-  Iwana, B.K. and Uchida, S., 2021, January. Time series data augmentation for neural networks by time warping with a discriminative teacher. In 2020 [25th International Conference on Pattern Recognition \(ICPR\)](#) (pp. 3558-3565). IEEE.
-  Le Guennec, A., Malinowski, S. and Tavenard, R., 2016, September. Data augmentation for time series classification using convolutional neural networks. In [ECML/PKDD workshop on advanced analytics and learning on temporal data](#).

Data Augmentation for Time Series Classification

Prototyping methods



Forestier, G., Petitjean, F., Dau, H.A., Webb, G.I. and Keogh, E., 2017, November. Generating synthetic time series to augment sparse datasets. In 2017 IEEE international conference on data mining (ICDM) (pp. 865-870). IEEE.

Experimental Setup

- **Amplitude Warping (AW), Amplitude Scaling (AS), Window Warping (WW) and Jittering** fixed parameters
- **Random and Discriminative Guided Warping (RGW and DGW)**
 - Dynamic Time Warping (DTW) with and without window constraint
 - Move Split Merge (MSM) with different cost value
 - ShapeDTW with different reach value
- **Weighted Barycenter Averaging**
 - with DTW BA (DBA) [1] with and without windowing
 - with MSM BA (MBA) [2] with different cost value
 - with ShapeDTW BA (ShapeDBA) [3] with different reach value
- 131 univariate Time Series Classification datasets (test sets were not used in this work)
- All series go through z-normalization prior to synthetic generation
- All experiments are repeated multiple times and averaged over multiple seeds to remove any possible bias

- 📖 [1] Petitjean, F., Ketterlin, A. and Gançarski, P., 2011. A global averaging method for dynamic time warping, with applications to clustering. *Pattern recognition*, 44(3), pp.678-693.
- 📖 [2] Holder, C., Guijo-Rubio, D. and Bagnall, A.J., 2023. Barycentre Averaging for the Move-Split-Merge Time Series Distance Measure. In *KDIR* (pp. 51-62).
- 📖 [3] **Ismail-Fawaz, A.**, Ismail Fawaz, H., Petitjean, F., Devanne, M., Weber, J., Berretti, S., Webb, G.I. and Forestier, G., 2023, September. Shapedba: Generating effective time series prototypes using shapedtw barycenter averaging. In *International Workshop on Advanced Analytics and Learning on Temporal Data* (pp. 127-142). Cham: Springer Nature Switzerland.

