

Back to Basics: A Sanity Check on Modern Time Series Classification Algorithms

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Abstract. The state-of-the-art in time series classification has come a long way, from the 1NN-DTW algorithm to the ROCKET family of classifiers. However, in the current fast-paced development of new classifiers, taking a step back and performing simple baseline checks is essential. These checks are often overlooked, as researchers are focused on establishing new state-of-the-art results, developing scalable algorithms, and making models explainable. Nevertheless, there are many datasets that look like time series at first glance, but classic algorithms such as tabular methods with no time ordering may perform better on such problems. For example, for spectroscopy datasets, tabular methods tend to significantly outperform recent time series methods. In this study, we compare the performance of tabular models using classic machine learning approaches (e.g., Ridge, LDA, RandomForest) with the ROCKET family of classifiers (e.g., Rocket, MiniRocket, MultiRocket). Tabular models are simple and very efficient, while the ROCKET family of classifiers are more complex and have state-of-the-art accuracy and efficiency among recent time series classifiers. We find that tabular models outperform the ROCKET family of classifiers on approximately 19% of univariate and 28% of multivariate datasets in the UCR/UEA benchmark and achieve accuracy within 10 percentage points on about 50% of datasets. Our results suggest that it is important to consider simple tabular models as baselines when developing time series classifiers. These models are very fast, can be as effective as more complex methods and may be easier to understand and deploy.

Keywords: Time series · Classification · Evaluation · Baselines

1 Introduction

Time series classification is a challenging task that has attracted significant research interest recently. The ever-evolving computational capabilities and abundant applications and use cases have led to the development of a wide range of time series classification methods, from simple distance-based methods (1-NN-DTW [1]) to complex deep learning models (Inception Time [2]).

Most of the research in time series classification is focused on establishing state-of-the-art results, developing scalable algorithms, and making models explainable. However, in this quest, it is often possible to forget the first principle of research, which is to compare with existing simpler methods.

Historically, there have been many instances where traditional models have outperformed deep learning methods on some tasks. For example, a recent study [3] showed that linear models can be more effective than deep learning networks for forecasting. Similarly, the work of [4] showed that linear models can outperform other complex models for classification tasks in spectroscopy data. However, there is less empirical work investigating the performance of classic tabular models on time series classification tasks.

In this study, we take a step back from the pursuit of providing yet another state-of-the-art method and perform some simple sanity checks, which are often missed. We compare the performance of tabular models with the ROCKET [5–7] family of classifiers, which are currently considered state-of-the-art for time series classification. In this paper, the main contributions are:

- We empirically compared tabular and time series methods on the established UCR/UEA benchmarks for univariate and multivariate time series classification.
- We analysed the accuracy-time tradeoffs for all the methods on both benchmarks and found that on about 50% of datasets in both benchmarks, the tabular methods perform within 10 percentage points accuracy of state-of-the-art time series classification methods, while being two orders of magnitude faster.
- We discussed the performance of tabular versus time series methods for different data and problem types and the potential implications for how the very popular UCR/UEA benchmarks are formed and used by the community. In particular, if tabular methods significantly outperform time series methods on some problem types, we raise the question of whether these datasets should be included in a time series benchmark.

2 Related Work

The UCR and UEA benchmarks. Univariate Time Series Classification (UTSC). State-of-the-art UTS classifiers are classifiers that have been shown to be the most accurate methods on the UCR/UEA benchmark. The most notable ones are ROCKET [5] and its variants (MiniROCKET, MultiROCKET and HYDRA [8]), due to their high accuracy and efficiency. These classifiers follow a two-step approach: transforming the time series into tabular features and classifying these transformations using linear models such as logistic regression. While deep learning methods (e.g., FCN, ResNet, InceptionTime [2]) or ensembles (e.g., HIVE-COTE [9], TDE [10]) are also as accurate, they often demand significantly more computing resources (time, CPU, GPU, etc.). Other notable classifiers include symbolic-classifiers such as WEASEL [11] and MrSQM [12] and shapelet-classifiers such as RDST [13]. The UCR/UEA time series archive is a public collection of time series datasets that has been used extensively as the unified benchmark by researchers in this area. The archive is the result of a massive collaborative effort lead by research groups from the University California Riverside (UCR) and the University of East Anglia (UEA), hence the name

of the benchmark. Starting with 85 univariate datasets in 2015, the archive was expanded to 128 datasets in 2018. The expansion also introduced a classification benchmark for multivariate time series which includes 30 datasets. The dedicated website¹ for the archive contains not only the downloadable datasets but also pointers to code, publications, and other information that can be useful to any interested party. Without a doubt, the archive is a major resource that pushes forward research in TSC. However, while extremely useful for providing an overview and comparing against existing work, it potentially creates a pitfall where new works only focus on "beating the benchmark" and neglect what makes a classifier useful in real-life applications.

Multivariate Time Series Classification (MTSC). In general, it can be said that the MTSC literature is less developed when compared to UTSC. The benchmark for MTSC was introduced later with fewer datasets. Most state-of-the-art MTSC methods are UTSC methods that are adapted for MTS data. The most straightforward approach is to learn from each channel independently (e.g., HIVE-COTE, WEASEL-MUSE [14]). On the other hand, some classifiers actually utilize channel dependency, and thus are called bespoke MTS classifiers. For example, the multivariate variants of ROCKET (and MiniROCKET, MultiROCKET) replace the 1D kernels with 2D kernels to produce multi-channel dependent features (see [7, 6] for details).

Tabular Methods. Classic machine learning models such as Random Forest, Logistic Regression, Linear Regression, seem to have been largely ignored in recent time series literature. Such methods often assume independence between values at different time points and thus are deemed unsuitable for time series data. The work in [15] employs tabular models, however, the models are trained on transformed data after applying techniques such as PCA, Spectral approaches and auto-correlation. Nonetheless, outside of the time series literature, these methods are still favourable choices in some communities. In particular, the work of [4, 16] investigated several approaches for modelling milk spectroscopy data and found that tabular methods significantly outperformed time series methods. While these datasets are not inherently time series data, spectroscopy data have been part of the UCR/UEA benchmark since its inception and have been widely accepted by the community as time series data. This finding suggests that not all datasets in the benchmark are suitable for time series methods. We further investigate this issue in the next sections.

3 Background

A **time series** is a sequence of numbers representing some measurements over time. For example, a time series could represent a person's heartbeat variation on a 30-minute morning run. Each value in a time series usually has significance with respect to the previous and next values.

A typical mathematical representation of time series is $T : \{x_0, x_1, x_2, \dots, x_n\}$ where $x \in \mathbb{R}$ and n is the length of the time series. When we assign a discrete

¹ <http://www.timeseriesclassification.com>

label to the time series, we can perform time series classification. We discuss two types of time series tasks in this paper, i.e., univariate time series classification (UTSC) and multivariate time series classification (MTSC). In univariate time series classification, data is recorded from a single source, meaning only one observed variable exists. On the other hand, multivariate time series classification involves recording data from multiple sources, resulting in the presence of multiple observed variables. A mathematical representation of multivariate time series can take the form:

$$T : \{ \langle x_0^0, x_1^0, \dots, x_n^0 \rangle \langle x_0^1, x_1^1, \dots, x_n^1 \rangle \dots \langle x_0^{m-1}, x_1^{m-1}, \dots, x_n^{m-1} \rangle \}$$

where m is the number of channels. If the time series is univariate, $m = 1$. It is common in some applications to convert multivariate time series to univariate time series by concatenating all the channels into a single univariate time series. After this transformation, univariate classifiers can be trained with this data.

