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Enhancing Robotic Process Automation Task Selection: An Integrated Approach Leveraging Process Mining and Feature Extraction

Shveta Yadav[1], Vivek Bhardwaj[2*], Deepak Thakur[3], Vikrant Sharma[4]

[1] School of Computer Science and Engineering, Lovely Professional University, Jalandhar 144001, India
[2] School of Computer Science and Engineering, Manipal University Jaipur, Jaipur 303007, India
[3] Chitkara University Institute of Engineering and Technology, Chitkara University, Punjab 140401, India
[4] Department of Computer Science and Engineering, Graphic Era Hill University, Dehradun 248002, India

Corresponding Author Email: vivek.bhardwaj@outlook.in

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ABSTRACT

Robotic Process Automation (RPA), an emergent technology, is increasingly being utilized for the automation of straightforward and structured tasks, due to its time efficiency and cost effectiveness. As organizations strive to automate processes, it becomes imperative to discern the most suitable technology for each task to optimize investments in automation. The surge in RPA usage illuminates the challenge of task selection for automation. In response to this challenge, our study presents an integrated approach of process mining and feature extraction to enhance RPA task selection. Organizations provide feature weights, based on which corresponding tasks are extracted. Each task is subsequently ranked, and an overall task rank is computed by summing the products of feature weights and individual feature ranks. This procedure is iteratively performed for all tasks, culminating in a feature matrix, which constitutes the output of this framework. By leveraging historical process data, this combined approach allows for the identification of tasks that exhibit characteristics amenable to automation, such as high frequency, low variability, and distinct decision points. Furthermore, the extraction of task features enables the prioritization of tasks based on their potential for automation, complexity, and anticipated benefits. Through the analysis of process mining data, this study offers an empirical snapshot of organizational activities and suggests tasks that are amenable to RPA. This prioritization of suitable tasks for automation potentially enhances the success of RPA implementation.

1. INTRODUCTION

In today's rapidly evolving and competitive business landscape, organizations are compelled to optimize their resources to maximize efficiency. One potential solution is the automation of daily tasks; however, automation implementation can be an arduous and costly process due to factors such as infrastructural changes and system design [1-3]. This is where Robotic Process Automation (RPA) fills the gap. RPA, a suite of tools designed to automate a system's User Interface (UI) without affecting the underlying system, provides an efficient, cost-effective automation solution that necessitates no changes to an organization's Information System [4, 5].

RPA utilizes software robots to perform tasks, thereby reducing the need for human intervention [1]. However, not all tasks are suitable for automation. Ideal tasks for RPA are rule-based, structured, repetitive, and mature, as well as those that are prone to errors and time-consuming [2, 3]. Automating such tasks liberates human resources, enabling employees to focus on problems requiring innovative solutions, creativity, and human judgement [6]. To justify the investment in RPA, tasks with a high volume are generally selected [4, 7, 8].

The selection of tasks for RPA is a critical factor in the success of an automation project [9]. In this context, both Process Mining and RPA play pivotal roles in optimizing business processes. Process Mining techniques offer insight into an organization's operations, revealing the actual sequences of activities performed, identifying bottleneck processes, and clarifying paths from one activity to another. On the other hand, RPA can automate simple, repetitive tasks, increase task efficiency, and free up human employees for more creative, decision-heavy tasks.

Despite their individual benefits, a significant knowledge gap exists in the application of Process Mining data for RPA task selection. The present study aims to bridge this gap by utilizing Process Mining data generated by organizations for RPA task selection. This approach amalgamates the benefits of both technologies, creating a potent blend of efficacy and efficiency.

The data from Process Mining, which presents the reality of an organization's operations through actual events created during task performance, can be used for task segmentation based on complexity, frequency, volume, exception rate, among other factors. The procedural nature of actual processes in the organization can be analyzed to identify tasks that are standard and rule-based. This task segmentation may prove instrumental in the process of task selection for RPA.

In essence, this paper proposes a framework for utilizing Process Mining data in RPA task selection. By basing the task selection steps in RPA implementation on actual data generated by the business process, better data-driven decisions can be made. The subsequent sections of this paper are organized as follows: Section II provides the background on RPA and the discipline of Process Mining. Section III explains each step in the proposed framework. In Section IV, the framework is applied to a real-world Process Mining dataset. Section V discusses the limitations observed in this framework. Section VI presents the results in the form of a feature matrix. Finally, Section VII discusses the conclusions drawn from the study.

