Learning to act:
a Reinforcement Learning approach to recommend the
best next activities

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Abstract. The rise of process data availability has recently led to the development of data-driven learning approaches. However, most of these approaches restrict the use of the learned model to predict the future of ongoing process executions. The goal of this paper is moving a step forward and leveraging available data to learning to act, by supporting users with recommendations derived from an optimal strategy (measure of performance). We take the optimization perspective of one process actor and we recommend the best activities to execute next, in response to what happens in a complex external environment, where there is no control on exogenous factors. To this aim, we investigate an approach that learns, by means of Reinforcement Learning, the optimal policy from the observation of past executions and recommends the best activities to carry on for optimizing a Key Performance Indicator of interest. The validity of the approach is demonstrated on two scenarios taken from real-life data.

Keywords: Prescriptive Process Monitoring; Reinforcement Learning; Next activity recommendations

1 Introduction

In the last few years, a number of works have proposed approaches, solutions and benchmarks in the field of Predictive Process Monitoring \cite{1437}. Predictive Process Monitoring leverages the analysis of historical execution traces in order to predict the unrolling of a process instance that has been only partially executed. However, most of these efforts have not used the predictions to explicitly support user with recommendations, i.e., with a concrete usage of these predictions. In fact, there is a clear need of actionable process management systems \cite{7} able to support the users with recommendations about the best actions to take.

The overall goal of this paper is therefore moving a step forward, towards the implementation of a learning to act system, in line with the ideas of Prescriptive Process Monitoring \cite{817}. Given an ongoing business process execution, Prescriptive Process Monitoring aims at recommending activities or interventions with the goal of optimizing a target measure of interest or Key Performance Indicator (KPI). State-of-the-art works have introduced methods for raising alarms or triggering interventions, to
prevent or mitigate undesired outcomes, as well as for recommending the best resource allocation. Only few of them have targeted the generation of recommendations of the next activity(ies) to optimize a certain KPI of interest [25,9,2], such as, the cycle time of the process execution. Moreover, none of them explicitly considers the process execution in the context of a complex environment that depends upon exogenous factors, including how the other process actors behave. In this setting, identifying the best strategy to follow for a target actor, is not straightforward.

In this paper, we take the perspective of one target actor and we propose a solution based on Reinforcement Learning (RL): to recommend to the actor what to do next in order to optimize a given KPI of interest for this actor. To this aim, we first learn, from past executions, the response of the environment (actions taken by other actors) to the target actor’s actions, and we then leverage RL to recommend the best activities/actions to carry on to optimize the KPI.

In the remainder of the paper after introducing some background concepts (Section 2), we present two concrete Prescriptive Process Monitoring problems that we have targeted (Section 3). Section 4 shows how a Prescriptive Process Monitoring problem can be mapped into RL, while Section 5 applies the proposed RL approach to the considered problems and evaluates its effectiveness. Finally, Section 6 and Section 7 present related works and conclusions, respectively.

2 Background

2.1 Event logs

An event log consists of traces representing executions of a process (a.k.a. a case). A trace is a sequence of events, each referring to the execution of an activity (a.k.a. an event class). Besides timestamps, indicating the time in which the event has occurred, events in a trace may have a data payload consisting of attributes, such as, the resource(s) involved in the execution of an activity, or other data recorded during the event. Some of these attributes do not change throughout the different events in the trace, i.e., they refer to the whole case (trace attributes); for instance, the personal data (Birth date) of a customer in a loan request process. Other attributes are specific of an event (event attributes), for instance, the employee who creates an offer (resource), which is specific of the activity Create offer.

2.2 Prescriptive Process Monitoring

Prescriptive Process Monitoring [8,17] is a branch of Process Mining that aims at suggesting activities or triggering interventions for a process execution for optimizing a desired Key Performance Indicator (KPI). Differently from Predictive Process Monitoring approaches, which aim at predicting the future of an ongoing execution trace, Prescriptive Process Monitoring techniques aim at recommending the best interventions for achieving a target business goal. For instance, a bank could be interested in minimizing the cost of granting a loan to a customer. In such a scenario, the KPI of interest for the bank is the cost of the activities carried out by the bank’s personnel in order to
reach an agreement with the customer. The best actions that the bank should carry out to achieve the business goal (reaching the agreement while minimizing the processing time) can be recommended to the bank.

### 2.3 Reinforcement Learning

Reinforcement Learning (RL)\(^\text{2,3,10}\) refers to techniques providing an intelligent agent the capability to act in an environment, while maximizing the total amount of reward received by its actions. At each time step \(t\), the agent chooses and executes an action \(a\) in response to the observation of the state of the environment \(s\). The action execution causes, at the next time step \(t+1\), the environment to stochastically move to a new state \(s'\), and gives the agent a reward \(r_{t+1} = R(s, a, s')\) that indicates how well the agent has performed. The probability that, given the current state \(s\) and the action \(a\), the environment moves into the new state \(s'\) is given by the state transition function \(P(s, a, s')\). The learning problem is therefore described as a discrete-time Markov Decision Process (MDP), which is formally defined by a tuple \(M = (S, A, P, R, \gamma)\):

- \(S\) is the set of states.
- \(A\) is the set of agent’s actions.
- \(P : S \times A \times S \rightarrow [0, 1]\) is the transition probability function. \(P(s, a, s') = Pr(s_{t+1} = s'|s_t = s, a_t = a)\) is the probability of transition (at time \(t\)) from state \(s\) to state \(s'\) under action \(a \in A\).
- \(R : S \times A \times S \rightarrow \mathbb{R}\) is the reward function. \(R(s, a, s')\) is the immediate reward obtained by the transition from state \(s\) to \(s'\) with action \(a\).
- \(\gamma \in [0, 1]\) is a parameter that measures how much the future rewards are discounted with respect to the immediate reward. Values of \(\gamma\) lower than 1 model a decision maker that discount the reward obtained in the more distant future\(^\text{2}\).