Tabular data is the most ubiquitous data type. It is a data structure that organizes data into rows and columns. Each row represents a single record, and each column represents a single attribute of that record. It has no concept of temporality. This means that the previous value has no impact on the current value. A time series can be considered a tabular vector and used as input to a tabular method, e.g., linear regression.

4 Experiments

4.1 Datasets

The UEA/UCR [17] benchmark datasets are mostly used in the empirical evaluation and comparison of various algorithms. Since the benchmark contains both univariate and multivariate datasets, it is popular for testing new algorithms on. Table 8 and 9 in the appendix provide the data dictionary for both types of datasets. As it is common in recent time series literature, we run experiments on 109 univariate datasets and 25 equal-length multivariate datasets. We make our code available on github².

4.2 Univariate Time Series Classification

Before comparing tabular versus time-series models, we compared a few popular methods within each group separately.

Tabular Methods Results. For tabular methods we select three linear methods known for their efficiency and effectiveness in real-world applications [4], as well as Random Forest to have an effective non-linear classifier. We run these methods using the sklearn implementation³ with default parameters. Later in the paper we also discuss parameter tuning and its impact on accuracy and runtime. In Figure 1, we compare the accuracy of four tabular models on univariate datasets: Random Forest, Logistic Regression, Ridge Regression (RidgeCV) and

² <https://github.com/mlgig/TabularModelsforTSC>

³ https://scikit-learn.org/stable/supervised_learning.html

Latent Dirichlet Analysis (LDA). The critical difference diagram [18] captures the average accuracy rank over all the datasets. The accuracy gain is evaluated using a Wilcoxon signed-rank test with Holm correction and visualised with the critical difference (CD) diagram with significance value (α) = 0.05. The figure illustrates Random Forest significantly outperforms the other three models and Logistic Regression outperforms the other linear models Table 1 illustrates the mean accuracy and total training and test computation time in minutes. The tabular results correspond to the tabular CD diagram, where Random Forest is the best classifier.

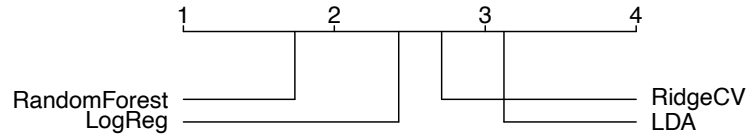


Fig. 1. Accuracy comparison of tabular methods on UTSC datasets.

Table 1. Mean accuracy and total computation time taken by tabular models on UTSC datasets.

	Mean Accuracy	Total Time (minutes)
RandomForest	0.74	0.886
LogReg	0.69	0.31
RidgeCV	0.67	0.09
LDA	0.63	0.09

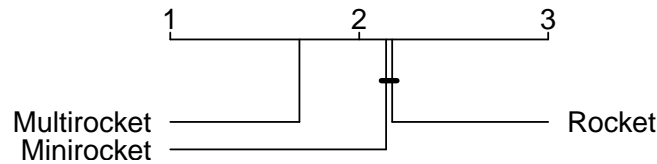


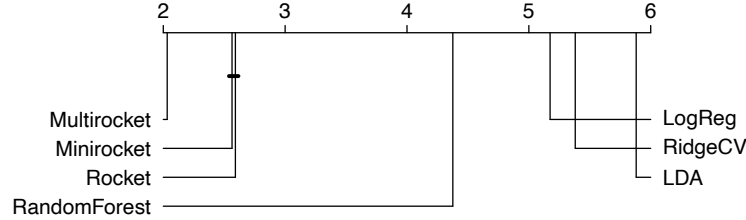
Fig. 2. Accuracy comparison of time-series methods on UTSC datasets.

Time Series Methods Results. Similarly, in Figure 2 and Table 2, we compare the accuracy of three time series classification models: Multirocket, MiniRocket, and Rocket. We use the implementation in the aeon-toolkit library⁴

⁴ https://www.aeon-toolkit.org/en/latest/api_reference/classification.html

Table 2. Mean accuracy and total computation time taken by time-series models on UTSC datasets.

	Mean Accuracy	Total Time (minutes)
Minirocket	0.86	34.56
Multirocket	0.86	73.46
Rocket	0.85	158.76

**Fig. 3.** Accuracy comparison of tabular and time series models on UTSC datasets.

with default parameters. From the critical difference diagram (Figure 2) we note that MultiRocket is significantly more accurate than MiniRocket and Rocket.

Time Series Methods vs Tabular Methods. In Figure 3, we compare the accuracy of time-series and tabular models. We can see that the time-series models have a higher mean accuracy rank than the tabular models. Multirocket is significantly more accurate than all other models, and Random Forest is the closest tabular model to the time-series models.

Detailed Analysis. Figure 3 provides a summary overview of the performance of classifiers using their average accuracy ranking across the datasets analysed. Average behaviour with respect to accuracy or rank is a common and useful summary to get an overview of the performance of multiple classifiers over multiple datasets. However, it is crucial to examine the performance of models at a finer level to understand the difference in behaviour between tabular and time-series models.

In Figure 4, we illustrate the accuracy of tabular and time series models on each dataset, focusing on comparing the best-performing tabular with the best-performing time series model. The plot is divided into three distinct regions: green, grey, and red.

- The green region illustrates the datasets where the tabular models outperform the time series models or where both models achieve the same accuracy.
- The grey region represents datasets where the two models have performance within a fixed threshold. It is crucial to consider the accuracy-time trade-off in this region when deciding the better model. Datasets in this region are highlighted when the difference between the best-performing time-series

model and the best-performing tabular model ranges from 1 to 9 percentage points.

- The red region represents the datasets where time series models outperform tabular models. The time series models in these datasets are at least 10 percentage points better than tabular models.

For the UEA benchmark, surprisingly, 19.2% of the datasets performed better with tabular models (green region), 31.1% performed within 10 percentage points with both tabular and time series models (grey region), and 49.5% performed better than 10 percentage points with time series models (red region).

The above numbers imply that on about 19% of the benchmark, there are only weak temporal patterns, and tabular methods that disregard time ordering are very competitive when compared with time series methods. As a result, for many of those datasets in the green and grey region, using a complex time series model would be like using a sledgehammer to crack a nut. We of course acknowledge that time series methods work very well for the datasets in the red region, but these account for slightly less than half of the benchmark. We also acknowledge that the Rocket algorithms have been tested outside of this benchmark with good results in many real time series applications [19–22]. The question remains though: should we include the datasets in the green and grey areas into a time series benchmark at all, given that tabular methods have similar accuracy to the best time series methods on those datasets.

Computation Time Analysis. Traditionally, tabular models are known for their computational speed. This is also evident from Tables 1 and 2, which show that tabular models are an order of magnitude faster than time series models. Figure 4 illustrates the various regions for accuracy, but it is worth highlighting that tabular models in the green and grey regions are faster and almost as accurate, or even more accurate than time series methods.

Figure 5 shows the tradeoff between the mean accuracy and total computation time for the various time-series and tabular models in grey region datasets. Multirocket and Random Forest are the most accurate models among time series and tabular models, respectively. The difference in accuracy between Multirocket and Random Forest is approximately 5 percentage points. However, Multirocket takes an average of 30 minutes longer to train.

Domain-wise Analysis. Table 3 shows the mean accuracy of different classifiers on datasets from various domains (as annotated by the meta-data in UCR/UEA). The benchmark is highly dominated by three domains: Image, Sensor, and Motion. About 63% of the benchmark comprises these three domains out of a total of 13 domains in the benchmark.



Fig. 4. Accuracy comparison of the best time series model with the best tabular model on univariate time series datasets. Red circles represent the tabular models, and blue circles represent the time series models. Each marker shows the maximum accuracy achieved by the tabular models versus the time series models.

