A genetic algorithm for process discovery guided by completeness, precision and simplicity

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Process Mining

Motivation

FOCUS ON COMPLETE, PRECISE AND SIMPLE MODELS... WHY?

Some domains, like **e-learning**, require:

High levels of completeness

The teacher needs to know all the behavior undertaken by the students to make a correct assessment

Precise models

The teacher only needs to know what the students did

Simple models

> The model must be readable



Process Mining

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Motivation

ProDiGen: Process Discovery through a Genetic algorithm

- Genetic algorithm that **searches** complete, precise and simple models
 - Hierarchical fitness based on completeness, precision and simplicity
 - ▷ New criteria for precision and simplicity
 - Heuristics in the crossover and mutation
 - Heuristics Miner's solution is incorporated to the initial population
 - **Binary tournament** selection
 - > Steady-state replacement with reinitializations



ProDiGen What is a genetic algorithm?

- Optimization algorithm
- Components
 - Individuals: potential solutions
 - Population: set of individuals

The population evolves until obtain an optimal solution





Genetic algorithm – Internal representation

Causal Matrix [1]: maps any Petri net in terms of causal dependencies





[1] *de Medeiros, A.K.A : Genetic Process Mining. PhD thesis, Technische Universiteit Eindhoven*

Initial Population – Building the initial population



Initial Population – Building the initial population



Evolutionary cycle – Evaluation

Each individual is evaluated with three objectives:

Completeness

Precision

Simplicity

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Evolutionary cycle – *Evaluation:* **Completeness**

- Completeness [1]: the retrieved model can reproduce all the behavior of the log
- Punish individuals with:
 - Tasks with incorrect input arcs (missing tokens)
 - Tasks with incorrect output arcs (extra tokens)

 $C_{f}(L, CM) = \frac{allParsedActivities(L, CM) - punishment}{numActivitiesLog(L)}$

 $punishment = \frac{allMissingTokens(L,CM)}{numTracesLog(L) - numTracesMissingTokens(L,CM) + 1}$

allExtraTokensLeftBehind(L,CM)

numTracesLog(L) - numTracesExtraTokensLeftBehind(L,CM) + 1

[1] de Medeiros, A.K.A : Genetic Process Mining. PhD thesis, Technische Universiteit Eindhoven

Evolutionary cycle – *Evaluation:* **Precision**

- Precision: the retrieved model avoids additional behavior, i.e, behavior not represented in the log
- Punish those individuals that enable too many activities during the parsing of the log
 - \triangleright For each enabled activity \rightarrow one possible path of execution

$$P_{f}(L, CM) = \frac{1}{allEnabledActivities(L, CM)}$$

Each individual's precision evolves regardless the rest of the population



ProDiGen Evolutionary cycle – *Evaluation:* <u>Simplicity</u>

Simplicity: discover learning paths with the minimal structure

Trace user 1 = (X,A,C,D,Y) Trace user 2 = (X,B,C,E,Y)



Both models have the same completeness and precision, but different simplicity



ProDiGen Evolutionary cycle – *Evaluation:* **Simplicity**

Counts the **number of relations** of the causal matrix

$$S_{f}(CM) = \frac{1}{\sum_{t \in CM} \left(\sum_{\Phi \in I(t)} |\Phi| + \sum_{\Psi \in O(t)} |\Psi| \right)}$$



ProDiGen Evolutionary cycle – *Evaluation:* Simplicity

Counts the **number of relations** of the causal matrix





ProDiGen Evolutionary cycle – *Evaluation:* Simplicity

Counts the **number of relations** of the causal matrix



ProDiGen Evolutionary cycle – Evaluation

Hierarchical fitness function

$$\begin{aligned} F(a) > F(b) \iff \{C_f(a) > C_f(b)\} \lor \{C_f(a) = C_f(b) \land P_f(a) > P_f(b)\} \\ \lor \{C_f(a) = C_f(b) \land P_f(a) = P_f(b) \land S_f(a) > S_f(b)\} \end{aligned}$$





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Evolutionary cycle – Selection

Binary Tournament







Evolutionary cycle – Recombination

Generate new individuals

Crossover

Combines the characteristics of two parents into two offspring

Mutation

Adds or removes characteristics from an individual







Evolutionary cycle – *Recombination*: **Crossover**

The crossover operator picks one task of the parent 1 and exchange the input and output dependencies with the same task of the parent 2



The size of the causal matrix **increases** with the number of activities in the log.