2. LITERATURE REVIEW

Robotic Process Automation (RPA) is defined as an assembly of tools explicitly designed to mimic human interactions with the user interface (UI) of an information system, thereby automating tasks without necessitating modifications to the underlying infrastructure [5, 8]. This unique ability of RPA to interface with a vast array of disparate, unlinked applications and assimilate them within an existing information system framework has been shown to expedite the development process, yielding a more efficient outcome compared to traditional automation methods.

It has been observed that the deployment of RPA systems significantly reduces human errors. A comparative analysis of RPA systems and human performance, as documented in a recent survey, revealed a notable discrepancy. While human performance demonstrated an accuracy of 90%, RPA systems exhibited an exceptional accuracy rate of 99.9% within auditing systems [7].

The integration of process mining into RPA has been identified as beneficial for process selection. This technique possesses the potential to automate even subprocesses that meet the RPA process selection criteria. In addition, process mining plays a pivotal role in predicting edge cases for transference to human operators. An increasing interest has been observed among vendors to harness the benefits offered by integrating process mining into RPA [8].

Institutional organizations, notably universities, are commonly known to operate a multitude of diverse and unrelated information systems [8]. These systems often span various domains, including learning management, salary administration, and other administrative tasks, and are typically disconnected. However, there remains a necessity for data across these systems, whether inserted, modified, or deleted, to be synchronized. Although these tasks might lack complexity, they are notably repetitive and time-consuming, requiring interaction with multiple user interfaces or systems. The potential for automation of these essential yet under-acknowledged tasks using RPA has been proposed [8].

RPA is achieved by the orchestration of a workflow to execute the processes initially performed by human workers. This is accomplished through the use of modules and functions either designed by vendors or programmed from scratch. The modular nature of RPA, alongside its operation on presentation layers or UIs, provides it with a potential for adoption and allows for agile development. Furthermore, the functional modules of RPA, which can be reused, enable its smooth integration into IT systems [10].

Considering that RPA systems operate on the top layer where human-machine interaction occurs, process mining techniques can be employed strategically to determine the tasks to be automated. This is achieved by analyzing an organization's event log. However, a market demand has been identified for a tool capable of recording and analyzing the logs of interactions between human operators and the UI elements of this top layer, where both RPA and human-machine interactions occur [11].

The utility of RPA systems in the utility sector has been investigated, with a focus on its implementation in the management of electricity billing at Bydgoszcz City Hall, Poland [12]. The results of these investigations have revealed that RPA systems can function as swift and cost-effective tools in the billing management process [12-14].

When appropriately deployed, RPA systems have been recognized for their ability to operate incessantly, thus augmenting efficiency and accelerating processes. These systems also contribute additional value by preserving progress, thereby enhancing accountability, and by their scalability. Furthermore, they are typically more cost-effective compared to traditional software automation systems engineered for process automation [5, 15]. In contrast, other forms of automation software often require modifications to the underlying system, which escalates both the time and cost for implementation [10, 16]. Due to the potential of RPA to reduce operational costs and increase productivity, its incorporation into systems is on the rise among organizations [17-19].

Process mining techniques are principally divided into three categories: the visualization of processes; the comparison of actual processes performed versus the designed process models; and the optimization of process flow [20, 21].

However, a noticeable gap in research has been identified pertaining to the selection of RPA tasks based on real-time data collected during ongoing business processes. Through the utilization of data derived from process mining, tasks can be tailored to the specific requirements of an organization, department, or task type. The combined deployment of RPA and process mining could unearth valuable insights into an organization's business processes. On one hand, the data and insights garnered from process mining can be applied across various stages of RPA [22]; on the other, the logs generated can be analyzed using process mining techniques to enhance the understanding of the business processes executed by the RPA bot [23].

For the selection of tasks for RPA, process mining techniques can facilitate the selection of only those tasks that require and are susceptible to automation using RPA [24, 25]. This method also ensures that decisions are data-driven [26].

A noteworthy partnership between UiPath and Celonis resulted in the addition of functionalities such as the visualization and selection of processes for RPA automation. This collaboration also aided in the development, testing, and deployment of RPA bots [8]. Leopold et al. [27] proposed a method employing supervised learning, a machine learning technique, to identify tasks from their descriptions and subsequently categorize them as fully automated, interactive between machine and human, or manual. Various studies have outlined the essential features required for a task to be successfully automated using RPA [28, 29].