An MDP satisfies the *Markov Property*, that is, given \(s_t\) and \(a_t\), the next state \(s_{t+1}\) is conditionally independent from all prior states and actions and it only depends on the current state, i.e., \(Pr(s_{t+1}|s_t, a_t) = Pr(s_{t+1}|s_0, \ldots, s_t, a_0, \ldots, a_t)\).

The goal of RL is computing a policy that allows the agent to maximize the cumulative reward. A policy \(\pi : S \rightarrow A\) is a mapping from each state \(s \in S\) to an action \(a \in A\), and the cumulative reward is the (discounted) sum of the rewards obtained by the agent while acting at the various time points \(t\). The value of taking the action \(a\) in state \(s\) and then continuing to use the policy \(\pi\), is the expected discounted cumulative reward of the agent, and it is given by the state-action value function: \(Q^\pi(s, a) = \mathbb{E}_\pi(\sum_{k=0}^{\infty} \gamma^k r_{k+t+1}|s = s_t, a = a_t)\), where \(r_{t+1}\) is the reward obtained at time \(t\). The optimal policy \(\pi^*\) dictates to a user in state \(s\) to perform the action that maximises \(Q(s, \cdot)\). Hence, the optimal policy \(\pi^*\) maximises the cumulative reward that the user obtains by following the actions recommended by the policy \(\pi^*\). Action-value functions can be estimated from experience, e.g., by averaging the actual returns for each state (action taken in that state), as with *Monte Carlo methods*.

\(^3\) In this paper we set \(\gamma = 1\), hence equally weighting the reward obtained at each action points of the target actor.
Different algorithms can be used in RL. Among them we can find the value and the policy iteration approaches. In the former the optimal action-value function $Q^*(s, a)$ is obtained by iteratively updating the estimate $Q^\pi(s, a)$. In the latter, the starting point is an arbitrary policy $\pi$ that is iteratively evaluated (evaluation phase) and improved (optimization phase) until convergence. Monte Carlo methods are used in the policy evaluation phase for computing, given a policy $\pi$, for each state-action pair $(s, a)$, the action-value function $Q^\pi(s, a)$. The estimate of the value of a given state-action pair $(s, a)$ can be computed by averaging the sampled returns that originated from $(s, a)$ over time. Given sufficient time, this procedure can construct a precise estimate $Q$ of the action-value function $Q^\pi$. In the policy improvement step, the next policy is obtained by computing a greedy policy with respect to $Q$: given a state $s$, this new policy returns an action that maximizes $Q(s, \cdot)$.

3 Two Motivating Scenarios

We introduce here the considered problem by showcasing two real processes that involve one target actor, whose reward is to be maximized, and some more actors, contributing to determine the outcome of the process (environment).

**Loan request handling (Loans).** In a financial institute handling loan requests, customers send loan request applications and the bank decide either to decline an application, or to request further details to the customer, or to make an offer and start a negotiation with the customer. During the negotiation phase, the bank can contact the customer and possibly change its offer to encourage the customer to finally accept the bank’s offer.

The bank aims at maximizing its payoff by trying to sign agreements with the customer, while reducing the costs of the negotiation phase, i.e., stopping negotiations that will not end up with an agreement. The bank is therefore interested to implement the best strategy to follow (actions) in order to maximize its interest.

**Traffic fine management (Fines).** In a police department in charge to collect road traffic fines, as in the scenario presented in [15], fines can be paid (partly or fully) either immediately after the fine has been issued, or after the fine notification is sent by the police to the offender’s place of residence, or when the notification is received by the offender. If the entire amount is paid, the fine management process is closed. After being notified by post, the offender can appeal against the fine through a judge and/or the prefecture. If the appeal is successful, the case ends.

In such a setting, the police department aims at collecting the payment of the invoice by the offender as soon as possible, so as to avoid money wastes due to delays in payments or the involvement of the prefecture/judge. The department indeed receives credits for fast payments, no credits for payments never received and discredits for incorrect fines. The department is therefore interested to receive best action recommendations to maximize the received credits.
4 Mapping PPM to RL

We would like to support a target actor of interest in a process, such as, the financial institute or the police department (see Section[3]), by providing them with recommendations for the best activities to execute in order to maximize their profit and their credits, respectively. To this aim, we leverage RL, by transforming the PPM problem of recommending the next activities to optimize a given KPI, into an RL problem, where the agent is the actor we are supporting in the decision making (e.g., the bank or the police department), and the environment is represented by the external factors—especially the activities carried out by the other actors involved in the process execution (e.g., the customer or the offender). We define our MDP so that:

