From Time Series to Process Model Forecasting

Johannes De Smedt[1], Anton Yeshchenko[2], Artem Polyvyanyy[3],
Jochen De Weerdt[1], and Jan Mendling[2]

[1] KU Leuven, Leuven, Belgium
{johannes.desmedt;jochen.deweerdt}@kuleuven.be
WU Vienna, Vienna, Austria
{anton.yeshchenko;jan.mendling}@wu.ac.at
[2] University of Melbourne, Melbourne, Australia
artem.polyvyanyy@unimelb.edu.au

Abstract. The surge in event-based data recorded during the execution of business processes is ever-growing and has spurred an array of process analytics techniques to support and improve information systems. A major strand of process analytics encompasses forecasting the process's future development, mostly focusing on next-step, remaining time, or goal-oriented predictions. The granularity of such approaches lies with the events in the process. This work approaches process forecasting at the level of the entire process model. This allows process analysts to act on predicted global and longer-term changes such as impending drifts in the process model rather than fine-granular ones such as next-step prediction. To this purpose, event data is captured at various intervals and aggregated in directly-follows graphs. The relation of each activity pair in the graph is monitored over these intervals, and their future values forecasted using standard time-series techniques. Experiments confirm that this approach is already well-capable of informing process analysts about the future status of the process.

Keywords: Process model forecasting, predictive process modelling, process mining, time series analysis

1 Introduction

The growth in the use of information systems has fuelled a wide range of data analysis techniques which intend to describe and improve their inner workings. Process mining [1] is one of the strongest-growing fields in information systems analysis and encompasses the wide range of analysis which can be performed on event data generated by these systems including the visualisation, conformance checking, and improvement of process models generating these events. More recently, predictive process analysis techniques, often referred to as predictive process monitoring, have surfaced to support the prediction of the next event/activity in the process, the remaining time, or other goal-oriented outcomes [4]. Various predictive techniques exist, which make use of various analytics architectures including neural networks [21], stochastic Petri nets [18], or general classification techniques [22].

These approaches, however, focus on a short time horizon (next-step/time-to-next-step prediction often fails to perform well over longer time horizons [15]) or a well-scoped outcome in terms of prediction [22]. This limits the range of insights that can be obtained as process analysts often strive to obtain a more evolutionary image of the process [16] which captures the evolution of many factors at the same time. A process (model) is ever-changing and while the outcome can be predicted accurately this might still obfuscate the underlying drivers which might not be fully understood by knowing which next activities/steps are likely due in the process.

This paper envisages a paradigm shift from these typical predictive applications as its focus is not on the level of single outcomes at the level of the trace and/or event but on the model. Current predictive techniques construct a predictive model to infer the future development of a trace, while the proposed forecasting approach infers the future development of a model which can generate future traces itself. This is achieved by an aggregation at the model level both at the input as well as the output of the learning process by using directly-follows (DF) relations over all activity pairs as a summary of the process model at various time steps, which are further extrapolated into the future using time series techniques modelling the number of DF occurrences over time and over longer horizons.

Given that the forecasting of many relations at once over a longer horizon results in a vast amount of information, we also present how to visualise the forecasted models and show how they exist of adaptations to the current as-is model [8].

This paper makes four contributions:

1. Proposes the first process model forecasting technique, which fits the the broader area of predictive process monitoring;
2. Evaluates the quality of the forecasted process models using standard conformance checking techniques from process mining;
3. Confirms that the achieved quality of forecasts is useful for practical applications.
4. Provides a Process Change Exploration (PCE) system which allows process analysts to compare as-is and forecasted process models.

To this purpose, a variety of time series analysis techniques are applied to 3 real-life event logs with two event log aggregations that establish suitable time series. A variety of considerations regarding the use of time series analysis for event logs are discussed, as well as the suitability of other predictive algorithms. Results show that simple forecasting techniques often already perform adequately without extensive parameter tuning. More intricate models often fail to report consistent performance.

This paper is structured as follows...

2 Motivation

The shift from fine-granular predictive process forecasting including best next-step, remaining time prediction, and goal-oriented prediction to model-based prediction allows to obtain new insights into the global development of the process. Consider the example in Figure 1 where the road fine traffic management event log[3] is partitioned into 100 intervals in which an equal number of DF relations occur. The DFs in the first 45 intervals are used to predict the final 25

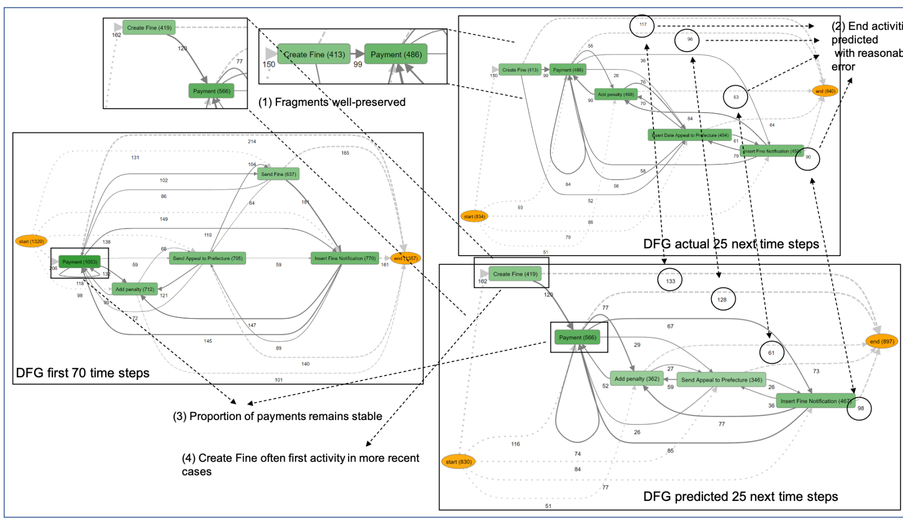


Fig. 1: Directly-follows graphs of the 45 first intervals of the event log, as well as a forecasted and actual DFG of the 25 next intervals.