Process mining, a data-driven technique, is employed to obtain insights into an organization's business processes [30]. Typically, data is sourced from the logs of actions performed by employees or machines. This provides valuable insights into how tasks and subtasks are executed, identifies dependencies between activities, detects bottlenecks, and more within the operations of an organization [31, 32].

3. METHODOLOGY

Before explaining the framework, the characteristics of the event log must be mentioned.

•Activity: The tasks performed, including in the event log.

•Event: The activity, with a timestamp

•Event ID: Unique identity to track a trace

•Trace: Collection of events for performing a sequence of tasks, to complete a process.

•Timestamp: Every event in the event log contains a timestamp when the event takes place

A. Task Selection Framework

For the analysis of the features of tasks performed, process mining is used as it includes the actual activities performed with respect to time in the organisation. For the purpose of task selection of RPA, the features of the tasks performed in the organisation have to be analysed. The overview of the task selection framework is shown in Figure 1. In this framework, all the features of the tasks are used to create a matrix which includes all the activities performed with the features of each activity, then this matrix is used to select the tasks to automate using RPA. Different phrases in the framework are:

3.1 Get process mining data

The information system of any organisation contains a large about of event logs, and the daily activities performed in the organisation are saved as an event log with a timestamp. This can be available in Customer Relationship Management (CRM), Supply Chain Management (SCM), and many more business process management tools. The process of mining data can be generated through these systems by getting the activity performed, at what time, and also a unique identifier for the ongoing trace. This dataset can be in the form of Comma Separated Values (CSV) file or an eXtensible Event Stream (XES) file [20]. This data will be used in this framework.

3.2 Data pre-processing

To ensure the quality of data for an accurate analysis, the cleaning is performed. This can include the removal of duplicates, null values, and noise; filtering of the data needed for the analysis according to departments, time-period, or tasks; handling of inconsistencies. As the data used is a process mining data, different process mining techniques can be used. It can be used to detect outliers, address mining vales and check for consistency of the data present.

In this phrase, the process mining dataset is clean for the next step. From this clean data, further useful activities are extracted, explained in the next step.

3.3 Extract activities

The activities are extracted for the process mining dataset. The extraction can include:

- all the unique activities performed in the event log, or
- activities are pre-defined, or
- activities according to the frequency, or
- bottleneck activities and so on.

If the organisation wants to automate the tasks of a department or want to automate a type of task from the organisation, the activities corresponding to the requirement can be extracted.

Now these extracted activities are used in the making of feature matrix.