Experimental Results - Fidelity

Mean-Diff-Fidelity	DGW-MSM-2 0.5223	RGW-MSM-2 0.6302	AS 0.6995	WSDBA-7 1.2196	WSDBA-15 1.3411	WDBA-None 1.5962	AW 6.7831	WW 8.1784	Jittering 323.2178
DGW-MSM-2 0.5223	Mean-Difference $t < c / r = c / r > c$ Wilcoxon p-value	-0.1079 270 / 13 / 110 ≤ 1e-04	-0.1772 125 / 9 / 259 ≤ 1e-04	-0.6974 272 / 8 / 113 ≤ 1e-04	-0.8188 280 / 10 / 103 ≤ 1e-04	-1.0739 251 / 7 / 135 ≤ 1e-04	-6.2608 259 / 6 / 128 ≤ 1e-04	-7.6561 330 / 4 / 59 ≤ 1e-04	-322.6955 232 / 4 / 157 ≤ 1e-04
RGW-MSM-2 0.6302		0.1079 110 / 13 / 270 ≤ 1e-04	-0.0693 110 / 6 / 277 ≤ 1e-04	-0.5895 238 / 5 / 150 ≤ 1e-04	-0.7110 248 / 5 / 140 ≤ 1e-04	-0.9660 221 / 4 / 168 ≤ 1e-04	-6.1530 239 / 4 / 150 ≤ 1e-04	-7.5482 289 / 4 / 100 ≤ 1e-04	-322.5876 224 / 3 / 166 ≤ 1e-04
AS 0.6995		0.1772 259 / 9 / 125 ≤ 1e-04	0.0693 277 / 6 / 110 ≤ 1e-04	-0.5202 299 / 8 / 86 ≤ 1e-04	-0.6416 300 / 9 / 84 ≤ 1e-04	-0.8967 302 / 13 / 78 ≤ 1e-04	-6.0837 353 / 13 / 27 ≤ 1e-04	-7.4789 350 / 1 / 42 ≤ 1e-04	-322.5183 285 / 22 / 86 ≤ 1e-04
WSDBA-7 1.2196		0.6974 113 / 8 / 272 ≤ 1e-04	0.5895 150 / 5 / 238 ≤ 1e-04	0.5202 86 / 8 / 299 ≤ 1e-04	-0.1215 234 / 17 / 142 ≤ 1e-04	-0.3765 196 / 9 / 188 0.3120	-5.5635 195 / 6 / 192 0.1476	-6.9587 212 / 2 / 179 0.2166	-321.9981 219 / 7 / 167 ≤ 1e-04
WSDBA-15 1.3411		0.8188 103 / 10 / 280 ≤ 1e-04	0.7110 140 / 5 / 248 ≤ 1e-04	0.6416 84 / 9 / 300 ≤ 1e-04	0.1215 142 / 17 / 234 ≤ 1e-04	-0.2550 200 / 10 / 183 0.6508	-5.4420 191 / 8 / 194 0.1623	-6.8372 208 / 1 / 184 0.7389	-321.8766 221 / 8 / 164 ≤ 1e-04
WDBA-None 1.5962		1.0739 135 / 7 / 251 ≤ 1e-04	0.9660 168 / 4 / 221 ≤ 1e-04	0.8967 78 / 13 / 302 ≤ 1e-04	0.3765 188 / 9 / 196 0.3120	0.2550 183 / 10 / 200 0.6508	-5.1870 211 / 7 / 175 0.0398	-6.5822 233 / 1 / 159 0.0495	-321.6216 207 / 10 / 176 0.0001
AW 6.7831		6.2608 128 / 6 / 259 ≤ 1e-04	6.1530 150 / 4 / 239 ≤ 1e-04	6.0837 27 / 13 / 353 ≤ 1e-04	5.5635 192 / 6 / 195 0.1476	5.4420 194 / 8 / 191 0.1623	5.1870 175 / 7 / 211 0.0398	-1.3952 196 / 1 / 196 0.1887	-316.4346 179 / 8 / 206 0.5215
WW 8.1784		7.6561 59 / 4 / 330 ≤ 1e-04	7.5482 100 / 4 / 289 ≤ 1e-04	7.4789 42 / 1 / 350 ≤ 1e-04	6.9587 179 / 2 / 212 0.2166	6.8372 184 / 1 / 208 0.7389	6.5822 159 / 1 / 233 0.0495	1.3952 196 / 1 / 196 0.1887	-315.0394 179 / 0 / 214 0.4650
Jittering 323.2178		322.6955 157 / 4 / 232 ≤ 1e-04	322.5876 166 / 3 / 224 ≤ 1e-04	322.5183 86 / 22 / 285 ≤ 1e-04	321.9981 167 / 7 / 219 ≤ 1e-04	321.8766 164 / 8 / 221 ≤ 1e-04	321.6216 176 / 10 / 207 0.0001	316.4346 206 / 8 / 179 0.5215	315.0394 214 / 0 / 179 0.4650