- an action, to be recommended, is an activity of the actor of interest (agent) (e.g., the bank activity Create offer);

- a state is defined by taking into account the following variables:
  - the last activity executed by the actor of interest (e.g., the creation of a new offer by the bank) or by the other actors defining the stochastic response of the environment (e.g., the bank offer acceptance by the customer);
  - some relevant information about the history of the execution (e.g., the number of phone calls between the bank and the customer);
  - other aspects defining the stochastic response of the environment (e.g., the amount of the requested loan);

  A state is hence represented by a tuple (LA, HF, EF), where LA is the last activity executed by the actor of interest or by one of the other actors involved in the process, HF is a vector of features describing some relevant information of the process execution history and EF is a vector of features further describing the environment response to the actions of the actor of interest.

- the reward function is a numerical value that transforms the KPI of interest, computed on the complete execution, in a utility function at the level of single action.

  Actions, states and reward function can be defined for each specific problem by leveraging the information contained in the event log and some domain knowledge. The activities we are interested to recommend and those describing the stochastic response of the environment can be extracted from the event log. The relevant information about the history of the process execution can also be extracted from the event log, with some domain-specific pre-processing (e.g., counting the number of phone calls between the bank and the customer). The stochastic responses of the environment to the actor’s actions can also be mined from the event log through trace attributes (e.g., the amount of the requested loan). Finally, information contained in event logs can be used to estimate the reward function for each state transition and action (e.g., in case the reward function is related to the process/event cycle time, the average duration of events of a certain type can be used to estimate the reward of a given state).

Figure[1] shows the architecture of the RL-based solution designed to solve the problem of recommending the next best activities to optimize a certain KPI. The input is an event log containing historical traces related to the execution of a process, and some domain knowledge, specifying the KPI of interest and the information that allows for the identification of actions, states and of the reward function. There are three main processing phases:
• **preprocessing phase:** the event log is preprocessed in order to learn a representation of the environment (i.e., the MDP). First, the event log is cleansed and the domain knowledge leveraged in order to annotate it. In detail, the event log is (i) filtered in order to remove low-frequency variants (with occurrence frequency lower than 10%) and activities that are not relevant for the decision making problem; (ii) enriched with attributes obtained by aggregating and preprocessing information related to the execution; (iii) annotated by specifying the agent’s activities to be considered as actions; attributes and environment activities to be used for the state definition; attributes to be used for the computation of the reward function.

Once the event log has been enriched and annotated, it can be used for building the MDP that defines the RL problem. To this aim, we start from the scenario-specific definition of action and state and, by replaying the traces in the event log, we build a directed graph, where each node corresponds to a state and each edge is labelled with the activity allowing to move from one node state to the other. Moreover, for each edge, the probability of reaching the target node (computed based on the number of traces in the event log that reach the corresponding state) and the value of the reward function are computed. Each edge is hence mapped to the tuple \((s, a, s', P(s'|s, a), R)\) where \(s\) is the state corresponding to the source node of the edge, \(a\) is the action used for labelling the edge, \(s'\) is the state corresponding to the target node of the edge, \(P(s'|s, a)\) is computed as the percentage of the traces that reach the state \(s'\) among the traces that reach state \(s\) and execute \(a\), and \(R\) is the value of the reward function.

• **RL phase:** the RL algorithm is actually applied to compute the optimal policy \(\pi^*\); in this paper we used policy iteration with Monte Carlo methods.

• **runtime phase:** given an empty or ongoing execution trace, the policy is queried by the recommender system to return the best activities to be executed next.

## 5 Evaluation of the Recommendation Policy

We investigate the capability of the proposed approach to recommend the process activities that allow the target actor to maximize a KPI of interest, i.e., the optimal policy \(\pi^*\), (i) when no activity has been executed yet, that is, the whole process execution is recommended; (ii) at different time steps of the process execution (i.e., at different prefix lengths), that is, when only a (remaining) part of the process execution is recommended. We hence explore the following research questions:
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| Dataset     | Trace # | Variant # | Event # | Event class # | Avg. trace length |
|-------------|---------|-----------|---------|---------------|------------------|
| BPI2012     | 13087   | 4366      | 262200  | 36            | 20               |
| Fines2015   | 150370  | 231       | 561470  | 11            | 5                |

Table 1: Dataset Description

**RQ1** How does the recommended sequence of activities (suggested by the optimal policy \( \pi^* \)) perform in terms of the KPI of interest when no activity has been executed yet?

**RQ2** How does the recommended sequence of activities (suggested by the optimal policy \( \pi^* \)) perform in terms of the KPI of interest at a given point of the execution?

Unfortunately, the complexity of evaluating recommendations in the Prescriptive Process Monitoring domain is well known \[5\]. It relates to the difficulty to estimate the performance of recommendations that have possibly not been followed in practice. In order to answer our research questions, we therefore approximate the value of the KPI of interest \((i)\) by leveraging a simulator (simulation evaluation); \((ii)\) by looking at similar executions in the actual event log (test log evaluation). In the next subsections we describe the dataset (Section 5.1), we detail the experimental setting (Section 5.2), and we finally report the evaluation results (Section 5.3).