intervals. The DFGs of the prefix set, as well as the actual and predicted interval set are displayed and show how process model forecasting can provide multiple unique insights at a glance:

1. The fragments and arc weights of the DFGs are well-preserved in the forecasted model;
2. The end activities are predicted with reasonable accuracy (+/- 10%);
3. Compared to the initial 45 intervals the proportion of fine payments stays stable;
4. The *Create Fine* activity appears as a start activity more often.

Being able to construct such a predictions allows stakeholders to make estimates regarding how the overall fine system will evolve and allows to answer questions such as ‘How many more fines will be received?’, ‘Will the backlog of fines be

[3]https://doi.org/10.4121/uuid:270fd440-1057-4fb9-89a9-b699b47990f5

reduced?', 'Will all fines be paid', and 'Will the ratio of unpaid fines stay the same?'

Note that the horizon is longer compared with next-step prediction, and that these results would only be obtainable if long next-step predictions were performed. However, for shorter prediction horizons next-step prediction will still outperform Nevertheless, the focus of model forecasting is different given that a high number of activity relations are forecasted instead of single steps. It still remains complementary with remaining time prediction, which could indicate what activities lead to what remaining time which could be combined with further annotation of the DFGs. The process model forecast can partially assume goal-oriented prediction, as the forecast DFG allows to answer multiple oftentimes used goal statements pertaining to the execution of a particular activity, or a precedence relationship of a particular activity pair [22] at the same time. This motivating example shows that where process mining/monitoring focuses on learning the as-is model to inform the to-be model and suggest potential repairs and improvements, process model forecasting allows to already grasp the future outcomes of the current as-is process which allows to shortcut potentially wrong outcomes [16].

3 Process model forecasting

This section outlines how directly-follows time series are extracted from event logs as well as how they are used to obtain process model forecasts with a range of widely-used forecasting techniques. Finally, the visualisation of such predictions is introduced.

3.1 From event log to directly-follows time series

An event log L which contains the recording of traces $\sigma \in L$ produced by an information system during its execution and contains a sequence of events. Events in these traces are part of the power set over the alphabet of activities Σ which exist in the information system $\sigma = \langle e_1, ..., e_{|\sigma|} \rangle \subseteq \Sigma^*$. Directly follows relations between activities in an event log can be expressed as a counting function over activity pairs $>_L \colon \Sigma \times \Sigma \rightarrow \mathbb{N}$ with $>_L (a_1, a_2) = |\{e_n = a_1, e_{n+1} = a_2, \forall e_i \in L\}|$. Directly follows relations can be calculated on traces and subtraces in a similar fashion. A Directly Follows Graph (DFG) of the process then exists as the weighted directed graph with the activities as nodes and their DF relations as weights $DFG = (\Sigma, >_L)$.

In order to obtain predictions regarding the evolution of the DFG we construct DFGs for subsets of the log. Many aggregations and bucketing techniques exist for next-step and goal-oriented outcome prediction [21, 22], e.g., predictions at a point in the process rely on prefixes of a certain length, or particular state aggregations [2]. In the proposed forecasting approach, however, not cross-sectional but time series data will be used. Hence, the evolution of the DFGs has to be monitored over intervals of the log where multiple aggregations are possible:

- **Equitemporal aggregation:** each sublog $L_s \in L$ contains a part of the event log of equal time duration. This can lead to sparsely populated sublogs when the events' occurrences are not uniformly spread over time, however, is easy to apply (on new traces).
- **Equisized aggregation:** each sublog $L_s \in L$ contains a part of the event log where an equal amount of events (and hence DFs) occurred. This leads to well-populated sublogs, however, might be harder to apply when new data does not contain sufficient new DF occurrences.

Tables 1 and 2 provide an example of both. These aggregations can be useful for the following reasons. Firstly, equisized aggregation will have a higher likelihood of the underlying DFs approaching a white noise time series which is required for a wide range of time series techniques [7]. Secondly, both offer a different threshold at which the forecasting can be applied in practice. In the case of equisized aggregation, it is easier to quickly construct a desired number of intervals by simply dividing an event log to obtain equisized intervals. However, most time series techniques rely on the time steps being of equal size which is embodied by the equitemporal aggregation [9].

Case ID	Activity	Timestamp
1	A1	11:30
1	A2	11:45
1	A1	12:10
1	A2	12:15
2	A1	11:40
2	A1	11:55
3	A1	12:20
3	A2	12:40
3	A2	12:45

Table 1: Example event log with 3 traces and 2 activities.

DF	Equitemporal	Equisized
$<_{L_s} (A1, A1)$	(0,1,0)	(1,0,0)
$<_{L_s} (A1, A2)$	(1,1,1)	(1,1,1)
$<_{L_s} (A2, A1)$	(0,1,0)	(0,1,0)
$<_{L_s} (A2, A2)$	(0,0,1)	(0,0,1)

Table 2: An example of using an interval of 3 used for equitemporal aggregation (75 minutes in 3 intervals of 25 minutes) and equisized intervals of size 2 (6 DFs over 3 intervals)).