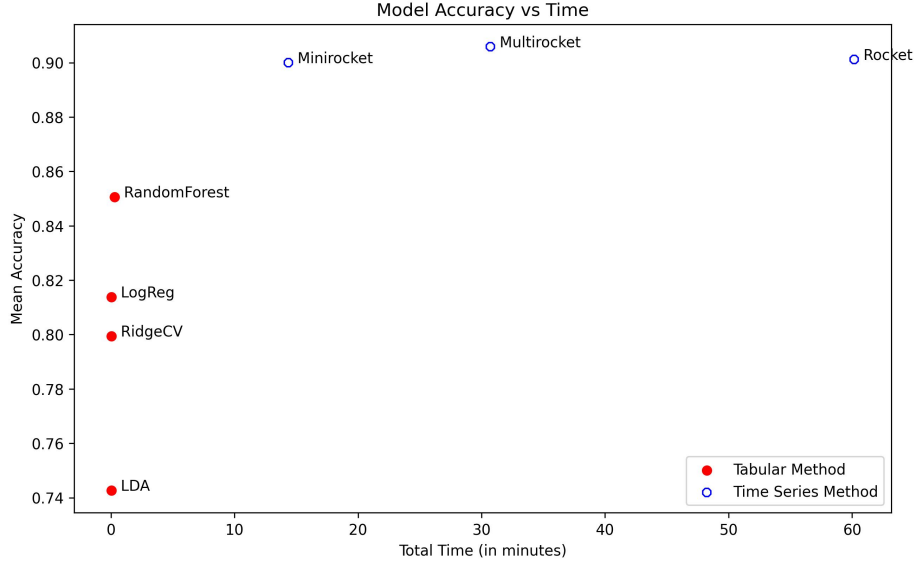


Fig. 5. Accuracy-Time tradeoff for datasets in the **grey region** shown in Figure 4. We observe a mean accuracy difference of about 5 percentage points, but at least an order of magnitude difference in computation time, between tabular and time series methods.

Table 3. Mean accuracy of classifiers by problem types on UCR univariate datasets.

Domain (#datasets)	Tabular Models				Time Series Models		
	RidgeCV	LDA	LogReg	RandomForest	Rocket	Minirocket	Multirocket
Image(31)	0.66	0.62	0.71	0.75	0.85	0.85	0.85
Sensor(20)	0.73	0.69	0.72	0.76	0.86	0.86	0.87
Motion(17)	0.58	0.46	0.58	0.70	0.84	0.84	0.85
Device(8)	0.48	0.44	0.48	0.62	0.76	0.74	0.77
Simulated(8)	0.78	0.82	0.81	0.88	0.99	0.98	0.99
Spectro(8)	0.86	0.90	0.86	0.82	0.84	0.86	0.86
ECG(4)	0.92	0.84	0.92	0.82	0.97	0.97	0.97
Spectrum(4)	0.75	0.67	0.74	0.67	0.83	0.82	0.88
Hemodynamics(3)	0.05	0.16	0.12	0.13	0.66	0.94	0.81
EOG(2)	0.3	0.28	0.37	0.43	0.59	0.57	0.60
EPG(2)	0.82	1.00	1.00	1.00	0.99	1.00	1.00
Power(1)	0.98	0.73	0.99	1.00	0.92	0.99	0.98
Traffic(1)	0.98	0.95	0.98	0.98	0.98	0.98	0.98

As expected, with regard to average accuracy in a specific domain, as also shown in Figure 3, time series models performed better than tabular models in most of the domains. However, we note that the tabular models performed especially well in the Spectro domain. This could be because the Spectro domain

does not have strong temporal features. Also, as we have seen in Figure 4, average behaviour can be misleading and we need to look at the accuracy on individual datasets to get a good idea of accuracy behaviour across the entire benchmark or specific domains.

4.3 Multivariate Time Series Classification

In addition to our analysis of univariate time series datasets, we also conducted an analysis on multivariate time series datasets. The UEA/UCR benchmark dataset we utilized for this analysis consisted of 26 datasets. However, to ensure consistency and comparability among the models, we narrowed down our focus to the 25 datasets that all models could run on. We filtered the datasets based on equal length, and one dataset (Pen Digits) was removed due to Minirocket, which cannot run on datasets with lengths less than 8.

Data Preprocessing: Unlike univariate time series, which have data from a single channel, multivariate time series data have multiple channels. To convert this data into a format that a tabular model can process, we first standardize each channel’s data and then concatenate the data across all channels.

Tabular Methods Results. After preprocessing the data, we followed a similar approach to our univariate analysis. We selected the same tabular models: Random Forest, LDA, Logistic Regression, and RidgeCV. The critical difference diagram (Figure 6) illustrates that Random Forest performed significantly better than the other three models, and Logistic Regression outperformed the other two linear models.

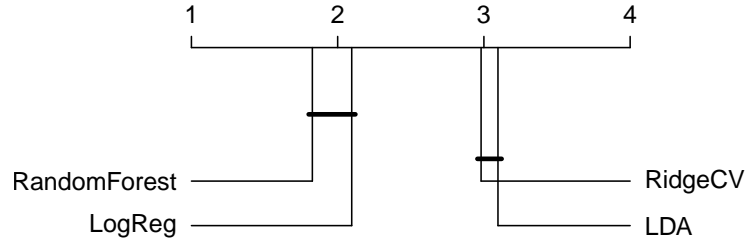


Fig. 6. Accuracy comparison of tabular methods on MTSC datasets.

Table 4 shows the total time taken by tabular models and their corresponding mean accuracy. The table corroborates the results of the critical difference diagram, which showed that Random Forest is the most accurate tabular model, closely followed by LogisticRegression and RidgeCV. RidgeCV is also the most time-efficient method.

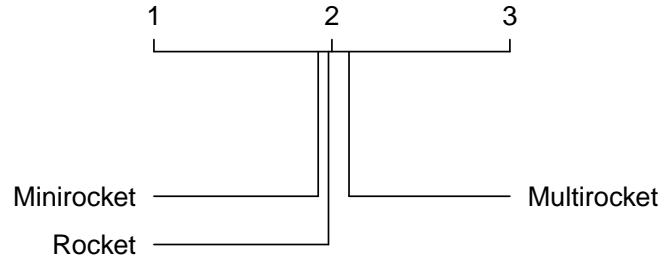
Time Series Methods Results. Similar to the tabular methods, we ran the multivariate time series methods, namely Minirocket, Multirocket, and Rocket,

Table 4. Mean accuracy and total computation time taken by tabular models on MTSC datasets.

	Mean Accuracy	Total Time (minutes)
RandomForest	0.61	6.40
LogisticRegression	0.59	6.20
RidgeCV	0.56	5.27
LDA	0.52	6.70

on the MTSC datasets. Since the implemented algorithm works well with multivariate time series, there was no need to preprocess the data in this case.

Figure 7 and Table 5 illustrate the performance of time series methods on the benchmark datasets. Both the figure and table show that Minirocket outperforms the other two classifiers. Additionally, Minirocket is also the fastest method among the three methods.

**Fig. 7.** Accuracy comparison of time-series methods on MTSC datasets.**Table 5.** Mean accuracy and total computation time taken by time series models on MTSC datasets.

	Mean Accuracy	Total Time (minutes)
Minirocket	0.71	49.33
Multirocket	0.70	67.10
Rocket	0.70	129.05

Time Series Methods vs Tabular Methods. Finally, we compared tabular and time series models, as shown in Figure 8. As expected, the time series models outperformed the tabular models in terms of average accuracy. However, we conducted a more detailed analysis to investigate the reasons for this difference. We discuss our findings below.