Mean-Difference

300
200
100
0
-100
-200
-300

Experimental Results - Fidelity

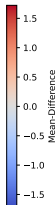
	DGW-MSM-2 0.5223	RGW-MSM-2 0.6302	AS 0.6995	WSDBA-7 1.2196	WSDBA-15 1.3411	WDBA-None 1.5962	AW 6.7831	WW 8.1784	Jittering 323.2178
Mean-Diff-Fidelity t < c / r = c / r > c Wilcoxon p-value									
DGW-MSM-2 0.5223	Mean-Difference -0.1079 270 / 13 / 110 ≤ 1e-04	-0.1079 270 / 13 / 110 ≤ 1e-04	-0.1772 125 / 9 / 259 ≤ 1e-04	-0.6974 272 / 8 / 113 ≤ 1e-04	-0.8188 280 / 10 / 103 ≤ 1e-04	-1.0739 251 / 7 / 135 ≤ 1e-04	-6.2608 259 / 6 / 128 ≤ 1e-04	-7.6561 330 / 4 / 59 ≤ 1e-04	-322.6955 232 / 4 / 157 ≤ 1e-04
RGW-MSM-2 0.6302	0.1079 110 / 13 / 270 ≤ 1e-04	-	-0.0693 110 / 6 / 277 ≤ 1e-04	-0.5895 238 / 5 / 150 ≤ 1e-04	-0.7110 248 / 5 / 140 ≤ 1e-04	-0.9660 221 / 4 / 168 ≤ 1e-04	-6.1530 239 / 4 / 150 ≤ 1e-04	-7.5482 289 / 4 / 100 ≤ 1e-04	-322.5876 224 / 3 / 166 ≤ 1e-04
AS 0.6995	0.1772 259 / 9 / 125 ≤ 1e-04	0.0693 277 / 6 / 110 ≤ 1e-04	-	-0.5202 299 / 8 / 86 ≤ 1e-04	-0.6416 300 / 9 / 84 ≤ 1e-04	-0.8967 302 / 13 / 78 ≤ 1e-04	-6.0837 353 / 13 / 27 ≤ 1e-04	-7.4789 350 / 1 / 42 ≤ 1e-04	-322.5183 285 / 22 / 86 ≤ 1e-04
WSDBA-7 1.2196	0.6974 113 / 8 / 272 ≤ 1e-04	0.5895 150 / 5 / 238 ≤ 1e-04	0.5202 86 / 8 / 299 ≤ 1e-04	-	-0.1215 234 / 17 / 142 ≤ 1e-04	-0.3765 196 / 9 / 188 0.3120	-5.5635 195 / 6 / 192 0.1476	-6.9587 212 / 2 / 179 0.2166	-321.9981 219 / 7 / 167 ≤ 1e-04
WSDBA-15 1.3411	0.8188 103 / 10 / 280 ≤ 1e-04	0.7110 140 / 5 / 248 ≤ 1e-04	0.6416 84 / 9 / 300 ≤ 1e-04	0.1215 142 / 17 / 234 ≤ 1e-04	-	-0.2550 200 / 10 / 183 0.6508	-5.4420 191 / 8 / 194 0.1623	-6.8372 208 / 1 / 184 0.7389	-321.8766 221 / 8 / 164 ≤ 1e-04
WDBA-None 1.5962	1.0739 135 / 7 / 251 ≤ 1e-04	0.9660 168 / 4 / 221 ≤ 1e-04	0.8967 78 / 13 / 302 ≤ 1e-04	0.3765 188 / 9 / 196 0.3120	0.2550 183 / 10 / 200 0.6508	-	-5.1870 211 / 7 / 175 0.0398	-6.5822 233 / 1 / 159 0.0495	-321.6216 207 / 10 / 176 0.0001
AW 6.7831	6.2608 128 / 6 / 259 ≤ 1e-04	6.1530 150 / 4 / 239 ≤ 1e-04	6.0837 27 / 13 / 353 ≤ 1e-04	5.5635 192 / 6 / 195 0.1476	5.4420 194 / 8 / 191 0.1623	5.1870 175 / 7 / 211 0.0398	-	-1.3952 196 / 1 / 196 0.1887	-316.4346 179 / 8 / 206 0.5215
WW 8.1784	7.6561 59 / 4 / 330 ≤ 1e-04	7.5482 100 / 4 / 289 ≤ 1e-04	7.4789 42 / 1 / 350 ≤ 1e-04	6.9587 179 / 2 / 212 0.2166	6.8372 184 / 1 / 208 0.7389	6.5822 159 / 1 / 233 0.0495	1.3952 196 / 1 / 196 0.1887	-	-315.0394 179 / 0 / 214 0.4650
Jittering 323.2178	322.6955 157 / 4 / 232 ≤ 1e-04	322.5876 166 / 3 / 224 ≤ 1e-04	322.5183 86 / 22 / 285 ≤ 1e-04	321.9981 167 / 7 / 219 ≤ 1e-04	321.8766 164 / 8 / 221 ≤ 1e-04	321.6216 176 / 10 / 207 0.0001	316.4346 206 / 8 / 179 0.5215	315.0394 214 / 0 / 179 0.4650	If in bold, then p-value < 0.05