Picking the crossover point at random produces a poor performance of the crossover



Evolutionary cycle – Recombination: Crossover

Guided by a *Probability Density Function* generated from the errors

- While parsing the log, each individual records the incorrectly parsed tasks
 - ▷ The **correctly parsed tasks** have a null chance for being crossed
 - The incorrectly parsed tasks have an uniform probability for being crossed
- The crossover point is selected from the incorrectly parsed tasks of the individual with the higher completeness
- The crossover is performed as defined in [1]



[1] de Medeiros, A.K.A : Genetic Process Mining. PhD thesis, Technische Universiteit Eindhoven

Evolutionary cycle – Recombination: Crossover





The crossover point is selected from *incorrectlyParsedTasks* of parent1:





Evolutionary cycle – *Recombination*: **Crossover**

Log = { *ABH*, *ACH*, *ADEFGH*, *ADFEGH* }



 \triangleright

Evolutionary cycle – *Recombination*: Mutation

The mutation operator can:

Add a new task to the input and/or output function of task





> Redistribute the elements of the input and/or output function of task



Evolutionary cycle – *Recombination*: Mutation

The mutation operator can:





Evolutionary cycle – *Recombination*: Mutation

Guided by the causal dependencies of the log

Two sets for each task:

inputDependencies(t):

The set of activities that appear before t in any trace of the log

- outputDependencies(t):
 - The set of activities that appear after t in any trace of the log

Reduce the search space to those models that are supported by the information in the log



Evolutionary cycle – Recombination: Mutation

Additionally, to **minimize duplicate** individuals:

The individual is iteratively modified until it is different from its parent

Only one task is affected by the mutation process

- Individuals are always forced to mutate
 - Mutation rate = 1



ProDiGen Evolutionary cycle – Replacement

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- Update of the population:
 - Combines and sorts parents and offsprings (2N size population)
 - The repeated individuals are placed at the bottom of the ranking
 - The N best individuals survive to the next cycle



Evolutionary cycle – Reinitialization

Indicators:

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- If the best solution does not change
- If there are not new individuals in the population
- Population generated as in the initial stage
- Adds a mutation of the best individual



Logs

- 21 models with their respective logs
- Both logs and models created by other authors [1,2]
- Used to validate:
 - Genetic Miner [1]
 - **ETM [2]**

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[1] de Medeiros, A.K.A : Genetic Process Mining. PhD thesis
[2] Buijs, J., van Dongen, B., van der Aalst, W.: On the role of fitness, precision, generalization and simplicity in process discovery.

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Metrics - Based on the original model [1]

To quantify the behavior similarity :

- Behavioral precision (B_p)
- Behavioral recall (B_r)
- To quantify the structural similarty :
 - Structural precision (S_p)
 - Structural recall (S_r)



[1] *de Medeiros, A.K.A : Genetic Process Mining. PhD thesis, Technische Universiteit Eindhoven*

Metrics - Based on the log [4]

To measure the completeness:

- Proper Completion (C): Percentage of correctly parsed traces. If all the traces are correctly parsed, then C = 1
- To measure the precision:
 - Alignment precision (P): If all the behavior allowed by the model is actually observed, then P = 1
- To measure the simplicity:
 - The weighted P/T average arc degree (S'): The lower is S, the higher the complexity

$$S = \frac{1}{1 + S'}$$



[4] van der Aalst, W., Adriansyah, A., van Dongen, B.: Replaying history on process models for conformance checking and performance analysis.