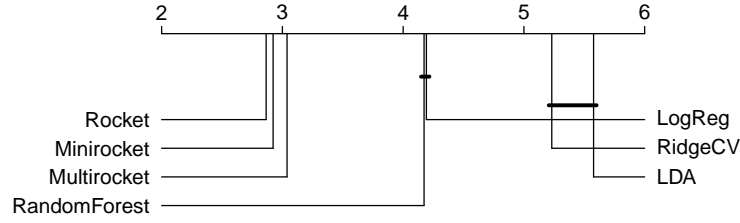


Fig. 8. Accuracy comparison time-series and tabular methods on MTSC datasets.

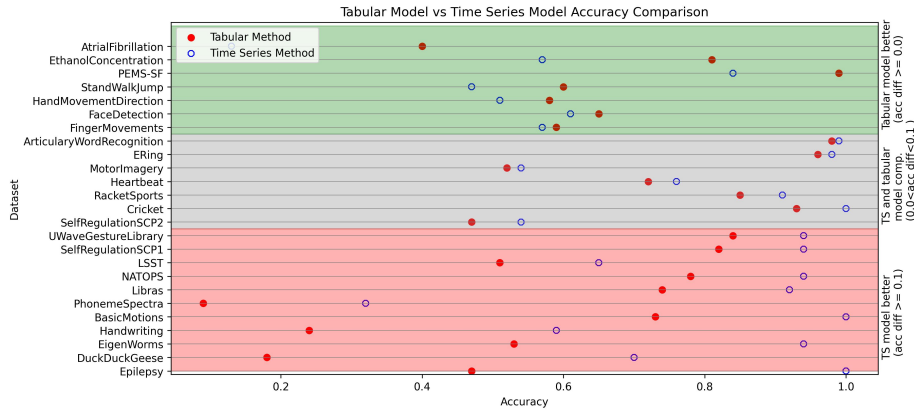


Fig. 9. Accuracy comparison of time series models with tabular models on multivariate time series datasets. Red circles represent tabular models, and blue circles represent time series models. Each marker shows the maximum accuracy achieved by the tabular models versus the time series models. Detailed results are provided with the code.

Figure 9 shows the difference in performance between the best-performing tabular model and the best-performing time series model. The performance of each model is highlighted in a different region, as defined above in Section 4.2. Approximately 28 percent of the datasets are represented in each green and grey region (56 percent total), indicating that the tabular model performs better or within 10 percentage points in these cases. Another 44 percent of the datasets fall within the red region, indicating that the time series models outperform the tabular models in those instances.

Computation Time Analysis For the same reasons as for the univariate time series classification task, we perform the time-accuracy tradeoff analysis for multivariate time series classification. Figure 10 illustrates the performance of various time-series and tabular models on the datasets in the grey region of Figure 9. Rocket is the most accurate among time-series models, and Random Forest is the most accurate model among tabular models. The difference between the mean accuracy of Rocket and the mean accuracy of Random Forest is about

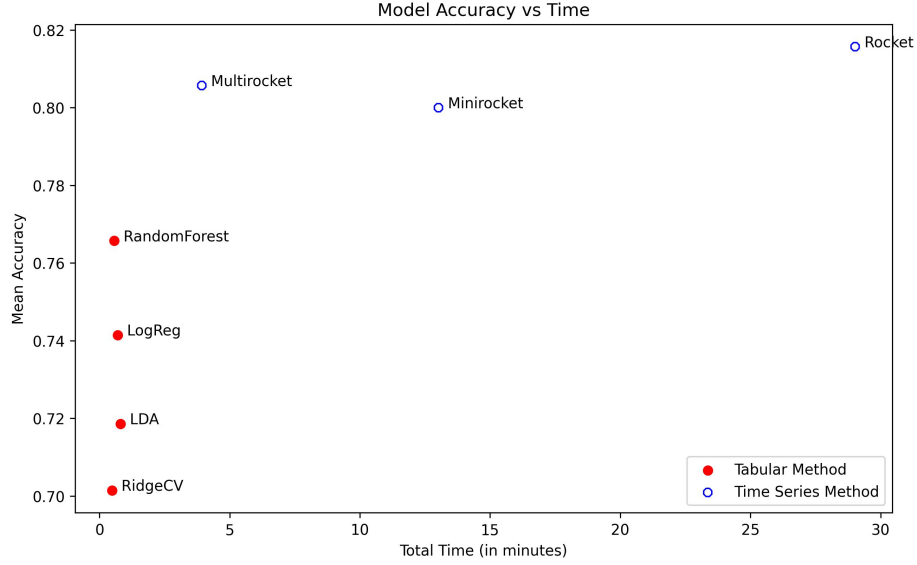


Fig. 10. Accuracy-Time tradeoff for datasets in the **grey region** in Figure 9.

5 percentage point, while the difference in total computation time is about 4 minutes.

In addition to considering the trade-off between time and accuracy, we also analyzed the domain-wise performance of tabular and time series models in multivariate datasets in Table 6. The datasets consisted of 6 domains, with 60% of the data coming from two domains (HAR and EEG). Time series models generally performed well, but tabular models performed better in the ECG and EEG/MEG domains.

Table 6. Mean accuracy of classifiers by problem types on UCR multivariate datasets.

Domain (#datasets)	Tabular Models				Time Series Models		
	RidgeCV	LDA	LogReg	RandomForest	Rocket	Minirocket	Multirocket
HAR(9)	0.67	0.53	0.74	0.78	0.92	0.94	0.94
EEG/MEG(6)	0.55	0.54	0.58	0.50	0.55	0.55	0.54
Audio Spectra(3)	0.18	0.16	0.18	0.18	0.46	0.70	0.52
Other(3)	0.52	0.58	0.65	0.74	0.84	0.83	0.80
ECG(2)	0.46	0.20	0.46	0.40	0.27	0.26	0.24
Motion(2)	0.59	0.65	0.65	0.72	0.99	1.00	1.00

4.4 Discussion and Lessons Learned

- **Redefining baselines:** Most previous research has considered 1NN-DTW as the baseline for time series classification. This is a reasonable choice, as 1NN-DTW is a simple and effective algorithm that is often competitive with more complex time series methods. However, our study suggests that simple tabular models can perform significantly well on some datasets, even when compared to recent state-of-the-art TSC algorithms. This finding suggests that there is a need to rethink how we do baseline comparisons for time series classification.
- **Not all that looks time series is a time series:** Our study demonstrated that tabular methods outperformed time series methods on some domains, specifically Spectro (Table 3), EEG or ECG (Table 6). This could be because the Spectro datasets did not contain strong temporal information. Either way, we need to ask whether it makes sense to have these datasets in a time series classification benchmark.
- **Considering trade-offs:** In our study we observed that time series models outperformed tabular models by a few percentage points on the red datasets. However, tabular models outperformed time series methods in the green datasets and were significantly faster to train and test. Therefore, especially for datasets in the grey region, where tabular and time series methods are close in accuracy, we recommend carefully considering whether tabular models are preferable to time series methods, especially if time is a constraint.

4.5 Improving Tabular Models

Since the above-mentioned experiments were conducted using the default hyperparameters, we wanted to investigate whether we could improve the performance of tabular models by tuning the hyperparameters. To do this, we performed hyperparameter tuning on Random Forest and Logistic Regression, since they were the best performing models in both univariate (Figure 5) and multivariate (Figure 10) experiments.

We performed hyperparameter tuning with a combination of scaling and regularization. Table 7 shows the results of the hyperparameter tuning and the improvement for the best tabular model. We found that hyperparameter tuning can increase accuracy, but it also takes a significant amount of time to find the best hyperparameters.

Table 7. Improvement on accuracy on univariate and multivariate datasets and mean computation time in minutes.