Mean-Difference

- DGW / RGW with MSM high cost value is the most fideliou approach
- WSDBA outperforms WDBA and WMBA
- AS could be promising
- Jittering completely fails in terms of fidelity

Experimental Results - Diversity

Mean-Diff-Diversity	AS 0.4278	DGW-MSM-2 0.4501	RGW-MSM-2 0.5158	WDBA-None 0.9971	WSDBA-15 1.0353	WSDBA-7 1.0426	WW 1.4940	Jittering 1.7606	AW 1.8626
AS 0.4278	Mean-Difference $t < c / t = c / t > c$ Wilcoxon p-value	-0.0223 378 / 5 / 272 $\leq 1e-04$	-0.0880 415 / 4 / 236 $\leq 1e-04$	-0.5694 423 / 6 / 226 $\leq 1e-04$	-0.6075 427 / 5 / 223 $\leq 1e-04$	-0.6148 432 / 5 / 218 $\leq 1e-04$	-1.0662 544 / 4 / 107 $\leq 1e-04$	-1.3329 410 / 3 / 242 $\leq 1e-04$	-1.4348 599 / 4 / 52 $\leq 1e-04$
DGW-MSM-2 0.4501	0.0223 272 / 5 / 378 $\leq 1e-04$	-	-0.0657 413 / 14 / 228 $\leq 1e-04$	-0.5471 391 / 6 / 258 $\leq 1e-04$	-0.5852 427 / 5 / 223 $\leq 1e-04$	-0.5925 430 / 5 / 220 $\leq 1e-04$	-1.0439 523 / 5 / 127 $\leq 1e-04$	-1.3106 374 / 1 / 280 $\leq 1e-04$	-1.4125 508 / 3 / 144 $\leq 1e-04$
RGW-MSM-2 0.5158	0.0880 236 / 4 / 415 $\leq 1e-04$	0.0657 228 / 14 / 413 $\leq 1e-04$	-	-0.4813 358 / 5 / 292 0.0026	-0.5195 404 / 4 / 247 $\leq 1e-04$	-0.5268 395 / 4 / 256 $\leq 1e-04$	-0.9782 481 / 5 / 169 $\leq 1e-04$	-1.2448 357 / 2 / 296 $\leq 1e-04$	-1.3468 484 / 4 / 167 $\leq 1e-04$
WDBA-None 0.9971	0.5694 226 / 6 / 423 $\leq 1e-04$	0.5471 258 / 6 / 391 $\leq 1e-04$	0.4813 292 / 5 / 358 0.0026	-	-0.0381 311 / 5 / 339 0.4294	-0.0454 327 / 5 / 323 0.6339	-0.4969 390 / 4 / 261 $\leq 1e-04$	-0.7635 320 / 1 / 334 0.2660	-0.8654 455 / 5 / 195 $\leq 1e-04$
