Trend-based Dynamic Selection of Machine Learning Models for Pandemic Time Series Forecasting

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Abstract. *Pandemic time series forecasting is challenging due to rapidly changing patterns, which general-purpose predictors often fail to capture. Recent studies suggest that specialized models are better suited for such complexity, especially when trend changes are key. This work proposes a forecasting approach that dynamically selects specialized Support Vector Regression (SVR) models based on trend classification (SVRTC). SVRTC maintains a pool of models, each tailored to exponential growth, plateau, or decline patterns. Using COVID-19 case series from eight countries, SVRTC was compared to traditional forecasting and existing dynamic selection methods. It achieved remarkable performance among traditional Machine Learning models and competitive results against state-of-the-art dynamic selection, with low computational cost, indicating strong potential for broader application.*

1. Introduction

Pandemics, while exhibiting some degree of predictability, still pose significant challenges for forecasting tasks [Machado and Lopes 2020]. The use of time series forecasting methods to address such events has become increasingly relevant in light of recent global health crises. During the COVID-19 pandemic, which had profound impacts on both health and economic systems worldwide [Chung et al. 2021], numerous researchers developed predictive models to better understand the disease's progression using time series analysis [Rahimi et al. 2023]. The incidence of COVID-19 over time typically displayed patterns of exponential growth, followed by a plateau and subsequent decline [Firmino et al. 2020]. These shifts in behavior have made it difficult for single models to robustly forecast the series [Ioannidis et al. 2022].

A widely adopted strategy to address the heterogeneous and dynamic behaviors characteristic of pandemic-related time series is the implementation of ensemble methods, also known as Multiple Predictor Systems (MPS) [Yao et al. 2019, Silva et al. 2021], which combine the strengths of multiple predictive models to improve the robustness and precision of forecasts. With the objective of creating a pool of specialized forecasters, several studies [de Sales et al. 2024, Sheikh and Coulibaly 2025, Stasiak and Staszak 2024, Tang et al. 2021] have utilized time series characteristics, such as seasonality, trend, local patterns, and structural breaks, to guide model specialization and selection, thereby improving forecasting accuracy. These features provide valuable information that enhances the ability of forecasting models to adapt to the distinct dynamics present in each time series. Thus, the incorporation of trend information holds significant potential for improving the accuracy of MPS in the modeling of pandemic time series. Consequently, this strategy emerges as a promising avenue for augmenting the predictive capabilities and overall performance of forecasting models [de Sales et al. 2024].

The present work proposes the Support Vector Regression Based on Trend Classification (SVRTC) system. It defines a single best-performing SVR model for each trend class. The SVR was chosen due to its robustness and stability in the forecasting task [Silva et al. 2021, de Oliveira et al. 2022, Silva et al. 2020, Saadallah 2023]. The proposed dynamic system aims at using dynamic selection of a single model specialized for each trend classification in order to outperform, in terms of root mean squared error (RMSE) and mean absolute error (MAE) measures, single model approaches of varying complexities, as well as another trend classification-based approach. By achieving this goal, the authors hope to broaden the understanding of dynamic selection based on the classification of the properties of a series, such as trend, as a means to ensure solid and reliable forecasts.

The main contributions presented in this paper are:

- A novel dynamic approach based on using a specialized SVR model for each trend class, SVRTC, has been proposed;
- SVRTC has achieved predictive performance comparable to DESTC and has consistently outperformed baseline models according to RMSE and MAE values.

The remainder of this paper is structured as follows: Section 2 presents the related works; Section 3 details the proposed method; Section 4 describes the experimental protocol and the performance measures; Section 5 discloses the results and discusses them; Section 6 concludes the present work while commenting on possible enhancements and future works.

2. Related works

Predicting the progression of a pandemic presents it own challenges. As an extreme event [Machado and Lopes 2020], there is a constant unpredictability inherent to the initial lack of information on the disease. The high risks associated with such a widespread epidemic require quick and constant action from governments [Chung et al. 2021]. Robust mechanistic methods such as the Susceptible-Infected-Removed (SIR) model find some shortcomings due to requiring precise parameters often only identified after the spread of the disease [Ahmetolan et al. 2020]. However, despite the existence of many variables in constant change, there are predictable behaviors that can be used to predict the phenomenon [Firmino et al. 2020]. First, it is prudent to consider the classic prediction strategies used in the literature.