	Mean Accuracy		Mean Computation Time (minutes)	
	Before	After	Before	After
Univariate	0.86	0.87	0.47	13.41
Multivariate	0.74	0.75	0.91	43.10

5 Conclusion

In this study, we compared the performance of tabular models with state-of-the-art time series models on the UCR/UEA univariate and multivariate time series classification benchmarks. We found that tabular models performed surprisingly well on many datasets, outperforming the recent Multirocket classifier on a significant percentage of the datasets. On many other datasets, the accuracy was comparable, but tabular models were more efficient in terms of computation time. Overall, in about half of the datasets in either the univariate or the multivariate benchmarks, tabular methods were within 10 percentage points accuracy of the time series methods.

Our findings suggest that tabular models should be considered as baselines for evaluating improvements in time series classifiers, and even for considering whether a dataset should be included in the time series classification benchmarks. Furthermore, tabular methods can be a viable alternative to time series models for some classification tasks. Tabular models are easier to train and deploy, and they are more efficient in terms of computation time. The performance of tabular models does vary depending on the characteristics of the dataset. In future work, we plan to further investigate the factors that contribute to the performance of tabular models on time series data, and include more tabular models and parameter tuning.

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Appendix

Table 8. Data dictionary for Multivariate time series classification.

Domain	Datasets	Train Size	Test Size	#Channels	TS-len	#Classes
Audio Spectra	DuckDuckGeese	50	50	1345	270	5
Other	PEMS-SF	267	173	963	144	7
EEG/MEG	FaceDetection	5890	3524	144	62	2
EEG/MEG	MotorImagery	278	100	64	3000	2
Audio Spectra	Heartbeat	204	205	61	405	2
EEG/MEG	FingerMovements	316	100	28	50	2
Human Activity Recognition	NATOPS	180	180	24	51	6
Audio Spectra	PhonemeSpectra	3315	3353	11	217	39
EEG/MEG	HandMovementDirection	160	74	10	400	4
Motion	ArticulatoryWordRecognition	275	300	9	144	25
EEG/MEG	SelfRegulationSCP2	200	180	7	1152	2
EEG/MEG	SelfRegulationSCP1	268	293	6	896	2
Human Activity Recognition	BasicMotions	40	40	6	100	4
Human Activity Recognition	Cricket	108	72	6	1197	12
Human Activity Recognition	EigenWorms	128	131	6	17984	5
Human Activity Recognition	LSST	2459	2466	6	36	14
Human Activity Recognition	RacketSports	151	152	6	30	4
ECG	StandWalkJump	12	15	4	2500	3
Human Activity Recognition	ERing	30	270	4	65	6
Human Activity Recognition	Handwriting	150	850	3	152	26
Human Activity Recognition	UWaveGestureLibrary	120	320	3	315	8
Motion	Epilepsy	137	138	3	206	4
Other	EthanolConcentration	261	263	3	1751	4
ECG	AtrialFibrillation	15	15	2	640	3
Motion	PenDigits	7494	3498	2	8	10
Other	Libras	180	180	2	45	15

Table 9: Data dictionary for Univariate time series classification.

Data	Train Size	Test Size	TS-Len	#Classes	Domain
ACSF1	100	100	1460	10	DEVICE
Adiac	390	391	176	37	IMAGE
ArrowHead	36	175	251	3	IMAGE

Beef	30	30	470	5	SPECTRO
BeetleFly	20	20	512	2	IMAGE
BirdChicken	20	20	512	2	IMAGE
BME	30	150	128	3	SIMULATED
Car	60	60	577	4	SENSOR
CBF	30	900	128	3	SIMULATED
Chinatown	20	345	24	2	Traffic
ChlorineConcentration	467	3840	166	3	SIMULATED
CinCECGTorso	40	1380	1639	4	ECG
Coffee	28	28	286	2	SPECTRO
Computers	250	250	720	2	DEVICE
CricketX	390	390	300	12	MOTION
CricketY	390	390	300	12	MOTION
CricketZ	390	390	300	12	MOTION
Crop	7200	16800	46	24	IMAGE
DiatomSizeReduction	16	306	345	4	IMAGE
DistalPhalanxOutlineAgeGroup	400	139	80	3	IMAGE
DistalPhalanxOutlineCorrect	600	276	80	2	IMAGE
DistalPhalanxTW	400	139	80	6	IMAGE
Earthquakes	322	139	512	2	SENSOR
ECG200	100	100	96	2	ECG
ECG5000	500	4500	140	5	ECG
ECGFiveDays	23	861	136	2	ECG
ElectricDevices	8926	7711	96	7	DEVICE
EOGHorizontalSignal	362	362	1250	12	EOG
EOGVerticalSignal	362	362	1250	12	EOG
EthanolLevel	504	500	1751	4	SPECTRO
FaceAll	560	1690	131	14	IMAGE
FaceFour	24	88	350	4	IMAGE
FacesUCR	200	2050	131	14	IMAGE
FiftyWords	450	455	270	50	IMAGE
Fish	175	175	463	7	IMAGE
FordA	3601	1320	500	2	SENSOR
FordB	3636	810	500	2	SENSOR
FreezerRegularTrain	150	2850	301	2	SENSOR
FreezerSmallTrain	28	2850	301	2	SENSOR
GunPoint	50	150	150	2	MOTION
GunPointAgeSpan	135	316	150	2	MOTION
GunPointMaleVersusFemale	135	316	150	2	MOTION
GunPointOldVersusYoung	135	316	150	2	MOTION
Ham	109	105	431	2	SPECTRO
Haptics	155	308	1092	5	MOTION
Herring	64	64	512	2	IMAGE
HouseTwenty	34	101	3000	2	DEVICE
InlineSkate	100	550	1882	7	MOTION

InsectEPGRegularTrain	62	249	601	3	EPG
InsectEPGSmallTrain	17	249	601	3	EPG
ItalyPowerDemand	67	1029	24	2	SENSOR
LargeKitchenAppliances	375	375	720	3	DEVICE
Lightning2	60	61	637	2	SENSOR
Lightning7	70	73	319	7	SENSOR
Mallat	55	2345	1024	8	SIMULATED
Meat	60	60	448	3	SPECTRO
MedicalImages	381	760	99	10	IMAGE
MiddlePhalanxOutlineAgeGroup	400	154	80	3	IMAGE
MiddlePhalanxOutlineCorrect	600	291	80	2	IMAGE
MiddlePhalanxTW	399	154	80	6	IMAGE
MixedShapes	500	2425	1024	5	IMAGE
MixedShapesSmallTrain	100	2425	1024	5	IMAGE
MoteStrain	20	1252	84	2	SENSOR
OliveOil	30	30	570	4	SPECTRO
OSULeaf	200	242	427	6	IMAGE
PhalangesOutlinesCorrect	1800	858	80	2	IMAGE
Phoneme	214	1896	1024	39	SOUND
PigAirwayPressure	104	208	2000	52	HEMODYNAMICS
PigArtPressure	104	208	2000	52	HEMODYNAMICS
PigCVP	104	208	2000	52	HEMODYNAMICS
Plane	105	105	144	7	SENSOR
PowerCons	180	180	144	2	DEVICE
ProximalPhalanxOutlineAgeGroup	400	205	80	3	IMAGE
ProximalPhalanxOutlineCorrect	600	291	80	2	IMAGE
ProximalPhalanxTW	400	205	80	6	IMAGE
RefrigerationDevices	375	375	720	3	DEVICE
Rock	20	50	2844	4	SPECTRO
ScreenType	375	375	720	3	DEVICE
SemgHandGenderCh2	300	600	1500	2	SPECTRO
SemgHandMovementCh2	450	450	1500	6	SPECTRO
SemgHandSubjectCh2	450	450	1500	5	SPECTRO
ShapeletSim	20	180	500	2	SIMULATED
ShapesAll	600	600	512	60	IMAGE
SmallKitchenAppliances	375	375	720	3	DEVICE
SmoothSubspace	150	150	15	3	SIMULATED
SonyAIBORobotSurface1	20	601	70	2	SENSOR
SonyAIBORobotSurface2	27	953	65	2	SENSOR
StarLightCurves	1000	8236	1024	3	SENSOR
Strawberry	613	370	235	2	SPECTRO
SwedishLeaf	500	625	128	15	IMAGE
Symbols	25	995	398	6	IMAGE
SyntheticControl	300	300	60	6	SIMULATED
ToeSegmentation1	40	228	277	2	MOTION