Time series for the DFs $>_{T_{a_1,a_2}} = \langle >_{L_1} (a_1, a_2), \ldots, >_{L_s} (a_1, a_2) \rangle, \forall a_1, a_2 \in \Sigma \times \Sigma$ can be obtained for all activity pairs where $\bigcup_{L_1}^{L_s} = L$ by applying the aforementioned aggregations to obtain the sublogs.

3.2 From DF time series to process model forecasts

A trade-off exists between approaching DFGs as a multivariate collection of DF time series, or treating each DF separately. The aforementioned time series techniques all use univariate data in contrast with, e.g., Vector AutoRegression (VAR) models, or machine learning-based methods such as neural networks or random forest regressors. Despite their simple setup, it is debated whether traditional statistical approaches are necessarily outperformed by machine learning methods. [13] found that this is not the case on a large number of datasets and note that the machine learning algorithms require significantly more computational power, a result that was later reaffirmed although it is noted that hybrid solutions are effective [14]. Especially for longer horizons traditional time series approaches still outperform machine learning-based models. Given the potentially high number of DF pairs in a process' DFG, the proposed approach uses a time series algorithm for each DF series separately. VAR models would require a high number of intervals (at least as many as there are DFs times the lag coefficient) to be able to estimate all parameters of such a high number of time series despite their potentially strong performance [23]. Machine learning models could potentially leverage interrelations between the different DFs but again would require long training times to account for dimensionality issues due to the potentially high number of DFs. Therefore, in this paper, traditional time series approaches are chosen and applied to the univariate DF time series where these have at least 1 observation per sublog/time step present.

Therefore, in this paper, we propose to use univariate time series techniques which can be used to forecast process models represented by DFGs by applying them to each DF time series separately to obtain a forecasted directly-follows graph $\widehat{DFG}_{T+h} = (\Sigma, \{\hat{>}_{T+h|T_{a_1,a_2}} | a_1, a_2 \in \Sigma \times \Sigma\})$.

3.3 Time series techniques

To model the time series of DFs, various algorithms can be used. In time series modelling, the main objective is to obtain a forecast or prediction $\hat{y}_{T+h|T}$ for a horizon $h \in \mathbb{N}$ based on previous T values in the series $(y_1, ..., y_T)$ [7]. For example, the naive forecast simply uses the last value of the time series T as its prediction $\hat{y}_{T+h|T} = y_T$. An alternative naive forecast uses the average value of the time series T as its prediction $\hat{y}_{T+h|T} = \frac{1}{T}\Sigma_i^T y_i$. A wide array of such forecasting techniques exist, ranging from simple models such as naive forecasts over to more advanced approaches such as exponential smoothing and auto-regressive models. Many also exist in a seasonal variant due to their application in contexts such as sales forecasting. We briefly discuss smoothing models, autoregressive, moving averages and ARIMA models, and varying variance models which make up the main families of traditional time series forecasting [7].

A Simple Exponential Smoothing (SES) model uses a weighted average of past values where their importance exponentially decays as they are further into the past where Holt's models introduce a trend in the forecast, meaning the forecast is not flat. Exponential smoothing models often perform very well despite their simple setup [13].

AutoRegressive Integrating Moving Average (ARIMA) models are based on auto-correlations within time series. They combine auto-regressions with a moving average over error terms. It is established by a combination of an AutoRegressive (AR) model of order p uses the past p values in the time series and applies a regression over them and a Moving Average (MA) model of order q which creates a moving average of the past forecast errors. Given the necessity of using a white noise series for AR and MA models, data is often differenced to obtain such series. ARIMA models then combine both AR and MA models where the integration is taking place after modelling as these models are fitted over differenced time series. ARIMA models are considered to be one of the strongest time series modelling techniques.

An extension to ARIMA which is widely used in econometrics exists in (Generalized) AutoRegressive Conditional Heteroskedasticity ((G)ARCH) models [5]. They resolve the assumption that the variance of the error term has to be equal over time, but rather model this variance as a function of the previous error term. For AR-models, this leads to the use of ARCH-models, while for ARMA models GARCH-models are used as follows. An ARCH(q) model captures the change in variance by allowing it to both gradually increase over time, or to allow for short bursts of increased variance. A GARCH(p,q) model combines both the past values of observations as well as the past values of variance. (G)ARCH models often outperform ARIMA models in contexts such as the prediction of financial indicators of which the variance often changes over time [5].

3.4 Process change exploration

In Sections 3.1 to 3.3 we described the approach for forecasting process models. To that end, gaining actual insights from such predicted values remains a difficult task for the analyst. This section sets off to present the design of a novel visualization system to aid analysts in exploration of the event logs.

We designed a Process Change Exploration (PCE) system to support the interpretation of the process model forecasts. In order to design the system we first established user tasks as a basis for the system design decisions. To derive the user tasks we focus on the requirements of process mining analysis with respect to process forecasting and visualization principles. The authors of [16] discuss the opportunities for process forecasting. They describe that the utility of process forecasting is an understanding of the incremental changes or adaptations that happen to the process model into the future. In designing an explorative visualization system, we also followed the "Visual Information-Seeking Mantra:" *overview first, zoom and filter, then details-on-demand* [20]. Thus, we expect the design of our system to assist in the following tasks:

R1. **Identify process adaptations:** The visualization system should assist the user in identifying the changes that happen in the process model of the future in respect to the past;

R2. **Allow for interactive exploration:** The user should be able to follow the visual information-seeking principles, including overview first, filtering, zooming, details-on-demand principles.;

Following the user tasks, we designed an PCE interactive visualization system that consists of three connected views.