WSDBA-15 1.0353	0.6075 223 / 5 / 427 $\leq 1e-04$	0.5852 223 / 5 / 427 $\leq 1e-04$	0.5195 247 / 4 / 404 $\leq 1e-04$	0.0381 339 / 5 / 311 0.4294	-	-0.0073 285 / 7 / 363 0.1784	-0.4587 369 / 4 / 282 $\leq 1e-04$	-0.7254 316 / 1 / 338 0.2573	-0.8273 429 / 4 / 222 $\leq 1e-04$
WSDBA-7 1.0426	0.6148 218 / 5 / 432 $\leq 1e-04$	0.5925 220 / 5 / 430 $\leq 1e-04$	0.5268 256 / 4 / 395 $\leq 1e-04$	0.0454 323 / 5 / 327 0.6339	0.0073 363 / 7 / 285 0.1784	-	-0.4515 369 / 4 / 282 $\leq 1e-04$	-0.7181 315 / 1 / 339 0.4052	-0.8200 429 / 4 / 222 $\leq 1e-04$
WW 1.4940	1.0662 107 / 4 / 544 $\leq 1e-04$	1.0439 127 / 5 / 523 $\leq 1e-04$	0.9782 169 / 5 / 481 $\leq 1e-04$	0.4969 261 / 4 / 390 $\leq 1e-04$	0.4587 282 / 4 / 369 $\leq 1e-04$	0.4515 282 / 4 / 369 $\leq 1e-04$	-	-0.2666 245 / 1 / 409 $\leq 1e-04$	-0.3685 396 / 3 / 256 $\leq 1e-04$
Jittering 1.7606	1.3329 242 / 3 / 410 $\leq 1e-04$	1.3106 280 / 1 / 374 $\leq 1e-04$	1.2448 296 / 2 / 357 $\leq 1e-04$	0.7635 334 / 1 / 320 0.2660	0.7254 338 / 1 / 316 0.2573	0.7181 339 / 1 / 315 0.4052	0.2666 409 / 1 / 245 $\leq 1e-04$	-	-0.1019 447 / 1 / 207 $\leq 1e-04$
AW 1.8626	1.4348 52 / 4 / 599 $\leq 1e-04$	1.4125 144 / 3 / 508 $\leq 1e-04$	1.3468 167 / 4 / 484 $\leq 1e-04$	0.8654 195 / 5 / 455 $\leq 1e-04$	0.8273 222 / 4 / 429 $\leq 1e-04$	0.8200 222 / 4 / 429 $\leq 1e-04$	0.3685 256 / 3 / 396 $\leq 1e-04$	0.1019 207 / 1 / 447 $\leq 1e-04$	If in bold, then p-value < 0.05