ToeSegmentation2	36	130	343	2	MOTION
Trace	100	100	275	4	SENSOR
TwoLeadECG	23	1139	82	2	ECG
TwoPatterns	1000	4000	128	4	SIMULATED
UMD	36	144	150	3	SIMULATED
UWaveGestureLibraryAll	896	3582	945	8	MOTION
UWaveGestureLibraryX	896	3582	315	8	MOTION
UWaveGestureLibraryY	896	3582	315	8	MOTION
UWaveGestureLibraryZ	896	3582	315	8	MOTION
Wafer	1000	6164	152	2	SENSOR
Wine	57	54	234	2	SPECTRO

Table 10: Accuracy of tabular and time series methods on UTSC datasets.

Name	RidgeCV	LDA	LogRegCV	RandomForest	Rocket	Minirocket	Multirocket
ACSF1	0.42	0.41	0.62	0.75	0.90	0.91	0.88
Adiac	0.44	0.53	0.73	0.65	0.79	0.83	0.83
ArrowHead	0.73	0.67	0.73	0.70	0.82	0.84	0.87
Beef	0.87	0.93	0.87	0.77	0.83	0.87	0.77
BeetleFly	0.85	0.75	0.85	0.85	0.90	0.90	0.85
BirdChicken	0.50	0.55	0.70	0.75	0.90	0.90	0.90
BME	0.91	0.95	0.91	0.97	1.00	1.00	1.00
Car	0.80	0.80	0.83	0.67	0.90	0.92	0.92
CBF	0.83	0.84	0.85	0.89	1.00	1.00	1.00
Chinatown	0.98	0.95	0.98	0.98	0.98	0.98	0.98
ChlorineConcentration	0.85	0.88	0.78	0.71	0.82	0.77	0.79
CinCECGTorso	0.39	0.45	0.45	0.72	0.83	0.87	0.95
Coffee	1.00	1.00	1.00	0.96	1.00	1.00	1.00
Computers	0.51	0.49	0.48	0.62	0.75	0.70	0.78
CricketX	0.27	0.13	0.27	0.55	0.82	0.81	0.81
CricketY	0.37	0.15	0.39	0.60	0.86	0.83	0.85
CricketZ	0.31	0.15	0.28	0.57	0.85	0.82	0.84
Crop	0.56	0.63	0.69	0.76	0.75	0.75	0.77
DiatomSizeReduction	0.96	0.96	0.95	0.90	0.98	0.92	0.96
DistalPhalanxOutlineAgeGroup	0.66	0.60	0.69	0.77	0.76	0.75	0.78
DistalPhalanxOutlineCorrect	0.66	0.66	0.65	0.76	0.76	0.79	0.79
DistalPhalanxTW	0.61	0.58	0.60	0.68	0.72	0.70	0.69
Earthquakes	0.75	0.65	0.68	0.75	0.75	0.75	0.75

ECG200	0.80 0.59 0.84 0.83	0.91 0.91 0.92
ECG5000	0.93 0.93 0.94 0.94	0.95 0.95 0.95
ECGFiveDays	0.99 0.94 0.97 0.80	1.00 1.00 1.00
ElectricDevices	0.44 0.46 0.47 0.65	0.73 0.73 0.73
EOGHorizontalSignal	0.34 0.27 0.39 0.44	0.64 0.59 0.65
EOGVerticalSignal	0.25 0.28 0.35 0.42	0.54 0.56 0.54
EthanolLevel	0.66 0.91 0.72 0.48	0.57 0.61 0.62
FaceAll	0.79 0.79 0.77 0.79	0.95 0.81 0.80
FaceFour	0.89 0.85 0.86 0.75	0.97 0.99 0.94
FacesUCR	0.70 0.62 0.73 0.77	0.96 0.96 0.96
FiftyWords	0.43 0.32 0.56 0.63	0.83 0.84 0.86
Fish	0.82 0.73 0.85 0.77	0.98 0.99 0.98
FordA	0.52 0.53 0.49 0.74	0.94 0.95 0.95
FordB	0.50 0.50 0.49 0.63	0.79 0.81 0.83
FreezerRegularTrain	0.99 0.98 0.98 0.95	1.00 1.00 1.00
FreezerSmallTrain	0.86 0.94 0.81 0.75	0.95 0.97 0.99
GunPoint	0.85 0.81 0.85 0.92	1.00 0.99 1.00
GunPointAgeSpan	0.87 0.57 0.89 0.97	1.00 0.99 1.00
GunPointMaleVersusFemale	0.97 0.68 0.99 0.97	1.00 1.00 1.00
GunPointOldVersusYoung	1.00 0.88 1.00 1.00	0.99 1.00 1.00
Ham	0.71 0.66 0.65 0.75	0.71 0.69 0.73
Haptics	0.43 0.35 0.38 0.44	0.52 0.53 0.56
Herring	0.59 0.58 0.63 0.66	0.70 0.66 0.67
HouseTwenty	0.73 0.72 0.72 0.71	0.97 0.97 0.99
InlineSkate	0.19 0.23 0.27 0.34	0.46 0.45 0.47
InsectEPGRegularTrain	0.82 1.00 1.00 1.00	1.00 1.00 1.00
InsectEPGSmallTrain	0.83 1.00 1.00 1.00	0.98 1.00 1.00
InsectWingbeatSound	0.62 0.26 0.58 0.63	0.66 0.67 0.68
ItalyPowerDemand	0.97 0.94 0.96 0.97	0.97 0.96 0.97
LargeKitchenAppliances	0.44 0.38 0.39 0.58	0.90 0.87 0.88
Lightning2	0.77 0.66 0.72 0.75	0.75 0.74 0.69
Lightning7	0.64 0.55 0.67 0.71	0.84 0.79 0.82
Mallat	0.76 0.86 0.82 0.91	0.96 0.95 0.92
Meat	0.98 0.98 0.93 0.92	0.95 0.97 0.93
MedicalImages	0.55 0.49 0.63 0.73	0.80 0.80 0.81
MiddlePhalanxOutlineAgeGroup	0.60 0.48 0.60 0.62	0.60 0.60 0.62
MiddlePhalanxOutlineCorrect	0.62 0.58 0.59 0.81	0.83 0.84 0.86
MiddlePhalanxTW	0.61 0.53 0.53 0.56	0.55 0.53 0.54
MixedShapes	0.79 0.71 0.82 0.87	0.97 0.97 0.98
MixedShapesSmallTrain	0.77 0.69 0.78 0.78	0.94 0.95 0.96
MoteStrain	0.86 0.72 0.86 0.88	0.91 0.93 0.95
OliveOil	0.90 0.90 0.90 0.90	0.90 0.93 0.97
OSULeaf	0.40 0.32 0.46 0.49	0.93 0.96 0.96
PhalangesOutlinesCorrect	0.67 0.66 0.67 0.82	0.83 0.84 0.85
Phoneme	0.11 0.08 0.10 0.13	0.28 0.27 0.35