### 5.1 Datasets

We have used two real-world publicly-available datasets that, describing the behaviour of more than one actor, allow us to take the perspective of one of them (target): the BPI Challenge 2012 event log \([4]\) (BPI2012) and the Road Traffic Fine Management event log \([4]\) (Fines2015).

The BPI Challenge 2012 dataset relates to a Dutch Financial Institute. The process executions reported in the event log refer to an application process for personal loan (see the Loans scenario in Section 3). In this scenario we want to optimize the profit of the bank \((\text{agent})\), i.e., to minimize the cost \(C\) of granting a loan to a customer \((\text{environment})\) while maximizing the interest \(I\) of the bank granting the loan. To this aim, we define the KPI of interest for a given execution \(e\) as the difference between the amount of interest \((\text{if the bank offer is accepted and signed by the customer, namely if the activity Offer accepted occurs in the trace})\) and the cost of the employees working time, that is, the value of the KPI for the execution \(e\) is \(\text{KPI}_{\text{BPI2012}}(e) = I(e) - C(e)\). The amount of interest depends on the amount class of the loan request: low (amount \(\leq 6000\)), medium (6000 < amount \(\leq 15000\)) and high (amount > 15000). For the low class, the average interest rate is 16\%, for the medium class, the average interest rate is 18\%, while for the high class is 20\%.\[4\] The cost of the employees’ working time is computed assuming an average salary of 18 euros/h.\[5\]

The second dataset collects data related to an information system of the Italian police. The information system deals with the management of road traffic fines procedures,

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\[4\] The information on the average interest rate is extracted from the BPI2017 \([5]\) dataset which contains data from the same financial institution.

\[5\] We estimate the average salary of a bank employed in the Netherlands from https://www.salaryexpert.com/salary/job/banking-disbursement-clerk/netherlands.
starting from the fine creation, up to the potential offender’s appeal to the judge or to the prefecture (see the Fines scenario described in Section 3). Here, we want to maximize the credits received by the police department (agent) based on the fine payments received by the offender (environment). The department receives 3, 2 or 1 credits if the fines are fully paid within 6, within 12 months, or after 12 months respectively; it does not receive any credits if the fine is not fully paid, while it receives a discredit if the offender appeals to a judge or to the prefecture and wins, since these cases correspond to a money waste of the police authority. The KPI value for the execution $e$ is $\text{KPI}_{\text{Fines2015}}(e)$, corresponding to the number of credits received for the execution.

Table 1 shows the number of traces, variants, events, event classes and average trace length of the considered datasets. Table 2 illustrates the MDP components for the two scenarios: the main MDP actions; the main MDP state components, i.e., the last activity (LA), the historical features (HF) and the environment features (EF); as well as the reward, including the main attributes used for its computation.

For example, Table 3 shows how a trace related to the Fines scenario is preprocessed and transformed into an annotated trace, and then into MDP actions, states and rewards. The trace activities are annotated according to whether they have been carried out either by the agent or by the environment, and the attributes 2months (the bimester since the fine creation), amClass (the fine amount class) and payType (type of payment performed) are computed. In the MDP construction step, the agent’s activities (with the bimester interval) are used as actions, while the state is built by leveraging the last executed activity (LA), the 2months and the amClass attributes. The reward is not null when the payment is finally received and since in this trace the full payment is received after 6 months, 2 credits are awarded.

Once the log is enriched it is passed to the MDP generation step. We build two MDPs: the MDP$_{\text{BPI2012}}$ for the Loan request handling scenario (with 982 states and 15 actions) and the MDP$_{\text{Fines2015}}$ for the Traffic fine management scenario (with 215 states and 70 actions).

5.2 Experimental Setting

In order to answer our research questions, the two event logs have been split in a training part, which is used in in the RL phase, and a test part, which is used for the evaluation of the learned policy. For evaluating the computed policies, since in this setting both training and test set size can impact the evaluation results, we use two different splitting criteria (defining the percentage of event log used for the training and the test set): (i)

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6 The complete MDP description is available at tinyurl.com/2p8aytrb
7 The MDP actions in this scenario take into account, besides the activity name, also the 2-month interval (since the creation of the fine) in which the activity has been carried out (2months).
8 The component of the reward for an MDP state $s$ related to the interest of the bank is multiplied by a coefficient $c(n) = \frac{(n/\lambda)^2}{1+(n/\lambda)^2}$ that depends on the number of occurrences $n$ of the event log traces that pass through the specific MDP edge with outgoing state $s$. $c$ goes to 1 when $n$ grows. Here $\lambda$ is a parameter that can be opportunely tuned, we selected $\lambda = 3$ which corresponds to the median number of edge occurrences in the MDP. This factor is needed to discourage during the RL training the exploitation of some actions that have a positive reward but have low statistic reliability.
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Scenario MDP description

| action | Bank activities: loan acceptance, loan rejection, offer creation and delivery, requests for customer response |
|--------|-------------------------------------------------------------------------------------------------------------|
| last activity of the agent (bank) or of the environment (customer) |
| Customer activities: application cancellation, offer sent back to the bank, offer acceptance |
| state |
| state |
| state |
| last activity of the agent (bank) or of the environment (customer) |
| Customer activities: application cancellation, offer sent back to the bank, offer acceptance |
| reward |
| duration activity average duration |
| granted whether the loan has been granted |
| The reward is computed for each MDP state so that the reward of the complete execution corresponds to the value of the KPI for that execution |