Adaptation Directly-Follows Graph (aDFG) view. This is the main view of the visualization that will show the model of the process. In order to accomplish the task R1, we modify DFG syntax. In order to display the process model adaptation from time range $T_{i_0,j_0}, i_0 < j_0$ to $T_{i_1,j_1}, i_1 < j_1$ we display the union of the process models of these regions, annotating the places and transitions with the numbers of both ranges. We color the aDFG as follows: we use color saturation to show the places with the higher values. We color transitions with the diverging saturation (red-black-green) schema. This coloring applies red color to transitions that are dominant in the T_{i_0,j_0} range, and green if transitions are dominant in the T_{i_1,j_1} range, otherwise the transition is close to black. For coloring transitions, we used idea of the three color schema from [10].

Timeline view with brushed regions. This view represents the area chart graph that shows how the number of activity executions change with time. The area chart color is split in two parts, one for the actual data, and the other one to show the time range where values are predicted. Analyst can brush one region in order to zoom in, creating one region of interest $T_{i_0,j_0}, i_0 < j_0$ that is displayed on the DFG. Analyst can also brush two regions of the area chart to select two time ranges, updating the DFG to aDFG representation. The brushed regions are colored accordingly to the schema for coloring aDFG transitions. The earlier brushed region is colored in the red, while the second one is colored green.

Activity and path sliders. We adopt the two sliders that are used to simplify DFG [11] and aDFG for detailed exploration of the models.

Based on described views, we conjecture that the analyst is able to accomplish the tasks R1, and R2 with ease.

4 Experimental evaluation

In this section, an experimental evaluation over three real-life event logs is reported. The aim of the evaluation is to measure to what extent the forecasted process models/DFGs are capable of correctly reproducing actual future DFGs in terms of their arc weights (measured as deviations or errors), as well as whether they are capable of reproducing the same process model behaviour (measured against the behaviour of the baseline actual DFG). This is done at various parts of the trace, i.e. forecasts for the middle of the event logs up to the later parts of the event log to capture the robustness of the forecasting techniques in terms of the amount of data required to obtain good prediction results. This is done for both the equisized and equitemporal aggregation.

4.1 Re-sampling and test setup

In order to obtain training data, time series are obtained by specifying a number of intervals (i.e. time steps in the DF time series) using either equitemporal or equisize aggregation a described in Section **??**. Time series algorithms are parametric and sensitive to sample size requirements [6]. Depending on the number of parameters a model uses, a minimum size of at least 50 steps is not uncommon, although typically model performance should be monitored at a varying number of steps. In the experimental evaluation, the event logs are divided into 100 time steps with a varying share of training and test steps:. A constant and long horizon $h = 25$ is used meaning all test sets contain 25 intervals, but the training sets are varied from $ts = 25$ to $ts = 75$ steps, meaning the forecasts progressively target the prediction of steps 25-50 (the second quarter of intervals) over to 75-100 (the last quarter of intervals). This allows to both inspect the difference in results when only few data points are used, and whether there is a difference forecasting data points in the middle or towards the end of the available event data.

Resampling is applied based on a 10-fold cross-validation constructed following a rolling window approach for all horizon values $h \in [1, 25]$ where a recursive strategy is used to iteratively obtain $\hat{y}_{t+h|T_{t+h-1}}$ with $(y_1, \ldots, y_T, \ldots, \hat{y}_{t+h-1})$ [24]. 10 training sets are hence constructed for each training set length ts and exist from $(y_1, \ldots, y_{T-h-f})$ and the test sets from $(y_{T-h-f+1}, \ldots, y_{T-f})$ with $f \in [0, 9]$ the fold index [3]. While direct strategies with a separate model for every value of h can be used as well and avoid the accumulation of error, they do not take into account statistical dependencies for subsequent predictions.

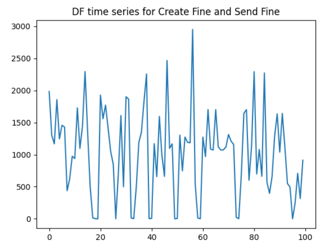
Three widely-used event logs are used: the 2012 BPI challenge log[4], the Sepsis cases event log[5], and the Road Traffic Fine Management Process log (RTFMP) event log (see Section 2. Each of these logs has a diverse set of characteristics in terms of case and activity volume, as well as average trace length as can be seen in Table 3.

Event log	# cases	# activities	Average trace length
BPI 12	13,087	36	20.020
Sepsis	1,050	16	14.490
RTFMP	150,370	11	3.734

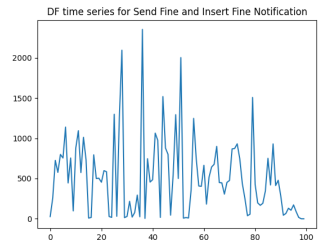
Table 3: Overview of the characteristics of the event logs used in the experimental evaluation.