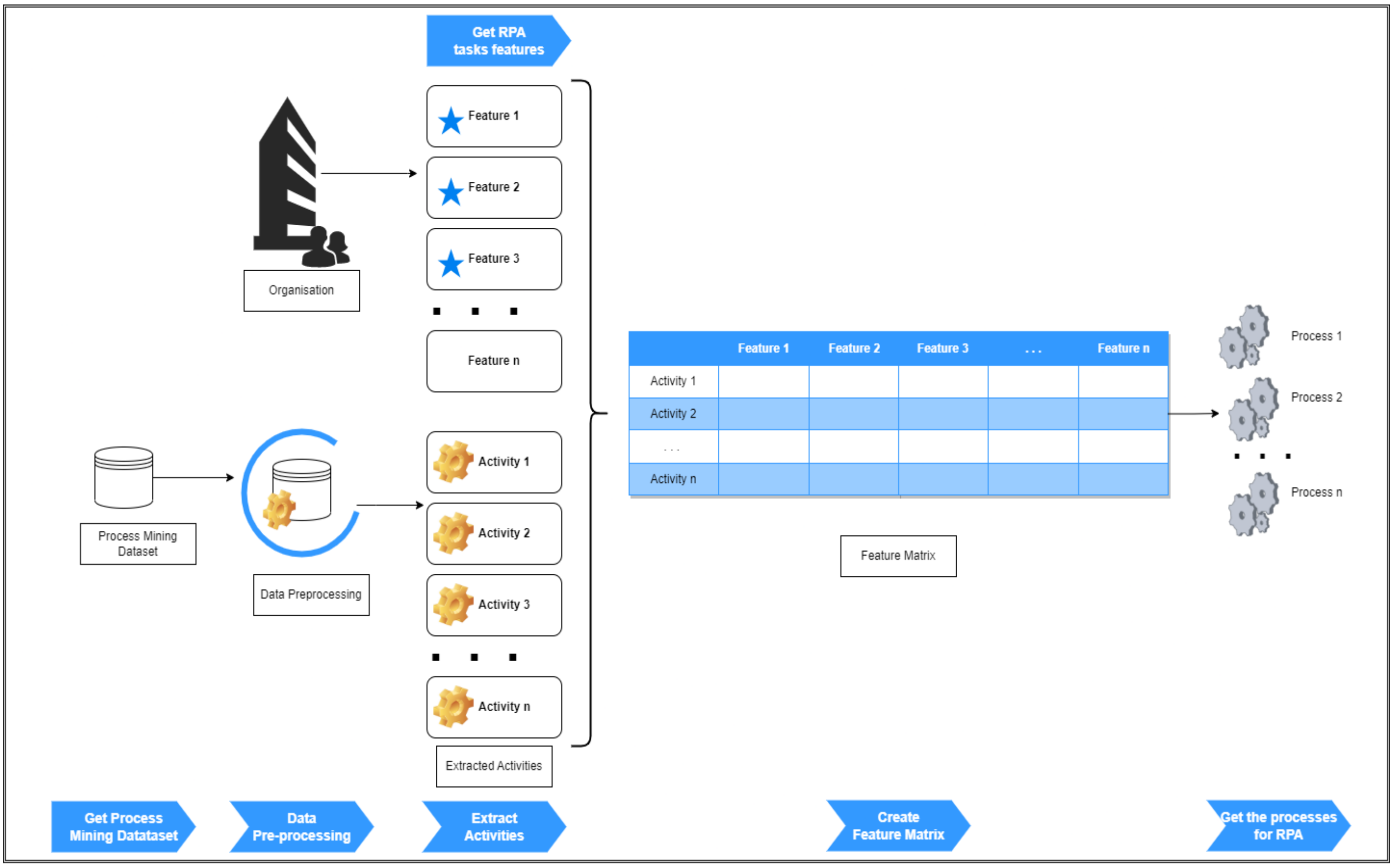

Figure 1. Task selection framework for RPA

3.4 Get RPA tasks features for automation

In this phase, the features required by the organizations for the automation task are realized. In this phase, the features needed for potential RPA tasks are revealed. This phase can be done through interviews and surveys from experts or specialists. This feature list can also contain the weight of all the features selected so that the priority list of the RPA tasks can be created.

The list of features to automate should be provided by the organization, it can include the activities which are costly, require more labor, are standardized, and so on.

The curated feature list with their weights and the extracted activities from the above step are inputs for the creation of feature matrix.

3.5 Create the feature matrix

The feature matrix is a table with rows as activities selected in the Extract activities phrase and columns as features selected in the Get RPA tasks feature phrase.

For Activity Ai from all Activities A1, A2, ...An. For Feature Fj from all Features F1, F2, ...Fm with Weight Wj for all the features, then

$$\text{Weighted Rank for Ai} = (F1 * W1 + F2 * W2 + ... + Fm * Wm) \tag{1}$$

In the Eq. (1), the weight of each feature is multiplied with each feature ranking to get an overall ranking of the activity Ai.

Firstly, every activity is ranked according to their feature, where every feature represents one column. And every feature Fj have a weight Wj assign to it. These are multiplied to get the resultant of rank of an activity.

3.6 Get the process for RPA

The process for automation is selected using the Feature matrix. The feature matrix gives the list of activities arranged in the order that seems to be best to be automated using RPA, i.e., the activity in the 1st row is the best option according to the given weight than the activity shown in the 5th row or 10th row while the activity in the 5th row is better option than the 10th row. The feature matrix only shows the comparisons of activities that are the best option to automate for the given features.

3.7 Evaluation of the framework

For the evolution of the framework several parameters can be compared between a RPA bot and a human employee, which includes: The time taken for the completion of the task; The difference in the error rates; The cost incurred to the organisation for the task's completion; Ability to scale and many more.