Table 2: MDP for the Loan request handling and the Traffic fine management scenarios.

| Trace activity | timestamp | amount | Enriched trace | actor | payType | MDP action | reward |
|----------------|-----------|--------|----------------|-------|---------|------------|--------|
| Create fine    | 1/1/2021  | 40     | 2months        | low agent | -        | create fine | (Create fine, 0, low) | 0       |
| Send fine      | 2/2/2021  | 40     | 2months        | low agent | -        | Send fine  | (Send fine, 0, low)  | 0       |
| Add penalty    | 3/2/2021  | 60     | 2months        | high agent | -        | Add penalty | (Add penalty, 0, high) | -       |
| Payment        | 4/2/2021  | 60     | 2months        | high env. | full | Payment    | (Payment, 0, high)  | 2       |

Table 3: Example of the transformation of a trace in the corresponding MDP components.

60%–40% (60% of the traces for the training set and 40% for the test set) and (ii) 80%–20% (80% for the training and 20% for the testing). For the evaluation of the optimal policy obtained by RL and for answering our two research questions, two different evaluations have been carried out: a simulation evaluation and a test log evaluation.

The simulation evaluation uses a Monte Carlo simulation similar to the one used in the training phase, but, differently from the training phase, where the MDP is obtained from the training log, here a test MDP, obtained from the test log, is leveraged to simulate the environment response. In this simulation, the optimal policy obtained from the RL approach is compared, in terms of the KPI of interest, against a random policy and against a policy corresponding to the most frequent decisions made by the actor in the actual traces. The value of the reward for each of the simulated policy is computed as the average over 100,000 simulated cases. This evaluation provides a preliminary answer to the first research question [RQ1].

The test log evaluation aims at comparing the optimal policy obtained from RL with the actual policies used in the process. It is used for answering both our research questions. For [RQ1], we focus on the policy recommended when no activity has been executed yet. In this setting, we compare the value of the KPI of interest for the traces in
Table 4: Results of the simulation evaluation for the Loan request handling and the Traffic fine management scenarios.

The test event log that follow the optimal policy (from the first activity) (i) with the value of the KPI of interest of all the traces in the event log, and (ii) with the value of the KPI of interest of the traces in the event log that do not follow the recommended optimal policy. For RQ2 we focus on the policy recommended for ongoing executions, i.e., when some activity has already been executed. We hence consider, for each trace in the test event log, all its prefixes and separately analyze each of them, as a potential ongoing execution. For each prefix $p$ of a trace $t$ in the test event log we compare the value of the KPI of interest of the trace $t$ once completed against an estimation of the value of the KPI obtained following the optimal policy from that execution point forward. The estimation is obtained by averaging the KPI values of the traces in the log that have the same prefix as the reference prefix $p$ and follow the optimal policy from there on.

5.3 Results

In this section we report the results of the two scenarios related to the event logs described in Section 5.1. For both scenarios, as described in Section 5.2 we show (i) the results related to the evaluation of the complete optimal policy (RQ1) by reporting first the simulation evaluation and then the test log evaluation; and (ii) the results related to the evaluation of the optimal policy on the test log assuming that some events have already been executed (RQ2).

Research Question [RQ1] Table 4 reports the results related to the simulation evaluation for both the Loan request handling and the Traffic fine management scenarios. For both splitting criterion (60%-40% and 80%-20%) and for each policy analysed, the average KPI value is displayed together with the percentage of executions for which the bank offer has been accepted by the customer (or the fines have been fully paid by the offender). The policies analysed are: the random policy (Random), the policy selecting the most frequent action in the log for each state (Customary) and the optimal (Optimal) policy.

The rows related to the Loan request handling scenario (Loans) show that for both splitting criteria, the optimal policy (Optimal) generates an average KPI value much higher than the one obtained with a random policy (Random), but also higher than the one obtained with a policy characterized by frequently taken actions (Customary). This result confirms that the proposed Optimal policy actually outperforms the policy that
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is frequently taken in the actual traces, which is considered to be an “optimal” policy by the target agent. Different optimal (and customary) policies are returned with different splitting criteria. When learning with a larger training set and simulating on a smaller test set, the average KPI value increases, for the optimal and the customary policy, while slightly decreases for the random policy. Moreover, the table also shows the percentage of traces that, based on the policy simulations, are finally accepted by the customer. By changing the data splitting criteria, the effect is similar to that observed for the average KPI value for the optimal and the customary policy, with a percentage of accepted offers raising from around 39% to 43% for the customary policy and from around 53% to more than 60% with the optimal policy. An almost null increase is observed instead for the random policy.