The classical forecasting approach consists of training multiple models, evaluating their performance, and selecting the one with the highest forecast accuracy [Santos et al. 2024]. A variety of generalist approaches have been developed for time series forecasting, such as exponential smoothing models [Tratar et al. 2016], autoregressive models [Kaur et al. 2023], artificial neural networks such as Multilayer Perceptron (MLP) [Tealab 2018], and Support Vector Regression (SVR) [Ahmadi and Khashei 2021]. These algorithms are well documented in the literature and have been successful in numerous case studies. More recently, Transformer-based models have been studied for time series forecasting [Zeng et al. 2023] and have brought promising results. In the specific context of COVID-19, however, they may not be able to adequately anticipate trend changes. Therefore, the aforementioned MPS are a more favorable starting step.

Since no single model can consistently outperform others in all scenarios, given the inherent limitations of each algorithm, ensembles proved to be quite promising [Yao et al. 2019, Silva et al. 2021]. MPS are composed of three phases: Generation, Selection, and Integration (Combination). In summary, a pool of base models is initially trained for further selection. The final phase is the combination of the pool [Silva et al. 2021]. The Selection phase can be carried out using either a static or dynamic approach. In the static approach, the set of selected models remains fixed and is used to predict all subsequent instances. On the other hand, in the dynamic approach, models are selected on the fly for each new instance to be predicted, allowing adaptation to its characteristics [Silva et al. 2021, de Sales et al. 2023, Yao et al. 2019].

MPS models were a highly prevalent strategy for predicting COVID-19 incidence. In some cases, a small number of models were trained and subsequently combined, without incorporating an explicit selection phase [Liapis et al. 2020, Maaliw et al. 2021, Qu et al. 2023]. [Liapis et al. 2020] proposed an ensemble strategy focused on forecasting cases from Central and South Europe. [Maaliw et al. 2021] presented a more broadly applicable approach based on the weighted combination of a linear model and a stacked recurrent neural network. [Qu et al. 2023] focused on also using a weighted ensemble of neural networks with a novel optimization strategy for the weights.

To better adapt to the instability of pandemic scenarios, dynamic selection approaches have also been proposed [Botz et al. 2024, de Sales et al. 2024]. [Botz et al. 2024] suggests a stacking ensemble for the prediction of cases which is combined with metadata based on queries of key symptoms in search engines. A meta-model uses the metadata as a means of selecting or weighting the predictions of the ensemble, thus producing a final prediction. This method resulted in robust error measures for predicting deceases caused by COVID-19 in Germany and France. However, few dynamic selection approaches for forecasting pandemic time series are found in the literature.

In the case of DESTC [de Sales et al. 2024], a pool base models was initially trained. In order to establish an impartial evaluation of each model, validation sets are divided based on the classification of time series trends (increasing, decreasing, and no trend). Those sets are used in the selection phase. The selection is then conducted with each validation set in order to select the best performing models. Consequently, different models are combined for each trend category. In the test phase, a test pattern undergoes trend classification, and the formerly selected models for that specific trend class have their predictions combined to produce a final prediction.

3. Proposed method

Figure 1 illustrates an overview of how the model operates. The training phase (a) begins with a trend classification of the validation data (Z_v), so it can be separated into three validation datasets based on trend classification (T_v). Afterwards, the optimization step of the SVR models begins. For every hyperparameter of an optimization gridsearch, a