An example of applying the equisize or equitemporal aggregation to the Sepsis event log with 100 intervals results in the DF time series of Figure 2 where the DF occurrences of the most frequently occurring activity pair is included. For the equisized aggregation the number of DFs is indeed relatively stable over the log's timeline where for the equitemporal aggregation a noticeable decline of DF pairs is visible towards the end of the series. This phenomenon is typical in event logs, as processes typically have particular endpoint activities, but can also be due to the unequal distribution of events over the event log's time line. If the

[4] https://doi.org/10.4121/uuid:3926db30-f712-4394-aebc-75976070e91f
[5] https://doi.org/10.4121/uuid:915d2bfb-7e84-49ad-a286-dc35f063a460



(a) Most common DF - equisize



(b) Most common DF - equitemp

Fig. 2: RTFMP

level of occurrences of the DF pair is low and close to 0, the series might be too unsuitable for analysis with white noise series analysis techniques that assume stationarity. Ideally, every time series is tested using a stationarity test such as the Dickey-Fuller unit root test [12] and an appropriate lag order is established for differencing. Furthermore for each algorithm, especially ARIMA-based models, (partial) auto-correlation could establish the ideal p and q parameters. However, for the sake of simplicity and to avoid solutions where each activity pair has to have different parameters, various values are used for p, d, and q and applied to all DF pairs where only the best-performing are reported below for comparison with the other time series techniques.

4.2 Evaluation criteria

Given that we want to evaluate the capability of the approach to accurately predict the evolution of the process model, the combination of all DF predictions to obtain a global DFG prediction is considered. The following two criteria are used:

- **Cosine distance:** measures the distance between two vectors and is often used to compare graph distance. This metric is used to compare the DFG's edge weight matrices between the actual and predicted number of DF relations.
- **Entropic relevance:** a measure for stochastic conformance checking computed as the average number of bits required to compress each of the log's traces based on the structure and information about relative likelihoods provided by the model [17].

These criteria balance a predictive and structural evaluation of the algorithms and report on both the numeric performance common in a forecasting setting as well as their appropriateness in terms of reproducing a structurally usable process model which allows for the observed process behaviour. In both cases a lower score is better. The entropic relevance also allows to compare the adequacy the forecasted DFGs with the actual DFGs.

4.3 Results

All pre-processing was done in Python with a combination of *pm4py*[6] and the *statsmodels* package [19]. The code is available

The results are displayed in Figures 3 to 8. - STILL NEED TO REDUCE THESE FIGURES. ANY INPUT WOULD BE HELPFUL (definitely no need to keep all ARIMAs I think).

NOTE THAT ALL FIGURES ARE AVAILABLE IN Results PMF 08-03.zip

Observations:

- Regardless of the aggregation type, only using 25-35 training points to forecast 25 test points creates very unstable results for all datasets and forecasting techniques both in terms of cosine distance and entropic relevance. Especially autoregressive models (both AR and ARIMA) from a higher order (2,4) suffer from very high cosine distances when few training points are used. This is potentially due to the inclusion of more distant observations in the prediction.
- Once a level of stability is present in the results, the difference between forecasting techniques is lower in terms of the cosine distance although GARCH and AR models still perform worse.
- In terms of entropic relevance, the actual DFGs do have better scores except for the BPI 12 log where GARCH even outperforms the actual DFG. In general, GARCH scores best in terms of entropic relevance while the other models perform similar to the naive model. ARIMA models perform worst overall.
- For the equitemporal aggregation this difference of the actual with the forecasts is less pronounced and the difference among the forecasts is minimal as well. The entropic relevance is also significantly higher for the equitemporal aggregation.

Implications:

- The entropic relevance learns us that the forecasting techniques are capable of obtaining similar results capturing as much of the process behavior as the actual DFGs generated by the process.
- The forecasting techniques used have little impact, meaning that even a naive forecast can produce good results, although GARCH models perform better, possibly due to their capturing a varying level of variance over time which seems especially suitable for DF relations which do not necessarily are generated by a white noise process. Note, however, that the confidence intervals have not yet been investigated.
- The results show that there is a need to have at least observed close to half of the process' events before reasonably stable predictions can be made.
- An equitemporal aggregation results in worse forecasts. This is potentially due to the inconsitent number of DF occurrences present, compared to the equisize aggregation which is stable and hence approaches a white noise process.

[6] https://pm4py.fit.fraunhofer.de

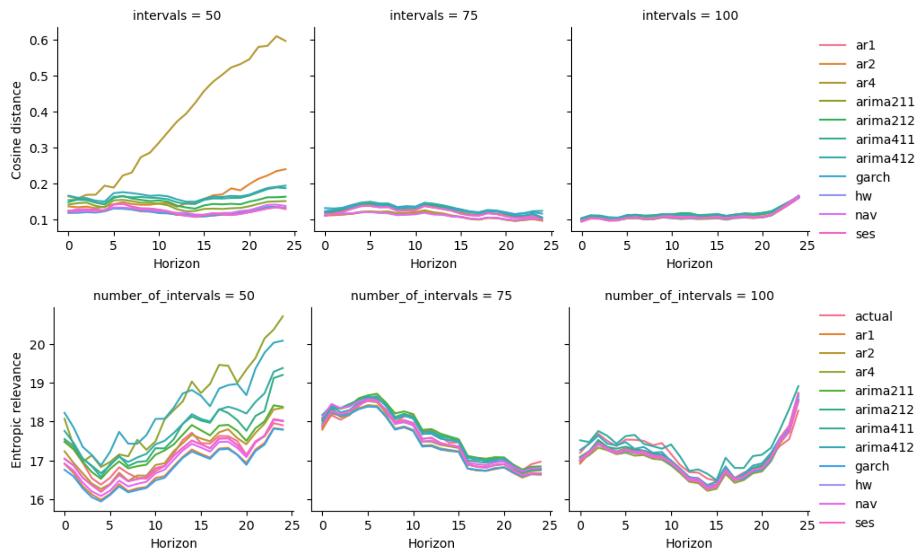


Fig. 3: Results for equi-size aggregation for the BPI12 event log.