Experimental Results - Diversity

Mean-Diff-Diversity	AS 0.4278	DGW-MSM-2 0.4501	RGW-MSM-2 0.5158	WDBA-None 0.9971	WSDBA-15 1.0353	WSDBA-7 1.0426	WW 1.4940	Jittering 1.7606	AW 1.8626
AS 0.4278	Mean-Difference $t < c$ / $t = c$ / $t > c$ Wilcoxon p-value	-0.0223 378 / 5 / 272 $\leq 1e-04$	-0.0880 415 / 4 / 236 $\leq 1e-04$	-0.5694 423 / 6 / 226 $\leq 1e-04$	-0.6075 427 / 5 / 223 $\leq 1e-04$	-0.6148 432 / 5 / 218 $\leq 1e-04$	-1.0662 544 / 4 / 107 $\leq 1e-04$	-1.3329 410 / 3 / 242 $\leq 1e-04$	-1.4348 599 / 4 / 52 $\leq 1e-04$
DGW-MSM-2 0.4501	0.0223 272 / 5 / 378 $\leq 1e-04$	-	-0.0657 413 / 14 / 228 $\leq 1e-04$	-0.5471 391 / 6 / 258 $\leq 1e-04$	-0.5852 427 / 5 / 223 $\leq 1e-04$	-0.5925 430 / 5 / 220 $\leq 1e-04$	-1.0439 523 / 5 / 127 $\leq 1e-04$	-1.3106 374 / 1 / 280 $\leq 1e-04$	-1.4125 508 / 3 / 144 $\leq 1e-04$
RGW-MSM-2 0.5158	0.0880 236 / 4 / 415 $\leq 1e-04$	0.0657 228 / 14 / 413 $\leq 1e-04$	-	-0.4813 358 / 5 / 292 0.0026	-0.5195 404 / 4 / 247 $\leq 1e-04$	-0.5268 395 / 4 / 256 $\leq 1e-04$	-0.9782 481 / 5 / 169 $\leq 1e-04$	-1.2448 357 / 2 / 296 $\leq 1e-04$	-1.3468 484 / 4 / 167 $\leq 1e-04$
WDBA-None 0.9971	0.5694 226 / 6 / 423 $\leq 1e-04$	0.5471 258 / 6 / 391 $\leq 1e-04$	0.4813 292 / 5 / 358 0.0026	-	-0.0381 311 / 5 / 339 0.4294	-0.0454 327 / 5 / 323 0.6339	-0.4969 390 / 4 / 261 $\leq 1e-04$	-0.7635 320 / 1 / 334 0.2660	-0.8654 455 / 5 / 195 $\leq 1e-04$
WSDBA-15 1.0353	0.6075 223 / 5 / 427 $\leq 1e-04$	0.5852 223 / 5 / 427 $\leq 1e-04$	0.5195 247 / 4 / 404 $\leq 1e-04$	0.0381 339 / 5 / 311 0.4294	-	-0.0073 285 / 7 / 363 0.1784	-0.4587 369 / 4 / 282 $\leq 1e-04$	-0.7254 316 / 1 / 338 0.2573	-0.8273 429 / 4 / 222 $\leq 1e-04$
WSDBA-7 1.0426	0.6148 218 / 5 / 432 $\leq 1e-04$	0.5925 220 / 5 / 430 $\leq 1e-04$	0.5268 256 / 4 / 395 $\leq 1e-04$	0.0454 323 / 5 / 327 0.6339	0.0073 363 / 7 / 285 0.1784	-	-0.4515 369 / 4 / 282 $\leq 1e-04$	-0.7181 315 / 1 / 339 0.4052	-0.8200 429 / 4 / 222 $\leq 1e-04$
WW 1.4940	1.0662 107 / 4 / 544 $\leq 1e-04$	1.0439 127 / 5 / 523 $\leq 1e-04$	0.9782 169 / 5 / 481 $\leq 1e-04$	0.4969 261 / 4 / 390 $\leq 1e-04$	0.4587 282 / 4 / 369 $\leq 1e-04$	0.4515 282 / 4 / 369 $\leq 1e-04$	-	-0.2666 245 / 1 / 409 $\leq 1e-04$	-0.3685 396 / 3 / 256 $\leq 1e-04$
Jittering 1.7606	1.3329 242 / 3 / 410 $\leq 1e-04$	1.3106 280 / 1 / 374 $\leq 1e-04$	1.2448 296 / 2 / 357 $\leq 1e-04$	0.7635 334 / 1 / 320 0.2660	0.7254 338 / 1 / 316 0.2573	0.7181 339 / 1 / 315 0.4052	0.2666 409 / 1 / 245 $\leq 1e-04$	-	-0.1019 447 / 1 / 207 $\leq 1e-04$
AW 1.8626	1.4348 52 / 4 / 599 $\leq 1e-04$	1.4125 144 / 3 / 508 $\leq 1e-04$	1.3468 167 / 4 / 484 $\leq 1e-04$	0.8654 195 / 5 / 455 $\leq 1e-04$	0.8273 222 / 4 / 429 $\leq 1e-04$	0.8200 222 / 4 / 429 $\leq 1e-04$	0.3685 256 / 3 / 396 $\leq 1e-04$	0.1019 207 / 1 / 447 $\leq 1e-04$	If in bold, then p-value < 0.05