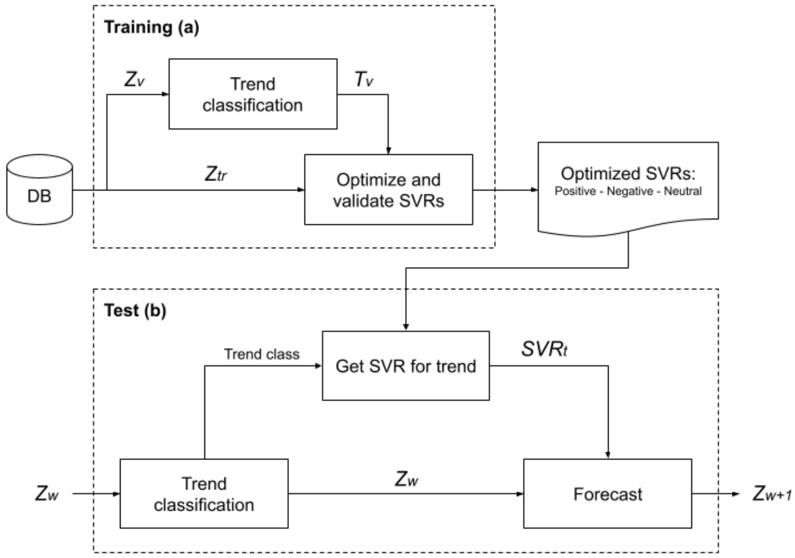

Figure 1. Flowchart of SVRTC. The training phase (a) involves optimizing the SVR models which are trained with the training data (Z_{tr}) and validating them for each trend according to the trend classes (T_v) of the validation data (Z_v). The best SVR for each trend is extracted and added to a pool from which the test phase (b) selects a model that matches the trend class of the test data Z_w. Lastly, the selected model (SVR_t) forecasts the next step of the test data, ending the pipeline.

model is trained with training data (Z_{tr}) and validated using T_v, with the RMSE values for that specific execution of the configuration being recorded. This process is repeated five times for every gridsearch configuration, after which the mean of the previously recorded values is calculated. If the mean RMSE is lower than the last value for a given validation set trend, which is initialized as a pseudo-infinite value, the trained model is saved as the SVR for that trend. In the end, three trained and optimized SVR models are stored for the test phase (b). It is important to emphasize that two or more trend patterns may have the same model configuration if it results in better mean RMSE values for more than one validation set.

The test phase (b) begins making a trend classification of the test element (Z_w). Further, its trend class is used to select the matching SVR for that given trend (SVR$_t$). Lastly, the test element Z_w is forecast one step ahead, and its prediction (Z_{w+1}) is then recorded for evaluation.

4. Experimental protocol

4.1. Datasets and preprocessing

The proposed method was applied to eight pandemic series and had its results compared to another approach that uses trend classification (DESTC) and classic models from the literature. Those series have the number of confirmed COVID-19 cases recorded across eight different countries (Brazil, Canada, France, Germany, Italy, Spain, United Kingdom, and United States of America). From the raw numbers, a 7-day rolling mean was extracted. This step was done in order to reduce the impacts of occasional delays of the records regarding weekend admissions. Table 1 describes each of the series in detail. All of them featured at least 820 values and at most 1003 values, ranging from February 1st 2020 to October 31st 2022.

Table 1. Description of each dataset, with start and end dates, and sample size.

Country	Start	End	Sample size
Brazil	01/02/2020	31/10/2022	1003
Canada	01/04/2020	30/06/2022	820
France	01/02/2020	31/07/2022	911
Germany	01/02/2020	31/08/2022	942
Italy	01/02/2020	31/08/2022	942
Spain	01/05/2020	31/07/2022	821
UK	01/02/2020	31/07/2022	911
USA	01/02/2020	31/10/2022	1003

Each time series was firstly split in a large train set with 85% of the values and a test set with 15% of the values. Both train and test sets were normalized into the interval [0.2; 0.8], based on the train set in order to prevent occasional data leaks. Once normalized, the series were ready to undergo the training and test phases.

4.2. Training and test phases

The approach has a three-steps optimization pipeline. Firstly, the train and test series were split by a sliding window algorithm. This step is optimized by varying the amount of lags the series would be split in order to isolate the configuration that brings the best results. Secondly, in order to assemble three validation sets, one for each trend class, the significance of the trend classification had to be defined. This step is optimized by varying the significance level of the Mann-Kendall statistical test for defining presence or absence of trend in a time window. Lastly, the training and test phases can finally begin. They involve the optimization of the SVR models in order to generate three specialized predictors for each series. Table 2 displays each hyperparameter of this pipeline. Lag defines the sizes of the time windows in the time window splitting step; Alpha defines the significance level of the Mann-Kendall statistical test of the trend classification step; Kernel, Gamma, Cost and Epsilons are hyperparameters used in the SVR optimization gridsearch step.