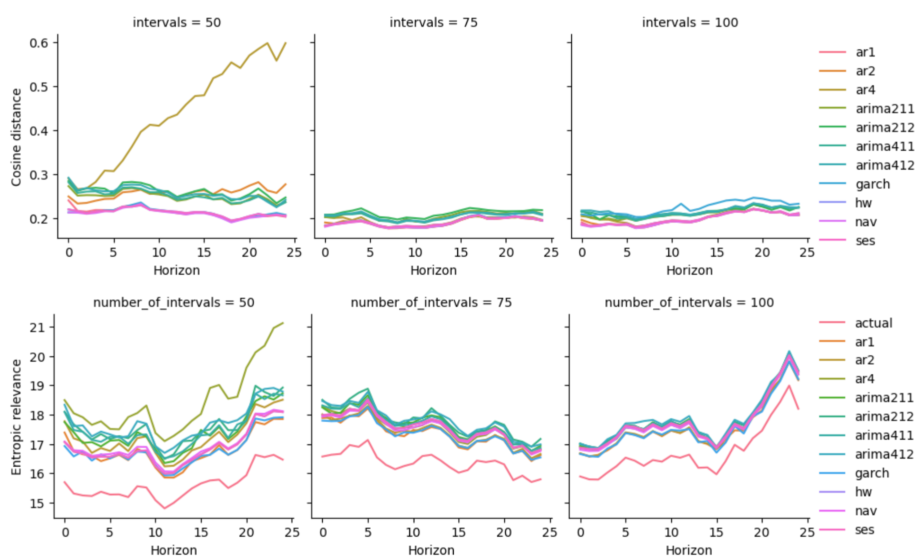


Fig. 4: Results for equi-size aggregation for the sepsis event log.

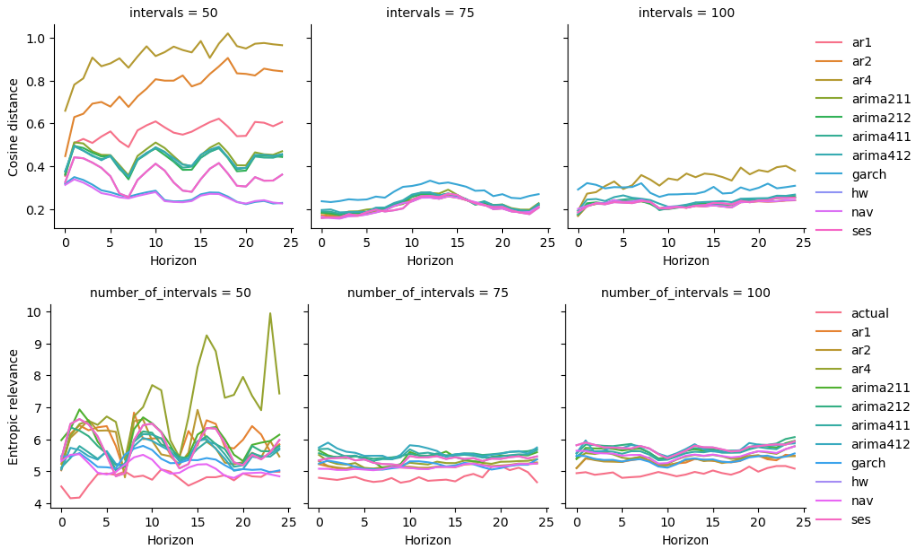


Fig. 5: Results for equi-size aggregation for the RTFMP event log.

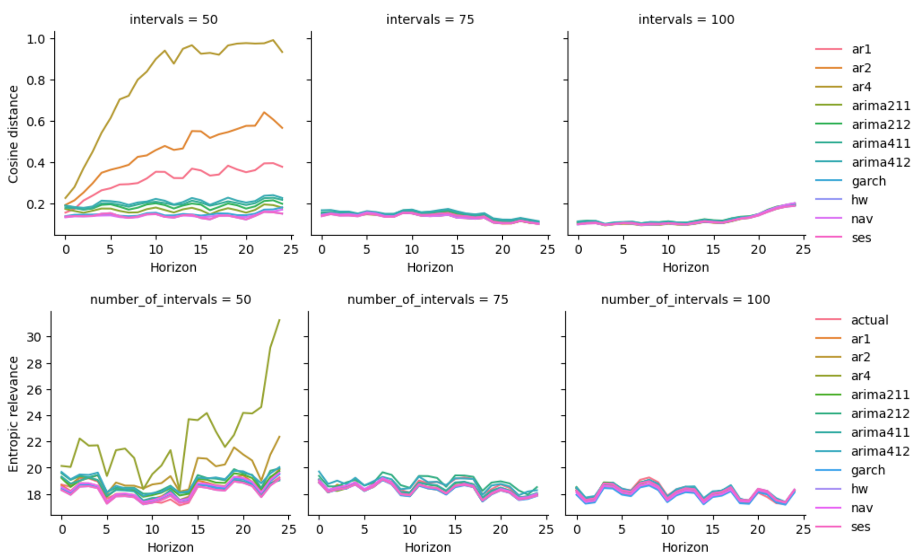


Fig. 6: Results for equi-temporal aggregation for the BPI12 event log.