4. IMPLEMENTATION: TASK SELECTION FRAMEWORK

4.1 Setup

Python 3.9.7 version was used to implement the framework, with pandas 1.3.4, pm4py 2.6.1, matplotlib 3.4.3, and NumPy 1.20.3 libraries.

4.2 Get process mining data

The already created data mining dataset was taken for the implementation purpose. The data consist of the Procurement-to-payment process of a multinational company with 60 subsidiaries, situated in the Netherlands [17].

4.3 Data pre-processing

Table 1. Overview of dataset: Number of events, traces, activities, and workers

Dataset	Events	Traces	Activities	Workers
BPI 2019	1,595,923	251,734	42	627 (607 humans and 20 machines)

Table 2. A sample of an event from the process mining data

Property	Value
Index	0
User	batch 00
Org: Resource	batch 00
Concept: Name	SRM: Created
Cumulative net worth (EUR)	298
Time: Timestamp	2018-01-02 12:53:00+00:00
Case: Spend area text	CAPEX & SOCS
Case: Company	Company ID 0000
Case: Document type	EC Purchase order
Case: Sub spend area text	Facility Management
Case: Purchasing document	2000000000
Case: PURCH. Doc. Category name	Purchase order
Case: Vendor	Vendor ID 0000
Case: Item type	Standard
Case: Item category	3-way match, invoice before GR
Case: Spend classification text	NPR
Case: Source	Source System ID 0000
Case: Name	vendor 0000
Case: Gr-based inv. Verif.	false
Case: Item	1
Case: Concept: Name	2000000000 00001
Case: Goods receipt	true

Table 3. Overview of dataset: Events each year, traces started and end each year

Year	No. of Events	No. of Traces Started	No. of Traces Ended
1948	10	5	
1993	9	9	
2001	22	17	
2008	45	45	
2015	3	2	
2016	6	2	
2017	223	184	
2018	1550468	251268	219052
2019	45135	202	32680
2020	2		2

The initial exploration of the event log helps understand the scope of events, traces, time duration of the dataset and much more. It also reveals the type of activities performed in the given time period. Table 1 outlines the dataset. There are 1,595,923 events with 251,734 traces. Table 2 shows a sample of an event from the dataset. The property concept: name tells all types of activities performed in handling the company's purchase order. There is a total of 42 activities performed. The dataset is from 1948-01-26 22:59:00+0000 to 2020-04-09 21:59:00+0000 but the number of events from the year 1948 to 2017 and from 2019 to 2020 is negligible as compared to in the year 2018, as shown in the Table 3. Therefore, for the analysis purpose, only the events of the year 2018 are used. Therefore, only the data from 2018 was used.

4.4 Extract activities

For this dataset, all the unique activities are taken for the creation of the matrix. There is a total of 42 activities.

4.5 Get RPA tasks features for automation

For implementing this framework, the features selected with their weights for RPA are shown in the Table 4. Here, the weight of each feature is assumed. In the real-life scenario, the weights should be given according to the importance of a feature needed to be automated.

Table 4. Weights for the selected features

Feature	Weight
Volume	3
Manual Work	5
Error-Prone	4

4.6 Create the feature matrix

For the creation of the Feature Matrix, each activity is ranked according to each feature, and then the overall rank of all the activities is calculated by multiplying the rank and weight.

Figure 2 shows how the volume of different activities is comparable to each other.

In the dataset, there were two types of uses, 'Batch' and 'Users' as define in the property org: resource as shown in the sample event from Table 2. The Users are human employees, from this, it can be found out which activity is manual, and which is automated. The blank value is not counted. Figure 3 shows the different manual and automated activities.

Error-prone activities are checked by finding the repeated activities in each trace. Figure 4 shows the number of times an activity is repeated in each trace.

Finally using these features, we can get the process for RPA. One limitation of this proposed framework is that the features and their weights must be independently decided by the organisation according to their need for RPA task selection. The efficiency of the framework highly depends upon the list of features with their respective weights for the creation of feature matrix. While the framework is able to extract the activities according to the features given by the organisation, the independently identification of the features with their weights can be difficult for the organisation. This can give rise to the need of an expert for feature identification, increasing the cost for RPA implementation in the process. Future research can include a method to automatically extract the feature with their weights from process mining data, which can reduce the manual work.