Table 2. Optimized hyperparameters of the model pipeline for each step.

Step	Hyperparameter	Values
Time window splitting	Lag size	5, 7, 10
Trend classification	α	0.01, 0.05, 0.1
SVR hyperparameters	Kernel	Linear, polynomial, radial
	γ	0.001, 0.01, 0.1
	Cost	0.01, 0.05, 0.1, 0.5, 1, 10, 100, 1000
	ϵ	0.001, 0.01, 0.1

For each time window size, both the large training series and the test series were divided into sliding time windows. From the large training series, 60% of the values were allocated to the training set and 25% to the validation sets. The validation phase used three distinct sets, each containing only series segments corresponding to a single trend pattern—increase, decrease, or no-trend—according to the trend classification step (see Figure 1). If, for a given series and significance level, the validation set for a specific trend was empty, that configuration was discarded and the next significance level or lag value was tested. The process continued until all three validation sets were non-empty, at which point the pipeline proceeded to the SVR hyperparameter grid search, as shown in the flowchart.

Once a given configuration went through every step of the pipeline, it underwent the test phase. Every test window went through the process illustrated in Figure 1 and had its prediction registered for later evaluation. After evaluation, as long as there were other pipeline configurations remaining, the pipeline restarted with the next remaining settings.

4.3. Performance evaluation

The evaluation process consists of analyzing RMSE and MAE, as well as the percentage differences of those performance measures to baseline literature models and the other trend classification-based model, DESTC. Those measures are highly used by the academia for evaluating time series forecasting methods according to [Silva et al. 2021], [Saadallah 2023] and [He et al. 2025]. The RMSE is a performance measure which offers an average error of the predictions which heavily penalizes greater deviations over lesser ones. It is calculated according to Equation 1:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(z_t - \hat{z}_t)^2}, \tag{1}$$

in which *n* is the amount of lags in the real test series, *t* is a given lag of the series, *zt* is an element of the actual series, and *z*-hat*t* is the predicted element of the model for that specific lag. However, it is not prudent to use a single measure for evaluating the effectiveness of a model, so the MAE value, which is not as sensitive to greater errors, is a desirable complimentary measure. Its equation goes as follows:

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}\left|z_t - \hat{z}_t\right|, \tag{2}$$

and its variables work in the same way as Equation 1. In order to properly grasp how better or worse a given model was compared to the proposed SVRTC approach, the rank of each metric was also calculated for each series, from the best to the worst values. Lastly, an average rank position according to each performance measure was calculated for each model.

Comparisons between SVRTC and DESTC can be further analyzed by observing the Percentage Difference (PD) in metrics. The equation for this evaluation measure goes as follows:

$$\text{PD} = \frac{P_{DESTC} - P_{SVRTC}}{P_{DESTC}} \times 100, \tag{3}$$

in which P_{DESTC} is the evaluation measure reached by the DESTC system for a given series and P_{SVRTC} is the evaluation measure of SVRTC for that same series. If the result is positive, this means SVRTC reached a lower value for the error measure, and was therefore better; if the result is negative, SVRTC reached a higher value, and therefore performed worse.

As for the chosen models for comparison, both classic literature models and a trend classification-based model were selected. The chosen literature models were Autoregressive Integrated Moving Average (ARIMA) [Hu and Zheng 2020], Exponential Smoothing (ETS) [Firmino et al. 2020], SVR [Saadallah et al. 2022], MLP [de Oliveira et al. 2022], Extreme Learning Machine (ELM) [de Sales et al. 2024], Long Short-Term Memory (LSTM) [Li et al. 2019], and Transformer (TSF) [Zeng et al. 2023]. Those models are widely used as benchmarks in the literature for a wide array of applications. The trend classification-based model was DESTC due to its application to the COVID-19 series according to [de Sales et al. 2024]. Table 3 discloses the hyperparameters used in the optimization of the baseline models for comparison.

Table 3. Hyperparameters of each model which are optimized in the gridsearch.