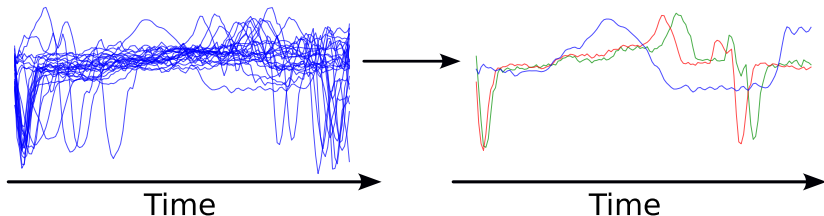
Mean-Difference

- AS is more promising compared to fidelity
- DGW / RGW MSM high cost still winning
- WSDBA less diverse than WDBA
- Jittering and AW fail by a lot

Takeaway

Given a set of time series

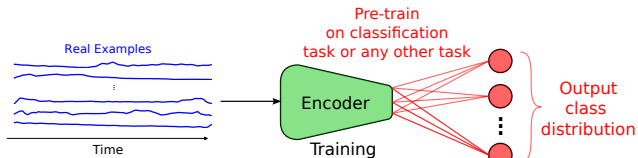
Create synthetic **realistic** series ?



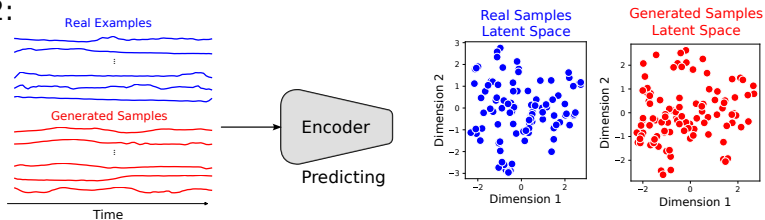
- **Title:** Re-framing Time Series Augmentation Through the Lens of Generative Models
- Why not evaluate synthetic generation methods prior to using them for data augmentation ?
- Is there a relation with performance gain ?
- Used offline or online data augmentation ?
- Are all metrics important for augmentation ?
- Contact: ali-el-hadi.ismail-fawaz@uha.fr
- Website: <https://hadifawaz1999.github.io/>
- GitHub: <https://github.com/MSD-IRIMAS/Data-Augmentation-4-TSC>

Feature Extraction Metrics

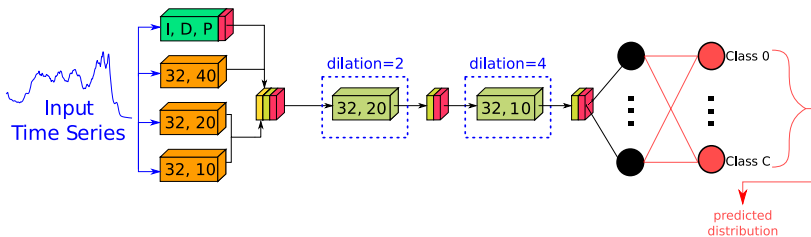
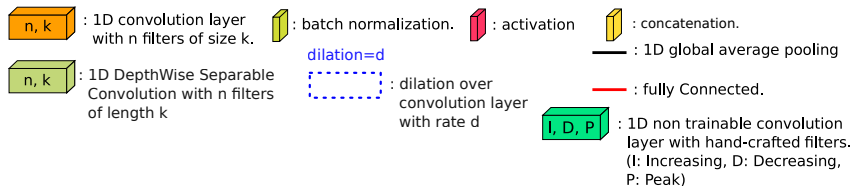
Step 1:




Step 2:



Feature Extractor



 **Ismail-Fawaz, A., Devanne, M., Berretti, S., Weber, J. and Forestier, G., 2023, October. Lite: Light inception with boosting techniques for time series classification. In 2023 IEEE 10th International Conference on Data Science and Advanced Analytics (DSAA) (pp. 1-10). IEEE.**