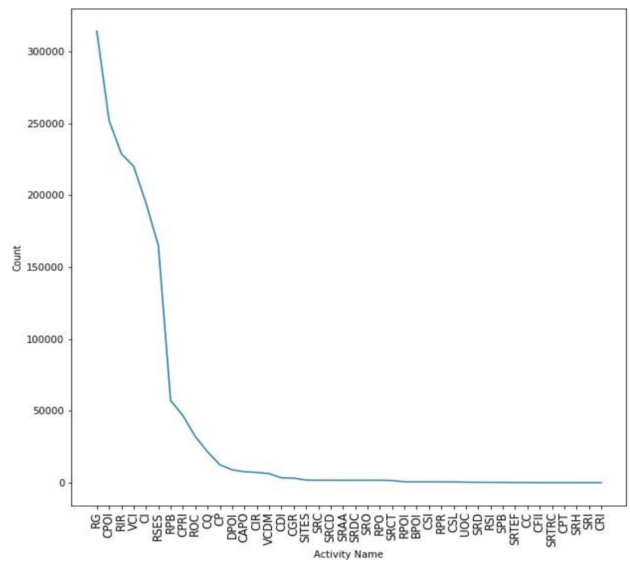

Figure 2. Volume of each activity in the process mining dataset

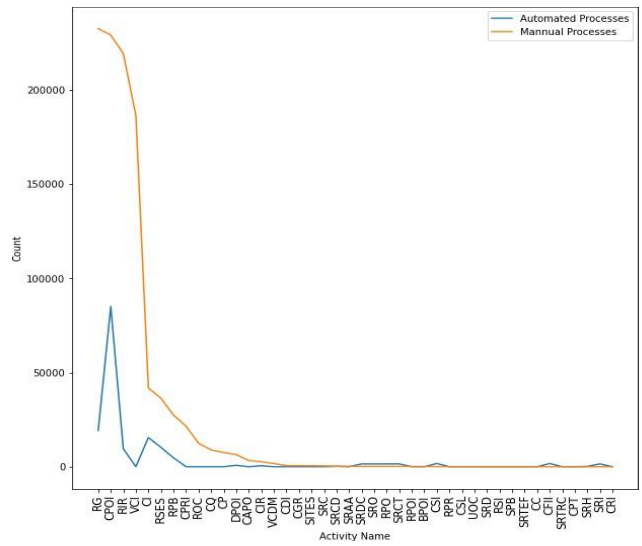

Figure 3. Manual vs. automated activities

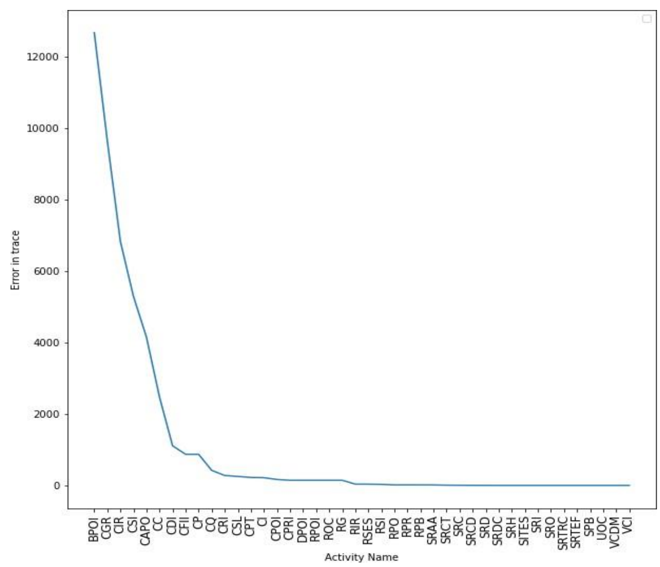

Figure 4. Error prone activities

The rank for the activity, “Change Quantity” is:
= Feature Rank of Volume * Weight of Volume +
Feature Rank of Manual Activities * Weight of Manual Activities +
Feature Rank of Error Prone Activities * Weight of Error Prone Activities
= 10 * 3 + 8 * 5 + 6 * 4
= 30 + 40 + 24
= 94
And the rank for the activity, “Delete Purchase Order” is:
= Feature Rank of Volume * Weight of Volume +
Feature Rank of Manual Activities * Weight of Manual Activities +
Feature Rank of Error Prone Activities * Weight of Error Prone Activities
= 12 * 3 + 10 * 5 + 21 * 4
= 36 + 50 + 84
= 170

5. RESULT

The Table 5 shows the feature matrix for this dataset. The output is the rank column, which shows the priority for the process to be automated. Here the activities with less rank are best for RPA. Therefore, the best process to automate is Record Goods Receipt with the selected features and their weights. The activities which are suitable for RPA is listed in feature matrix with the first being the best. This gives the organizations freedom to select the number of activities the organizations want to automate according to their needs.