PigAirwayPressure	0.02 0.21 0.08 0.09	0.09 0.88 0.60
PigArtPressure	0.10 0.12 0.17 0.19	0.95 0.99 0.95
PigCVP	0.04 0.14 0.10 0.11	0.93 0.95 0.88
Plane	0.98 0.99 0.98 0.98	1.00 1.00 1.00
PowerCons	0.98 0.73 0.99 1.00	0.92 0.99 0.98
ProximalPhalanxOutlineAgeGroup	0.84 0.83 0.85 0.86	0.85 0.85 0.86
ProximalPhalanxOutlineCorrect	0.84 0.84 0.85 0.86	0.90 0.91 0.91
ProximalPhalanxTW	0.75 0.75 0.76 0.80	0.81 0.82 0.82
RefrigerationDevices	0.35 0.35 0.37 0.53	0.53 0.48 0.50
Rock	0.88 0.94 0.84 0.66	0.90 0.80 0.86
ScreenType	0.44 0.40 0.39 0.42	0.49 0.47 0.57
SemgHandGenderCh2	0.85 0.76 0.82 0.85	0.92 0.90 0.96
SemgHandMovementCh2	0.50 0.39 0.50 0.50	0.62 0.71 0.78
SemgHandSubjectCh2	0.78 0.59 0.81 0.68	0.89 0.87 0.92
ShapeletSim	0.49 0.51 0.48 0.51	1.00 1.00 1.00
ShapesAll	0.50 0.11 0.63 0.73	0.91 0.92 0.93
SmallKitchenAppliances	0.54 0.35 0.41 0.71	0.81 0.82 0.82
SmoothSubspace	0.80 0.83 0.86 0.99	0.98 0.94 0.98
SonyAIBORobotSurface1	0.69 0.70 0.68 0.67	0.92 0.89 0.89
SonyAIBORobotSurface2	0.83 0.81 0.81 0.81	0.91 0.92 0.94
StarLightCurves	0.85 0.81 0.92 0.95	0.98 0.98 0.98
Strawberry	0.93 0.95 0.95 0.96	0.98 0.98 0.98
SwedishLeaf	0.66 0.72 0.83 0.87	0.97 0.97 0.98
Symbols	0.77 0.82 0.82 0.85	0.97 0.98 0.98
SyntheticControl	0.80 0.93 0.91 0.96	1.00 0.98 1.00
ToeSegmentation1	0.57 0.55 0.58 0.62	0.96 0.96 0.95
ToeSegmentation2	0.55 0.54 0.56 0.75	0.92 0.92 0.92
Trace	0.61 0.70 0.76 0.83	1.00 1.00 1.00
TwoLeadECG	0.94 0.89 0.95 0.73	1.00 1.00 1.00
TwoPatterns	0.79 0.84 0.84 0.83	1.00 1.00 1.00
UMD	0.82 0.79 0.84 0.95	0.99 0.99 0.99
UWaveGestureLibraryAll	0.85 0.28 0.81 0.93	0.98 0.97 0.98
UWaveGestureLibraryX	0.63 0.51 0.63 0.76	0.86 0.85 0.87
UWaveGestureLibraryY	0.53 0.42 0.58 0.68	0.77 0.78 0.80
UWaveGestureLibraryZ	0.51 0.45 0.55 0.71	0.79 0.80 0.82
Wafer	0.94 0.94 0.94 0.99	1.00 1.00 1.00
Wine	0.83 0.91 0.89 0.78	0.81 0.83 0.89
WordSynonyms	0.38 0.23 0.46 0.55	0.75 0.76 0.78
Worms	0.38 0.42 0.34 0.55	0.74 0.75 0.75
WormsTwoClass	0.55 0.62 0.52 0.62	0.81 0.77 0.78
Yoga	0.65 0.59 0.67 0.81	0.91 0.91 0.92

Table 11: Computation time (in minutes) for univariate datasets.

Name	RidgeCV	LDA	LogReg	RandomForest	Rocket	Minirocket	Multirocket
ACSF1	0.03	0.04	0.29	0.19	0.83	0.12	0.26
Adiac	0.03	0.02	0.12	0.40	0.38	0.07	0.17
ArrowHead	0.01	0.01	0.03	0.11	0.14	0.02	0.07
Beef	0.01	0.01	0.05	0.10	0.08	0.02	0.04
BeetleFly	0.01	0.01	0.02	0.09	0.06	0.01	0.04
BirdChicken	0.01	0.01	0.04	0.09	0.06	0.02	0.04
BME	0.01	0.00	0.01	0.09	0.07	0.01	0.04
Car	0.01	0.01	0.06	0.11	0.19	0.04	0.09
CBF	0.01	0.00	0.01	0.09	0.31	0.05	0.18
Chinatown	0.01	0.00	0.01	0.09	0.03	0.01	0.03
ChlorineConcentration	0.02	0.02	0.04	0.40	1.85	0.28	1.08
CinCECGTorso	0.03	0.03	0.15	0.14	5.69	0.90	2.35
Coffee	0.01	0.01	0.02	0.09	0.04	0.02	0.03
Computers	0.03	0.05	0.04	0.28	0.87	0.21	0.37
CricketX	0.04	0.03	0.11	0.36	0.57	0.13	0.31
CricketY	0.03	0.03	0.11	0.34	0.57	0.15	0.31
CricketZ	0.03	0.03	0.13	0.37	0.57	0.13	0.31
Crop	0.08	0.05	0.53	2.98	4.23	1.86	5.57
DiatomSizeReduction	0.01	0.01	0.04	0.09	0.29	0.05	0.12
DistalPhalanxOutlineAgeGroup	0.01	0.01	0.03	0.18	0.13	0.04	0.09
DistalPhalanxOutlineCorrect	0.01	0.01	0.02	0.26	0.20	0.05	0.13
DistalPhalanxTW	0.01	0.01	0.03	0.18	0.12	0.04	0.08
Earthquakes	0.03	0.04	0.02	0.29	0.58	0.13	0.35
ECG200	0.01	0.01	0.01	0.11	0.05	0.02	0.04
ECG5000	0.02	0.02	0.05	0.26	1.66	0.32	0.83
ECGFiveDays	0.01	0.00	0.01	0.09	0.28	0.05	0.14
ElectricDevices	0.24	0.10	0.15	6.60	6.03	2.79	6.49
EOGHorizontalSignal	0.09	0.14	0.47	0.51	2.19	0.44	0.94
EOGVerticalSignal	0.06	0.14	0.44	0.53	2.18	0.42	0.95
EthanolLevel	0.16	0.30	0.41	0.86	4.29	0.81	1.66
FaceAll	0.02	0.02	0.13	0.40	0.69	0.13	0.36
FaceFour	0.02	0.01	0.04	0.11	0.10	0.02	0.06
FacesUCR	0.02	0.01	0.06	0.20	0.67	0.14	0.34
FiftyWords	0.05	0.04	0.46	0.73	0.58	0.13	0.24
Fish	0.02	0.03	0.15	0.21	0.38	0.08	0.16
FordA	0.58	0.45	0.19	5.25	6.03	1.44	2.77
FordB	0.78	0.34	0.23	5.80	5.51	1.34	2.62
FreezerRegularTrain	0.02	0.03	0.02	0.16	2.03	0.34	0.98