The results related to the Traffic fine management scenario are similar to the results of the loan scenario, as shown in the row Fines of Table 4. As for the loan scenario, also in this case, for both splitting criteria, the optimal policy returns higher average KPI values (and hence lower money waste) and produces a higher percentage of traces with fully paid fines than the random and the customary policies. Also in this case, the difference between the optimal and the customary policy confirms that the proposed recommendation policy improves the policy actually used in practice. In this scenario, however, the difference in terms of percentage of traces for which fines have fully been paid between the optimal and the random policy is lower than for the Loan request handling case. This is possibly due to the overall higher percentage of traces in the Fines2015 event log for which the fines have been fully paid (40%) with respect to the percentage of traces in the BPI2012 log for which the loan offer has been accepted by the customer (17%), as well as to the higher number of actions of MDP_fines2015 with respect to the number of actions of MDP_BPI2012. Moreover, differently from the Loan request handling scenario, there is an overall decrease in terms of average KPI value and of traces with fully paid fines when using a larger training set and a smaller test set (80%-20% splitting criterion).

Table 5 shows the results related to the test log evaluation. For each of the two scenarios and for each splitting criterion, we report the number of traces, the average KPI value, as well as the percentage of traces for which the offer has been accepted (or the fines have been fully paid) for (i) all traces in the test set (All), (ii) the traces in the test set that follow the optimal policy (Optimal P); (iii) the traces in the test set that do not follow the optimal policy (Non-Optimal P).

The results of the test log evaluation for the Loan request handling scenario (Loans) confirm the results obtained with the simulation evaluation. For both splitting criteria, indeed, the average KPI value of the traces following the optimal policy (Optimal P) is higher than the average KPI value of all the traces (All), which in turn is higher than the average KPI value of the traces that do not follow the optimal policy (Non-Optimal P). The traces following the optimal policy generate an average bank profit of more than 500 euros higher than the average bank profit of all the traces in the event log, as well as of more than 750 euros higher than the average bank profit of the traces that do not follow the optimal policy. The same ranking is obtained if the compared approaches are ordered by the percentage of traces for which the offer by the bank has been accepted by the customer: around 30% for the traces following the optimal policy, around 15%
for all traces, and less than 10% for the traces not following the optimal policy. No major differences can be observed between the two splitting criteria, except for a small decrease of the average KPI value and of the percentage of accepted offers.

Similarly to the Loan request handling scenario, also in the Traffic fine management scenario (rows Fines in Table 5) the results of the test log evaluation confirm the findings of the simulation evaluation. Indeed, for both splitting criteria, the traces following the optimal policy (Optimal P.) obtain an average KPI value higher than the average KPI value of all the traces (ALL), which in turn is higher than the average KPI value of the traces that do not follow the optimal policy (Non-Optimal P.). The traces following the optimal policy can produce an average credit value of more than 1 credit higher than the average credit value of all the traces in the event log, as well as of more than 2 credits higher than the average credit value of the traces that do not follow the optimal policy. The trend is also similar for the percentage of traces for which the fine is fully paid. Around 90% of the traces that follow the optimal policy are able to get fully paid fines for both the splitting criteria. While, as in the Loan request handling, the percentage of traces with a fully paid fine decreases from the 40% test event log to the 20% event log for the ALL and Non-Optimal P. policies, for Optimal P. the percentage of traces for which the full payment is received is higher for the 20% than for the 40% test event log.

The above results of the two scenarios clearly show that, when no activity has been executed before the target agent starts following the recommendations, the sequence of next activities suggested by the optimal policy generates an average value for the KPI of interest higher than a random policy and than a policy following the most frequently taken actions and, on average, higher than the average KPI value obtained by the actual executions in the test event log (RQ1). No clear trends can be observed for different splitting criteria.

Research Question **RQ2** As described in Section 5.2, we also evaluate the optimal policies at different prefix lengths, that is, by assuming that a part of the execution has already been carried out, before the target agent starts adopting the optimal policy. Fig. 2 and Fig. 3 show the average delta KPI value for each prefix length, as well as the prefix occurrence per prefix length. The delta KPI value for each trace and prefix length is computed as the difference between the KPI value obtained by following the optimal policy from that prefix on and the KPI value of the complete trace related to that prefix.

| Scenario | Splitting criterion | traces | trace # | avg KPI | Offer accepted / full Payment |
|----------|---------------------|--------|---------|---------|-------------------------------|
| Loans 60%-40% | Optimal P. | 1384 (26.6%) | 1249.7 | 34.4% |
| Non-Optimal P. | 3813 (73.4%) | 341.5 | 9.4% |
| Loans 80%-20% | Optimal P. | 753 (29%) | 1082.2 | 30.4% |
| Non-Optimal P. | 1847 (71%) | 315.1 | 7.7% |
| Fines 60%-40% | Optimal P. | 22665 (37.8%) | 2.68 | 90.9% |
| Non-Optimal P. | 37281 (62.2%) | 0.15 | 9.9% |
| Fines 80%-20% | Optimal P. | 21073 (30.8%) | 2.76 | 92.7% |
| Non-Optimal P. | 20730 (69.2%) | 0.16 | 8.9% |

Table 5: Results related to the test log evaluation for the Loan request handling and the Traffic fine management scenario.
The plot corresponding to the Loan request handling scenario (Fig. 2a) shows that for both splitting criteria and for prefix lengths up to 18 there is an average positive delta KPI value, while for longer prefixes a negative or almost null average KPI values are observed. These results can be explained by the low number of traces with length higher than 18 in the test event logs, as it is shown in Fig. 2b.