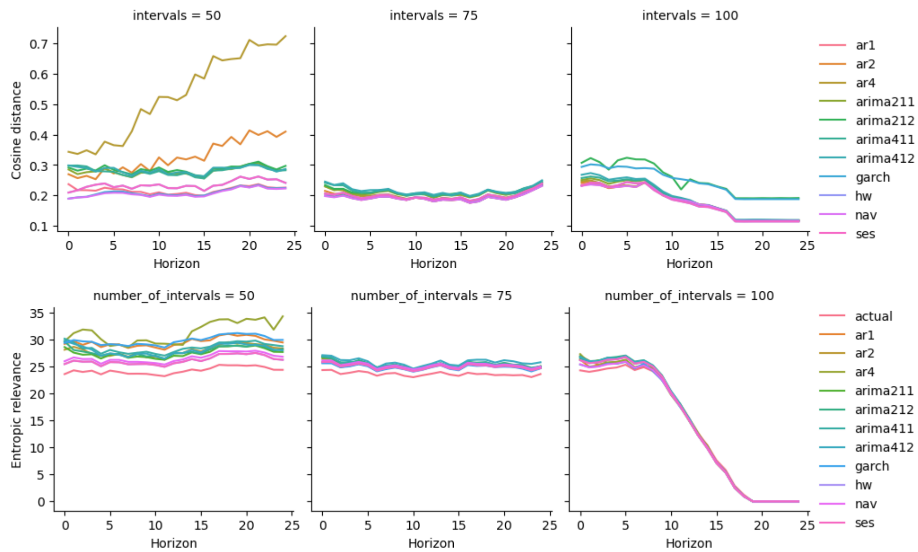


Fig. 7: Results for equi-temporal aggregation for the sepsis event log.

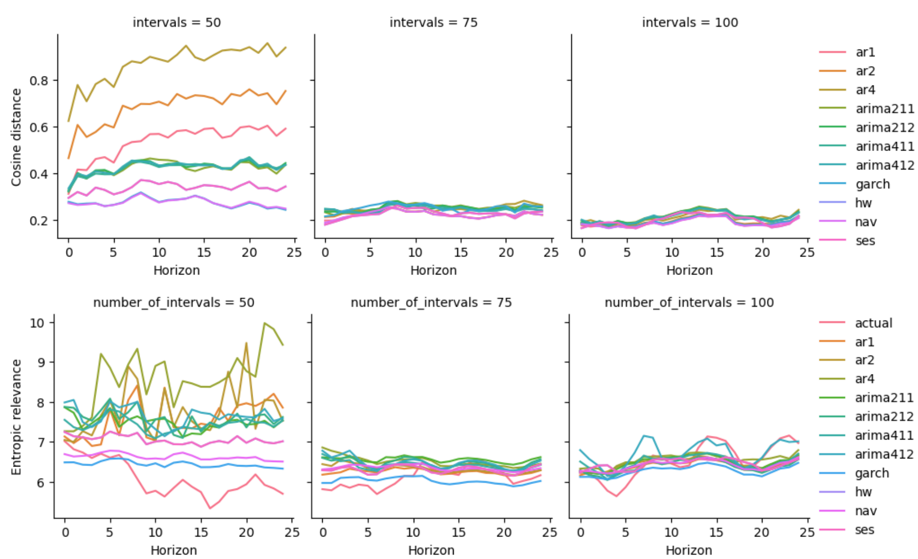


Fig. 8: Results for equi-temporal aggregation for the RTFMP event log.

5 Visualising Process Model Forecasts

In Section 4 we evaluated forecasting results, ensuring the relevance of the predicted process models. To that end, gaining actual insights from such predicted data remains a difficult task for the analyst. This section sets off to present the implementation of a novel visualization system to aid analysts in exploration of the event logs. The process of designing and implementing the system started by designing several prototypes that undergone rounds of discussions to mature into the implemented visualization system.

The design of the PCE system is shown in Figure 9. It shows an interactive visualization system with several connected views. The system is implemented with D3.js JavaScript library and is available at [7].

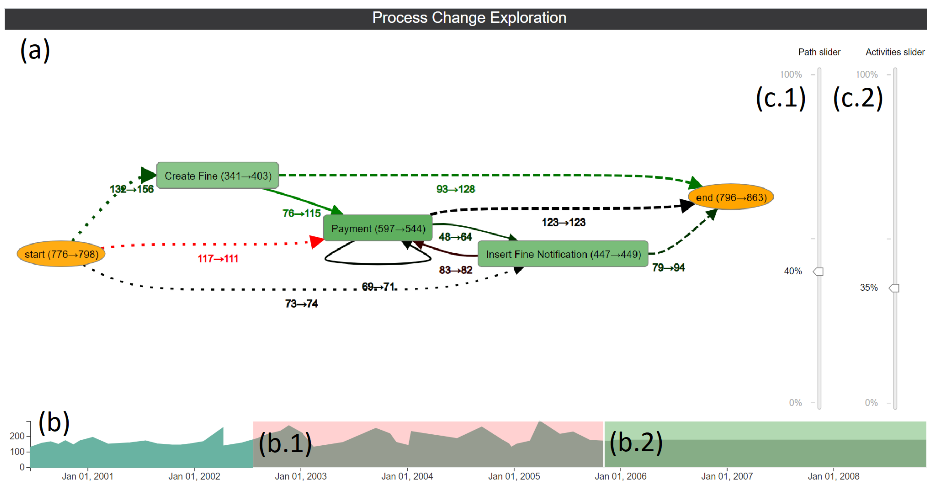


Fig. 9: Process Change Exploration (PCE) system. *(a)* shows *Adaptation Directly-Follows Graph (aDFG)* view. *(b)* shows the *Timeline view with brushed regions* view. Users can brush one or more regions on this graph in order to filter the scope of the analysis *(b.1*, and *b.2)*. Two additional views *(c.1)*, and *(c.2)* show the *activity and path sliders*.