FreezerSmallTrain	0.01	0.01	0.03	0.12	1.93	0.31	0.92
GunPoint	0.01	0.01	0.03	0.11	0.08	0.02	0.04
GunPointAgeSpan	0.01	0.01	0.02	0.13	0.16	0.03	0.08
GunPointMaleVersusFemale	0.01	0.01	0.01	0.12	0.16	0.03	0.08
GunPointOldVersusYoung	0.01	0.01	0.01	0.11	0.16	0.03	0.08
Ham	0.02	0.03	0.02	0.14	0.22	0.05	0.10
Haptics	0.03	0.05	0.14	0.24	1.17	0.21	0.44
Herring	0.02	0.02	0.03	0.13	0.16	0.03	0.07
HouseTwenty	0.04	0.06	0.07	0.14	0.74	0.13	0.35
InlineSkate	0.06	0.08	0.40	0.25	2.79	0.45	1.18
InsectEPGRegularTrain	0.02	0.02	0.03	0.11	0.43	0.07	0.21
InsectEPGSmallTrain	0.01	0.02	0.04	0.12	0.36	0.06	0.18
InsectWingbeatSound	0.03	0.02	0.09	0.23	1.26	0.21	0.48
ItalyPowerDemand	0.01	0.01	0.01	0.11	0.07	0.02	0.06
LargeKitchenAppliances	0.08	0.10	0.21	0.44	1.27	0.24	0.45
Lightning2	0.01	0.02	0.03	0.12	0.18	0.04	0.10
Lightning7	0.02	0.01	0.05	0.14	0.11	0.02	0.06
Mallat	0.03	0.04	0.15	0.17	5.47	0.94	1.77
Meat	0.01	0.01	0.04	0.11	0.13	0.03	0.06
MedicalImages	0.02	0.01	0.04	0.25	0.27	0.06	0.14
MiddlePhalanxOutlineAgeGroup	0.01	0.01	0.03	0.20	0.12	0.04	0.08
MiddlePhalanxOutlineCorrect	0.01	0.01	0.02	0.29	0.19	0.05	0.12
MiddlePhalanxTW	0.01	0.01	0.04	0.22	0.11	0.04	0.08
MixedShapes	0.11	0.17	0.24	0.67	6.73	1.20	2.49
MixedShapesSmallTrain	0.04	0.04	0.14	0.20	5.77	1.01	2.06
MoteStrain	0.01	0.00	0.01	0.11	0.24	0.05	0.13
OliveOil	0.03	0.01	0.06	0.11	0.09	0.03	0.04
OSULeaf	0.06	0.03	0.16	0.22	0.44	0.09	0.19
PhalangesOutlinesCorrect	0.04	0.02	0.03	0.97	0.56	0.19	0.37
Phoneme	0.05	0.08	0.93	0.77	4.86	0.93	1.98
PigAirwayPressure	0.08	0.08	1.96	0.63	1.43	0.27	0.61
PigArtPressure	0.07	0.08	2.12	0.60	1.43	0.27	0.54
PigCVP	0.06	0.08	1.98	0.62	1.44	0.30	0.62
Plane	0.01	0.01	0.03	0.13	0.08	0.02	0.04
PowerCons	0.02	0.01	0.01	0.13	0.13	0.03	0.07
ProximalPhalanxOutlineAgeGroup	0.01	0.01	0.03	0.19	0.13	0.05	0.08
ProximalPhalanxOutlineCorrect	0.01	0.01	0.02	0.28	0.18	0.05	0.12
ProximalPhalanxTW	0.01	0.01	0.03	0.20	0.13	0.03	0.08
RefrigerationDevices	0.05	0.09	0.08	0.44	1.26	0.27	0.59
Rock	0.05	0.05	0.35	0.14	0.46	0.10	0.19
ScreenType	0.09	0.08	0.13	0.43	1.25	0.30	0.49
SemgHandGenderCh2	0.06	0.12	0.13	0.42	3.09	0.68	1.57
SemgHandMovementCh2	0.11	0.20	0.33	0.77	3.14	0.78	1.63
SemgHandSubjectCh2	0.14	0.19	0.29	0.72	3.13	0.79	1.62
ShapeletSim	0.01	0.01	0.01	0.11	0.23	0.05	0.13

ShapesAll	0.16	0.13	0.86	1.71	1.42	0.34	0.60
SmallKitchenAppliances	0.05	0.08	0.10	0.40	1.25	0.29	0.46
SmoothSubspace	0.01	0.01	0.01	0.11	0.02	0.01	0.02
SonyAIBORobotSurface1	0.01	0.00	0.01	0.10	0.10	0.03	0.06
SonyAIBORobotSurface2	0.01	0.00	0.01	0.10	0.15	0.04	0.09
StarLightCurves	0.39	0.56	0.35	1.04	21.16	4.04	6.29
Strawberry	0.04	0.03	0.04	0.34	0.55	0.14	0.25
SwedishLeaf	0.02	0.02	0.09	0.34	0.35	0.09	0.18
Symbols	0.01	0.01	0.05	0.11	0.90	0.20	0.34
SyntheticControl	0.01	0.01	0.03	0.17	0.09	0.03	0.07
ToeSegmentation1	0.01	0.01	0.02	0.11	0.17	0.04	0.08
ToeSegmentation2	0.01	0.01	0.02	0.11	0.13	0.03	0.07
Trace	0.01	0.01	0.04	0.13	0.13	0.04	0.08
TwoLeadECG	0.01	0.01	0.01	0.10	0.22	0.05	0.11
TwoPatterns	0.05	0.03	0.05	0.69	1.46	0.33	0.84
UMD	0.01	0.01	0.02	0.11	0.07	0.02	0.04
UWaveGestureLibraryAll	0.38	0.34	0.42	1.13	9.54	1.97	3.71
UWaveGestureLibraryX	0.10	0.08	0.13	0.79	3.17	0.70	1.19
UWaveGestureLibraryY	0.08	0.06	0.17	0.83	3.18	0.69	1.21
UWaveGestureLibraryZ	0.13	0.06	0.13	0.82	3.15	0.63	1.20
Wafer	0.03	0.03	0.03	0.66	2.44	0.48	1.18
Wine	0.01	0.01	0.02	0.11	0.07	0.02	0.04
WordSynonyms	0.02	0.02	0.18	0.33	0.56	0.12	0.22
Worms	0.03	0.05	0.14	0.27	0.55	0.13	0.25
WormsTwoClass	0.03	0.05	0.06	0.24	0.55	0.13	0.25
Yoga	0.03	0.04	0.06	0.31	3.10	0.55	1.18
Sum	5.88	5.75	18.38	53.16	158.77	34.56	73.47

Table 12. Computation time (in minutes) for multivariate datasets.

Dataset	RidgeCV	RandomForest	LogRegCV	LDA
DuckDuckGeese	0.18	0.18	0.18	0.16
PEMS-SF	0.87	0.99	0.84	0.58
FaceDetection	0.57	0.61	0.65	0.57
MotorImagery	0.47	0.50	0.47	0.52
Heartbeat	0.65	0.72	0.67	0.72
FingerMovements	0.58	0.49	0.59	0.56
NATOPS	0.73	0.78	0.74	0.76
PhonemeSpectra	0.05	0.09	0.05	0.04
HandMovementDirection	0.54	0.47	0.58	0.49
ArticulatoryWordRecognition	0.87	0.98	0.97	0.97
SelfRegulationSCP2	0.43	0.47	0.44	0.46
BasicMotions	0.63	0.73	0.63	0.35
Cricket	0.82	0.89	0.92	0.93
EigenWorms	0.50	0.52	0.53	0.44
LSST	0.30	0.51	0.25	0.26
RacketSports	0.72	0.85	0.76	0.55
SelfRegulationSCP1	0.73	0.82	0.77	0.73
ERing	0.95	0.95	0.96	0.88
StandWalkJump	0.60	0.47	0.53	0.20
Epilepsy	0.31	0.47	0.33	0.33
EthanolConcentration	0.48	0.43	0.65	0.81
Handwriting	0.17	0.20	0.24	0.15
UWaveGestureLibrary	0.67	0.84	0.78	0.53
AtrialFibrillation	0.33	0.33	0.40	0.20
Libras	0.52	0.74	0.63	0.51