In the Traffic fine management scenario, the plot in Fig. 3a shows a relatively high delta average KPI value for short prefixes (prefixes of length 1 and 2), while the average delta KPI value starts decreasing for traces of prefix length 3. Also in this case, as for the other scenario, the decrease in terms of delta KPI value is mainly due to an overall decrease of the number of traces after prefix 3 (see Fig. 3b). Differently from the Loan request handling scenario, as already observed during the discussion of RQ1, the average delta KPI value obtained with the 80%-20% splitting criterion is higher than the one obtained with the 60%-40% splitting criterion, except that for prefix length 3.

In conclusion, these results confirm that even when considering ongoing executions, the recommended sequence of next activities suggested by the proposed optimal policy generates higher average KPI values than the ones obtained by actual executions in the test event log (RQ2).

Beyond the performance perspective, we briefly comment here on the plausibility of the optimal policies obtained. The major contributions of the policies for the two cases...
are clear and reasonable. In the Loan request handling scenario the policy advises to accept more loan applications, so as to increase the number of possible accepted loans. Moreover, it advises to increase the interaction between the bank and the customer, with the creation of multiple offers and the subsequent call to the customer. In the Traffic fine management scenario the policy advises to send the fine early to the offender, so as to raise the probability that he/she pays the fine on time.

6 Related Work

The state-of-the-art works related to this paper pertain to two fields: Prescriptive Process Monitoring and Reinforcement Learning. The section is hence structured by first presenting Prescriptive Process Monitoring related works and then Reinforcement Learning state-of-the-art works, applied to process mining problems.

Several Prescriptive Process Monitoring techniques have been recently proposed in the literature. Focusing on the type of interventions that the approaches recommend, we can roughly classify existing work in Prescriptive Process Monitoring in three main groups: (i) those that recommend different types of interventions to prevent or mitigate the occurrence of an undesired outcome [24][8][17][20]; (ii) those that take a resource perspective and recommend a resource allocation [22][19]; (iii) those that provide recommendations related to the next activity to optimize a given KPI [25][24].

The approach presented in this paper falls under this third family of prescriptive process monitoring approaches. Only a small amount of research has been done in this third group of works. Weinzierl et al. in [25] discuss how the most likely behavior does not guarantee to achieve the desired business goal. As a solution to this problem, they propose and evaluate a prescriptive business process monitoring technique that recommends next best actions to optimize a specific KPI, i.e., the time. Gröger et al. in [2] present a data-mining driven concept of recommendation-based business process optimization supporting adaptive and continuously optimized business processes. De Leoni et al. in [2] discuss Process-aware Recommender (PAR) systems, in which a prescriptive-analytics component, in case of executions with a negative outcome prediction, recommends the next activities that minimize the risk to complete the process execution with a negative outcome. Differently from these state-of-the-art works, however, in this work we take the perspective of one of the actors of the process and we aim at optimizing a domain-specific KPI of interest for this actor by leveraging an RL approach.

In the literature, only few RL approaches have been proposed for facing problems in the process mining field. Silvander proposes using Q-Learning with function approximation via a deep neural network (DQN) for the optimization of business processes [21]. He suggests defining a so called decay rate to reduce the amount of exploration over time. Huang et al. employ RL for the dynamic optimization of resource allocation in business process executions [11]. Metzger et al. propose an alarm-based approach to prevent and mitigate an undesired outcome [17]. They use online RL to learn when to trigger proactive process adaptations based on the reliability of predictions. Although all these works use RL in the process mining field, none of them use it for recommending the next actions to perform in order to optimize a certain KPI of interest, as in this work.
Finally, some works have applied RL and Inverse Reinforcement Learning (IRL) approaches to recommend the next actions on temporal data [16] or on data constrained by temporal constraints [1].

7 Conclusion

In this paper we have proposed the use of RL in the solution of the problem of computing next activity recommendations in Prescriptive Process Monitoring problems.

Differently from other state-of-the-art works our model handles non deterministic processes, in which only part of the activities are actually actionable and the rest of them are, from the target actor point of view, stochastically selected by the system environment. This is a common situation in multi-actors processes. By taking the decision making perspective of one of the actors involved in a process (target actor), we first learn from past executions the behaviour of the environment and we then use RL to recommend the best activities to carry on in order to optimize a measure of interest. The obtained results show the goodness of the proposed approach in comparison to the policy used by the actor, i.e., without using recommendations.

We plan to extend this approach by including in the MDP state the raw information related to the history of the process execution, so as to automate as much as possible the pre-processing phase of our computational pipeline. However, in that case the consequent increase of the state space dimension and its cardinality would require the usage of state generalisation techniques, such as, those implemented with Deep Reinforcement Learning or by applying smart clustering techniques. Moreover, we would like to explore the possibility to use declarative constraints for defining and enforcing domain knowledge constraints.