Table 5. Feature matrix

Activity	Short Form of Activity	Volume	Manual Activity	Errorprone	Rank
Record Goods Receipt	RG	1	2	1	17
Record Invoice Receipt	RIR	3	3	2	32
Clear Invoice	CI	5	4	3	47
Remove Payment Block	RPB	7	5	7	74
Change Quantity	CQ	10	8	6	94
Change Price	CP	11	9	8	110
Change Approval for Purchase Order	CAPO	13	11	9	130
Cancel Invoice Receipt	CIR	14	12	10	142
Change Delivery Indicator	CDI	16	13	11	157
Create Purchase Order Item	CPOI	2	1	37	159
Cancel Goods Receipt	CGR	17	14	12	169
Delete Purchase Order Item	DPOI	12	10	21	170
Receive Order Confirmation	ROC	9	7	29	178
Create Purchase Requisition Item	CPRI	8	6	37	202
Release Purchase Order	RPO	24	15	14	203
Vendor creates invoice	VCI	4	38.5	4	220.5
Record Service Entry Sheet	RSES	6	38.5	5	230.5
SRM: In Transfer to Execution Syst.	SITES	18	28	13	246
SRM: Awaiting Approval	SRAA	21	23	18	250
SRM: Complete	SRC	21	23	18	250
SRM: Document Completed	SRDC	21	23	18	250
SRM: Created	SRCD	21	25	18	260
Block Purchase Order Item	BPOI	27	17	25	266
Reactivate Purchase Order Item	RPOI	26	16	27	266
Cancel Subsequent Invoice	CSI	28	18	25	274
Change Storage Location	CSL	30	19	23	277
Vendor creates debitmemo	VCDM	15	38.5	15	297.5
Update Order Confirmation	UOC	31	21	25	298
SRM: Ordered	SRO	21	38.5	18	327.5
Release Purchase Requisition	RPR	29	20	37	335
Record Subsequent Invoice	RSI	33	26	28	341
Set Payment Block	SPB	34	27	30	357
SRM: Deleted	SRD	32	38.5	22	376.5
SRM: Transfer Failed (E.Sys.)	SRTEF	35	29	37	398
Change Currency	CC	36	30	37	406
Change Final Invoice Indicator	CFII	37	31	37	414
SRM: Change was Transmitted	SRCT	25	38.5	37	415.5
Change Rejection Indicator	CRI	42	34	31	420
SRM: Transaction Completed	SRTRC	38	32	37	422
Change payment term	CPT	39	33	37	430
SRM: Held	SRH	40.5	38.5	37	462
SRM: Incomplete	SRI	40.5	38.5	37	462

6. CONCLUSIONS

There is lack of literature on discussion on using real world data for the RAP task selection. The process mining data collected from different logs of activities performed in the organization can give the insight from within the organization, i.e., how a particular task was completed, how this task is dependent, if it in structured or if there are many edge cases, and so on. From answering these types of question using process mining dataset, the findings are customized to the organization giving it the flexibility to change and adopted to different situations.

Therefore, the framework for the task selection for RPA using the process mining dataset is presented in this paper. In the proposed framework, first data is collected and pre-processed. The proposed framework uses real event data as input to extract their features and rank the activities according to them. The rank of all the activities with respect to the features is used to create a feature matrix, in which a new column is also added which shows the weighted rank of activities with respect to all the features. This gives the list of activities actually performed in the real life with priority. This matrix can be used to select tasks for the RPA.

With the help of this framework, the selection of tasks is made easier, and as the framework depends on real-life event datasets, it helps in the knowledge of the nature of activities run in the organization and will decrease the chance of failure of the RPA implementation.

The result of the framework depends on the actual data generated in the business processes. For the evaluation of this framework, the comparison between the RPA bot and human employees are needed on different parameters such as time taken, errors occurred, cost incurred, etc. There can be future research on the selection of features and calculation of their weights. This can further remove the manual work in the framework.

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