Model	Hyperparameters	Values
ARIMA	p, d, q	As proposed by [Hyndman and Athanasopoulos 2018]
ETS	E, T, S	As proposed by [Hyndman and Athanasopoulos 2018]
SVR	Lags	5, 7, 10
	Kernel	linear, radial
	γ	1, 0.1, 0.001
	Cost	1, 100, 1000
	ϵ	0.1, 0.01, 0.001
	Tolerance	0.001
MLP	Lags	5, 7, 10
	Activation function	Sigmoid
	Hidden layer size	10, 15, 20
	Optimization	Adam
ELM	Lags	5, 7, 10
	Activation function	relu, tanh, rbf
	Hidden layer size	25, 50, 100, 150, 200
LSTM	Lags	5, 7, 10
	Activation function	relu
	Hidden layer size	10, 100, 500
	Optimization	adam
TSF	Lags	5, 7, 10
	Head size	5, 10, 20
	Number of attention heads	1, 2, 4
	Hidden layer size	10, 25, 50, 100

5. Results and discussion

Table 4 presents the performance of SVRTC in comparison to the single models used as baselines, as well as the rankings for each series. The best value for each performance measure (RMSE and MAE) for each series as well as the best average ranking of the models are showed in bold, and the second best values and average rankings are underlined. The results for literature comparison were extracted from [de Sales et al. 2024]. At first, the DESTC was not considered in those comparisons due to it being an ensemble approach. As such, comparing it to single-model approaches would not give a clear indication on whether its performance was more affected by its dynamic selection properties or its MPS ones.

According to the aforementioned table, SVRTC was the model with both the lowest RMSE and MAE values on the Canada, Spain and USA series. No other baseline model reached that level of consistency on more than one series. ETS displayed solid results on the Germany series, reaching best RMSE and MAE values. TSF was particularly

Table 4. Test RMSE and MAE of SVRTC compared to baseline models, with the rank in parenthesis. At the bottom, the average rank for each model for each measure is calculated. Bold and underline indicate respectively best and second-best results for both measures and average ranks.

Country	Measure	ARIMA	ETS	SVR	MLP	ELM	LSTM	TSF	SVRTC
Brazil	RMSE	2187.5 (8)	2104.4 (6)	**1828.2** (1)	2056.3 (4)	2070.5 (5)	2169.8 (7)	1956.2 (2)	2020.3 (3)
	MAE	1124.6 (6)	1122.8 (5)	**973.5** (1)	1080.0 (4)	1056.5 (3)	1140.9 (8)	1021.3 (2)	1127.4 (7)
Canada	RMSE	398.9 (4)	372.3 (3)	423.1 (5)	485.5 (7)	606.9 (8)	432.4 (6)	356.2 (2)	**352.6** (1)
	MAE	220.8 (4)	202.0 (2)	237.7 (5)	355.0 (7)	356.8 (8)	258.5 (6)	208.2 (3)	**193.0** (1)
France	RMSE	3898.1 (4)	3879.9 (3)	4695.9 (6)	14250.8 (8)	4070.4 (5)	4987.9 (7)	**3702.4** (1)	3748.1 (2)
	MAE	2395.3 (2)	2461.5 (4)	2808.1 (6)	10175.3 (8)	2446.6 (3)	3242.5 (7)	**2308.1** (1)	2514.3 (5)
Germany	RMSE	2814.4 (2)	**2736.7** (1)	2883.0 (4)	17328.5 (8)	2851.9 (3)	6802.8 (7)	3223.5 (6)	2888.1 (5)
	MAE	1975.2 (6)	**1515.0** (1)	1759.2 (3)	13405.2 (8)	1721.0 (2)	5204.8 (7)	1913.6 (5)	1837.5 (4)
Italy	RMSE	1725.3 (3)	1687.0 (2)	**1558.4** (1)	5546.9 (8)	2202.9 (6)	3948.9 (7)	1764.5 (4)	1815.3 (5)
	MAE	1060.1 (2)	**935.3** (1)	1079.1 (3)	3678.1(8)	1563.6 (6)	3213.5 (7)	1205.8 (5)	1104.5 (4)
Spain	RMSE	1984.0 (8)	1498.7 (5)	1443.9 (4)	1608.1 (6)	1889.4 (7)	1264.1 (2)	1287.4 (3)	**1209.1** (1)
	MAE	1154.4 (8)	775.4 (4)	769.1 (5)	989.7 (6)	1040.6 (7)	696.7 (3)	664.1 (2)	**636.0** (1)
UK	RMSE	451.7 (5)	419.9 (4)	372.8 (3)	3069.0 (8)	**320.5** (1)	2629.5 (7)	479.1 (6)	370.1 (2)
	MAE	265.1 (5)	243.7 (4)	**227.7** (1)	2340.8 (7)	228.0 (2)	2504.6 (8)	306.9 (6)	238.9 (3)
USA	RMSE	6456.6 (8)	5934.1 (5)	6021.2 (6)	5908.5 (4)	6043.8 (7)	5547.8 (3)	5448.9 (2)	**4681.2** (1)
	MAE	2781.0 (7)	2554.1 (4)	2585.9 (5)	4283.7 (8)	2671.8 (6)	2422.9 (2)	2444.9 (3)	**2410.6** (1)
Average	RMSE	5.25	3.63	3.75	6.63	5.25	5.75	3.25	**2.50**
	MAE	5.00	**3.13**	3.63	7.00	4.63	6.00	3.38	3.25