References

1. De Giacomo, G., Iocchi, L., Favorito, M., Patrizi, F.: Foundations for restraining bolts: Reinforcement learning with ltl/lflf restraining specifications. In: Proc. of the 29th Int. Conf. on Automated Planning and Scheduling, ICAFS 2018. pp. 128–136. AAAI Press (2019)
2. de Leoni, M., Dees, M., Reulink, L.: Design and evaluation of a process-aware recommender system based on prescriptive analytics. In: 2nd Int. Conf. on Process Mining (ICPM 2020). pp. 9–16. IEEE (2020)
3. Di Francescomarino, C., Ghidini, C., Maggi, F.M., Milani, F.: Predictive process monitoring methods: Which one suits me best? In: Business Process Management - 16th Int. Conf., BPM 2018, Proceedings. LNCS, vol. 11080, pp. 462–479. Springer (2018)
4. van Dongen, B.: Bpi challenge 2012 (Apr 2012). https://doi.org/10.4121/uuid:3926db30-f712-4394-aebc-75976070e91f
5. van Dongen, B.: Bpi challenge 2017 (Feb 2017). https://doi.org/10.4121/uuid:5f3067df-f10b-45da-b98b-86ae4c7a310b
6. Dumas, M.: Constructing digital twins for accurate and reliable what-if business process analysis. In: Proc. of the Int. Workshop on BPM Problems to Solve Before We Die (PROBLEMS 2021). CEUR Workshop Proceedings, vol. 2938, pp. 23–27. CEUR-WS.org (2021)
7. Dumas, M., Fournier, F., Limonad, D., Marrella, A., Montali, M., Rehse, J., Accorsì, R., Calvanese, D., De Giacomo, G., Fahland, D., Gal, A., La Rosa, M., Völzer, H., Weber, I.: Augmented business process management systems: A research manifesto. CoRR abs/2201.12855 (2022), https://arxiv.org/abs/2201.12855
8. Fahrenkrog-Petersen, S.A., Tax, N., Teinemaa, I., Dumas, M., de Leoni, M., Maggi, F.M., Weidlich, M.: Fire now, fire later: alarm-based systems for prescriptive process monitoring. arXiv preprint arXiv:1905.09568 (2019)
9. Grüger, C., Schwarz, H., Mitschang, B.: Prescriptive analytics for recommendation-based business process optimization. In: Int. Conf. on Business Information Systems. pp. 25–37. Springer (2014)
10. Hu, J., Niu, H., Carrasco, J., Lennox, B., Arvin, F.: Voronoi-based multi-robot autonomous exploration in unknown environments via deep reinforcement learning. IEEE Transactions on Vehicular Technology 69(12), 14413–14423 (2020)
11. Huang, Z., van der Aalst, W., Lu, X., Duan, H.: Reinforcement learning based resource allocation in business process management. Data & Knowl. Eng. 70(1), 127–145 (2011)
12. Kurbak, K., Milani, F., Nolte, A., Dumas, M.: Prescriptive process monitoring: Quo vadis? CoRR abs/2112.01769 (2021), https://arxiv.org/abs/2112.01769
13. de Leoni, M., Mannhardt, F.: Road traffic fine management process (Feb 2015). https://doi.org/10.4121/uuid:276fd440-1057-4fb9-89a9-b699b4799f05
14. Maggi, F.M., Di Francescomarino, C., Dumas, M., Ghidini, C.: Predictive monitoring of business processes. In: Advanced Information Systems Engineering - 26th Int. Conf., CAiSE 201. Proc. LNCS, vol. 8484, pp. 457–472. Springer (2014)
15. Mannhardt, F., de Leoni, M., Reijers, H.A., van der Aalst, W.M.P.: Balanced multi-perspective checking of process conformance. Computing 98(4), 407–437 (2016)
16. Massimo, D., Ricci, F.: Harnessing a generalised user behaviour model for next-poi recommendation. In: Proc. of the 12th ACM Conf. on Recommender Systems, RecSys 2018. pp. 402–406. ACM (2018)
17. Metzger, A., Kley, T., Palm, A.: Triggering proactive business process adaptations via online reinforcement learning. In: Int. Conf. on Business Process Management. pp. 273–290. Springer (2020)
18. Metzger, A., Neubauer, A., Bohn, P., Pohl, K.: Proactive process adaptation using deep learning ensembles. In: Int. Conf. on Advanced Information Systems Engineering. pp. 547–562. Springer (2019)
19. Park, G., Song, M.: Prediction-based resource allocation using LSTM and minimum cost and maximum flow algorithm. In: Int. Conf. on Process Mining, ICPM 2019. pp. 121–128. IEEE (2019)
20. Shoush, M., Dumas, M.: Prescriptive process monitoring under resource constraints: A causal inference approach. CoRR abs/2109.02894 (2021), https://arxiv.org/abs/2109.02894
21. Silvander, J.: Business process optimization with reinforcement learning. In: International Symposium on Business Modeling and Software Design. pp. 203–212. Springer (2019)
22. Sindigatta, R., Ghose, A., Dam, H.K.: Context-aware analysis of past process executions to aid resource allocation decisions. In: Advanced Information Systems Engineering. pp. 575–589. Springer (2016)
23. Sutton, R.S., Barto, A.G.: Reinforcement Learning: An Introduction. The MIT Press, 2nd edn. (2018)
24. Teinemaa, I., Tax, N., de Leoni, M., Dumas, M., Maggi, F.M.: Alarm-based prescriptive process monitoring. In: Business Process Management Forum. pp. 91–107. Springer (2018)
25. Weinzierl, S., Dunzer, S., Zilker, S., Matzner, M.: Prescriptive business process monitoring for recommending next best actions. In: Business Process Management Forum. pp. 193–209. Springer International Publishing, Cham (2020)