6 Conclusion

In this paper we investigated the potential of using time series forecasting for process model monitoring.

In future research we will cover more intricate forecasting techniques and compare with machine learning-based models. Furthermore, we will perform an extensive prediction confidence interval analysis.

[7] google.com

References

1. van der Aalst, W.: Data Science in Action. In: Process Mining. Springer (2016)
2. van der Aalst, W.M.P., Rubin, V.A., Verbeek, H.M.W., van Dongen, B.F., Kindler, E., Günther, C.W.: Process mining: a two-step approach to balance between underfitting and overfitting. Softw. Syst. Model. 9(1), 87–111 (2010)
3. Bergmeir, C., Benítez, J.M.: On the use of cross-validation for time series predictor evaluation. Information Sciences 191, 192–213 (2012)
4. Francescomarino, C.D., Ghidini, C., Maggi, F.M., Milani, F.: Predictive process monitoring methods: Which one suits me best? In: BPM. Lecture Notes in Computer Science, vol. 11080, pp. 462–479. Springer (2018)
5. Francq, C., Zakoian, J.M.: GARCH models: structure, statistical inference and financial applications. John Wiley & Sons (2019)
6. Hanke, J.E., Reitsch, A.G., Wichern, D.W.: Business forecasting, vol. 9. Prentice Hall New Jersey (2001)
7. Hyndman, R.J., Athanasopoulos, G.: Forecasting: principles and practice. OTexts (2018)
8. Kabicher, S., Kriglstein, S., Rinderle-Ma, S.: Visual change tracking for business process models. In: ER. Lecture Notes in Computer Science, vol. 6998, pp. 504–513. Springer (2011)
9. Kil, R.M., Park, S.H., Kim, S.: Optimum window size for time series prediction. In: Proceedings of the 19th Annual International Conference of the IEEE Engineering in Medicine and Biology Society.'Magnificent Milestones and Emerging Opportunities in Medical Engineering'(Cat. No. 97CH36136). vol. 4, pp. 1421–1424. IEEE (1997)
10. Kriglstein, S., Rinderle-Ma, S.: Change visualizations in business processes - requirements analysis. In: GRAPP/IVAPP. pp. 584–593. SciTePress (2012)
11. Leemans, S., Poppe, E., Wynn, M.: Directly follows-based process mining: A tool. In: Proceedings of the ICPM Demo Track 2019 (CEUR Workshop Proceedings, Volume 2374). Vol. 2374. pp. 9–12. Sun SITE Central Europe (2019)
12. Leybourne, S.J., et al.: Testing for unit roots using forward and reverse dickey-fuller regressions. Oxford Bulletin of Economics and Statistics 57(4), 559–571 (1995)
13. Makridakis, S., Spiliotis, E., Assimakopoulos, V.: Statistical and machine learning forecasting methods: Concerns and ways forward. PloS one 13(3), e0194889 (2018)
14. Makridakis, S., Spiliotis, E., Assimakopoulos, V.: The m4 competition: 100,000 time series and 61 forecasting methods. International Journal of Forecasting 36(1), 54–74 (2020)
15. Park, G., Song, M.: Predicting performances in business processes using deep neural networks. Decision Support Systems 129, 113191 (2020)
16. Poll, R., Polyvyanyy, A., Rosemann, M., Röglinger, M., Rupprecht, L.: Process forecasting: Towards proactive business process management. In: BPM. Lecture Notes in Computer Science, vol. 11080, pp. 496–512. Springer (2018)
17. Polyvyanyy, A., Moffat, A., García-Bañuelos, L.: An entropic relevance measure for stochastic conformance checking in process mining. In: ICPM. pp. 97–104. IEEE (2020)
18. Rogge-Solti, A., Weske, M.: Prediction of Remaining Service Execution Time Using Stochastic Petri Nets with Arbitrary Firing Delays. In: ICSOC. Lecture Notes in Computer Science, vol. 8274, pp. 389–403. Springer (2013)
19. Seabold, S., Perktold, J.: Statsmodels: Econometric and statistical modeling with python. In: Proceedings of the 9th Python in Science Conference. vol. 57, p. 61. Austin, TX (2010)

20. Shneiderman, B.: The eyes have it: A task by data type taxonomy for information visualizations. In: VL. pp. 336–343. IEEE Computer Society (1996)
21. Tax, N., Verenich, I., Rosa, M.L., Dumas, M.: Predictive business process monitoring with LSTM neural networks. In: CAiSE. Lecture Notes in Computer Science, vol. 10253, pp. 477–492. Springer (2017)
22. Teinemaa, I., Dumas, M., Rosa, M.L., Maggi, F.M.: Outcome-oriented predictive process monitoring: Review and benchmark. ACM Trans. Knowl. Discov. Data 13(2), 17:1–17:57 (2019)
23. Thomakos, D.D., Guerard Jr, J.B.: Naive, arima, nonparametric, transfer function and var models: A comparison of forecasting performance. International Journal of Forecasting 20(1), 53–67 (2004)
24. Weigend, A.S.: Time series prediction: forecasting the future and understanding the past. Routledge (2018)