effective on the France Series, reaching the best RMSE and MAE values. The standard SVR had competitive values on the Brazil series, but it also performed well on the Italy and UK ones. No baseline model had the best RMSE and MAE measures simultaneously on more than one series.

Analyzing the rankings of the RMSE and MAE values, also recorded on Table 4, SVRTC had the best average position for RMSE, and the second-best MAE ranking, outperformed by ETS. While not being reasonable to find a single best method for every possible case, SVRTC presents itself as being the most consistent approach, never reaching the worst value and often reaching competitive ones, if not the best. As it can be noted, the RMSE was a much more favorable measure than MAE for the proposed method, but both of them point towards SVRTC as the preferable predictor.

Those differences between RMSE and MAE might point towards SVRTC avoiding sudden peaks and valleys, but with some delay. Since RMSE penalizes larger deviations more harshly than MAE and the proposed model performed better according to the former, it can be concluded that its deviations were small, but frequent. Those measures might point towards delays in the predictions, which can be better pinpointed through visualizations.

However, it is also prudent to analyze how SVRTC performs compared to the state-of-the-art trend classification approach DESTC. Table 5 displays how each trend classification-based method performed on the same series as well as the percentage differences (PD) of either approach. The best values for each series are highlighted in bold, and the PD row discloses how better or worse SVRTC performed compared to DESTC, which means positive values are favorable to SVRTC and negative values are favorable towards DESTC.

As showcased by the table, DESTC had the best values on the Brazil, France, Germany, Italy and UK series. However, the difference in the least favorable scenario

Table 5. RMSE and MAE of SVRTC compared to trend-based model DESTC, with percentage differences in the last two rows. Bold highlights indicate the best results. Positive percentage differences indicate SVRTC had better results, meanwhile negative ones indicate otherwise.

Model	Measure	Brazil	Canada	France	Germany	Italy	Spain	UK	USA
DESTC	RMSE	**1806.4**	377.3	**3655.6**	**2426.6**	**1621.5**	1449.5	**369.8**	5012.9
	MAE	**1024.0**	204.4	**2222.9**	**1554.7**	**1071.3**	811.9	**227.0**	2414.3
SVRTC	RMSE	2020.3	**352.6**	3748.1	2888.1	1815.3	**1209.1**	370.1	**4681.2**
	MAE	1127.4	**193.0**	2514.3	1837.5	1104.5	**636.0**	238.9	**2410.6**
PD	RMSE	-11.84	6.55	-2.53	-19.02	-11.95	16.59	-0.08	6.62
	MAE	-10.10	5.58	-13.11	-18.19	-3.10	21.67	-5.24	0.15

for the proposed method, Germany, did not reach 20% for neither metric, meanwhile the most favorable scenario, Spain, had a PD of over 20% for the MAE. This showcases how SVRTC, a much less complex system, is competitive to an ensemble approach. Visualizations may further corroborate this conclusion, as well as explore if the occasional shortcomings of the proposed method regarding possible delays are confirmed.

Figure 2 illustrates a series of predictions in which SVRTC performed well and a series in which its performance was somewhat lackluster. As it can be seen, both SVRTC and DESTC tend to produce similar outputs, but while SVRTC seems to fluctuate a bit more often, its peaks and valleys are not as sudden or drastic as the ones produced by DESTC even on series the single-model system performed considerably worse. As indicated by the measures, some delay can be noted in the predictions of the proposed method.

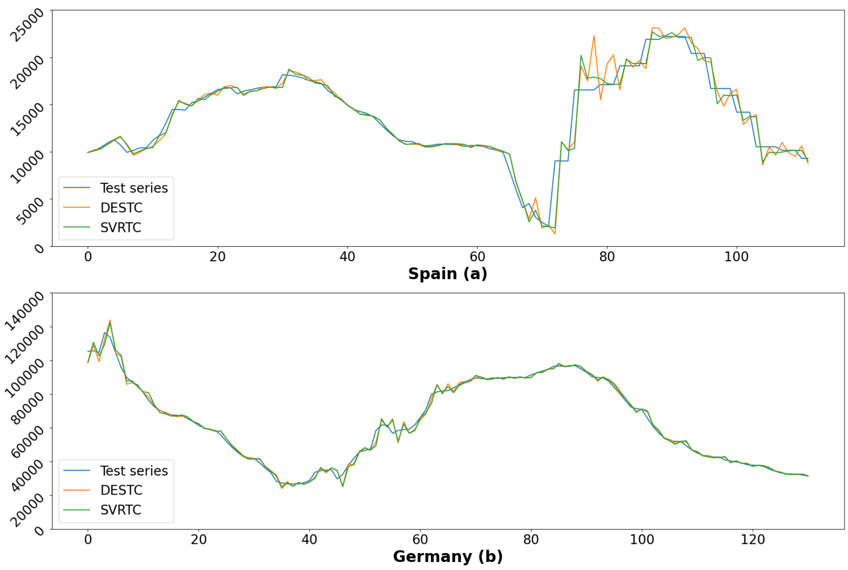

Figure 2. Predictions of SVRTC and DESTC across the Spain and Germany series, in which SVRTC achieved the best (a) and worst (b) performances compared to DESTC, respectively.

SVRTC was already expected to have better visual results on the Spain series due to its evaluated measures. The series displays a clear advantage of the SVRTC model over DESTC, since the ensemble-based method made several wrong predictions between indexes 70 and 85 without clear adjustments towards the test series. This scenario greatly favors the single-model approach with the dynamic selection based on trend classification strategy.

The predictions of the Germany series did not feature particularly remarkable visual differences. Both the predictions of SVRTC and of DESTC had inconsistent peaks across the series, and no model seemed to be visually much more effective. Overall, DESTC and SVRTC had visually similar predictions, and they did seem to follow the shape and trends of the series very well, without drastic delays. Reaching such similar results with a much less complex model for the worst-performing predictions favors the proposed approach once again. Therefore, despite there being room for improvements, using a single model for each trend classification managed to be efficient and effective.

When comparing SVRTC and DESTC in terms of computational cost, it is important to note that DESTC utilizes a pool of 51 forecasting models for each trend, including both statistical and Machine Learning methods, whereas SVRTC employs only a single model. So, SVRTC attained a competitive performance with a simpler approach regarding DESTC.

6. Conclusions

When time series exhibit different patterns over time, general-purpose predictors may struggle to model them effectively. Using specialized models chosen through dynamic selection can better capture these patterns, with the changing trend of the series being a key feature. This work presented preliminary results for a time series forecasting model using dynamic selection of specialized SVR models based on trend classification, SVRTC, which combined a less complex approach with robust results.

The results presented here indicate that the proposed approach is robust, and the trend classification performs reliably when compared to baseline models. Although it was not the top-performing model for every evaluated time series, it achieved the highest score more frequently than the others. However, underperforming results suggested a limitation of the chosen model despite its standard robustness. Its slightly higher MAE values could indicate low but frequent errors due to delays in specific series.

Future experiments applying SVRTC to a broader range of time series could provide deeper insights into its strengths and limitations. Additionally, other Machine Learning models could be evaluated in conjunction with trend classification. Incorporating a model selection step may help identify the most suitable models for each trend. Furthermore, additional time series characteristics or metafeatures could be leveraged to construct a more diverse pool of specialized models.

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