Results

ProDiGen finds the original model in the 81% (17 out of 21) of the cases

			Logs																				
			÷	de de	\$ ¹ *	ŝ	40 00	50	de la	de Cal	\$10	\$22	\$13	824	515	\$19	\$20	\$22	\$2 ² 2	\$ ² 3	\$24	\$25	EMT
ProDiGen	Model metrics	$B_p \\ B_r \\ S_p \\ S_r$	$1.0 \\ 1.0 \\ 1.0 \\ 1.0 \\ 1.0$	$1.0 \\ 1.0 \\ 1.0 \\ 1.0$	$1.0 \\ 1.0 \\ 1.0 \\ 0.97$	$1.0 \\ 1.0 \\ 1.0 \\ 1.0 \\ 1.0$	$1.0 \\ 1.0 \\ 1.0 \\ 1.0 \\ 1.0$	$1.0 \\ 1.0 \\ 1.0 \\ 1.0$	$1.0 \\ 1.0 \\ 1.0 \\ 0.94$	$1.0 \\ 1.0 \\ 1.0 \\ 1.0 \\ 1.0$	$1.0 \\ 1.0 \\ 1.0 \\ 1.0 \\ 1.0$	$1.0 \\ 1.0 \\ 1.0 \\ 1.0 \\ 1.0$	$1.0 \\ 1.0 \\ 1.0 \\ 1.0$	$1.0 \\ 1.0 \\ 1.0 \\ 1.0 \\ 1.0$	$1.0 \\ 1.0 \\ 1.0 \\ 1.0$	$1.0 \\ 1.0 \\ 1.0 \\ 1.0$	$1.0 \\ 1.0 \\ 1.0 \\ 1.0$	$1.0 \\ 1.0 \\ 1.0 \\ 1.0$	$1.0 \\ 1.0 \\ 1.0 \\ 1.0$	$1.0 \\ 1.0 \\ 1.0 \\ 1.0 \\ 1.0$	$1.0 \\ 1.0 \\ 1.0 \\ 0.98$	0.96 0.99 0.91 0.91 0.91	5 1.0 9 1.0 1 1.0 1 1.0
	Log metrics	C P S	$1.0 \\ 0.9 \\ 0.3$	$1.0 \\ 0.82 \\ 0.3$	0.78 0.98 0.31	$1.0 \\ 0.98 \\ 0.31$	1.0 0.95 0.31	$1.0 \\ 0.88 \\ 0.32$	0.52 0.86 0.28	$1.0 \\ 0.92 \\ 0.31$	$1.0 \\ 0.89 \\ 0.3$	$1.0 \\ 0.97 \\ 0.31$	1.0 0.93 0.3	$1.0 \\ 0.93 \\ 0.31$	$1.0 \\ 0.86 \\ 0.25$	$ \begin{array}{r} 1.0 \\ 0.92 \\ 0.3 \end{array} $	1.0 0.78 0.29	$1.0 \\ 0.91 \\ 0.31$	$1.0 \\ 0.9 \\ 0.3$	$1.0 \\ 0.58 \\ 0.3$	1.0 0.89 0.29	0.98 0.74 0.31	8 1.0 40.87 10.27
$_{ m GM}$	Model metrics	B_p B_r S_p S_r	$1.0 \\ 1.0 \\ 1.0 \\ 1.0 \\ 1.0$	0.61 0.97 0.81 0.81	0.78 0.97 0.81 0.81	$1.0 \\ 1.0 \\ 1.0 \\ 1.0$	$1.0 \\ 1.0 \\ 1.0 \\ 1.0$	$1.0 \\ 1.0 \\ 1.0 \\ 1.0$	$ \begin{array}{r} 0.84 \\ 1.0 \\ 1.0 \\ 0.94 \end{array} $	0.96 1.0 0.97 0.98	0.99 0.97 0.9 0.92	$1.0 \\ 1.0 \\ 1.0 \\ 1.0 \\ 1.0$	0.98 0.99 0.95 0.94	$0.61 \\ 1.0 \\ 0.95 \\ 0.94$	0.8 0.97 0.88 0.87	0.98 0.9 0.95 0.89	$1.0 \\ 1.0 \\ 1.0 \\ 1.0$	$1.0 \\ 1.0 \\ 1.0 \\ 1.0 \\ 1.0$	0.97 1.0 0.85 0.85	$\begin{array}{c} 0.57 \\ 0.88 \\ 0.76 \\ 0.74 \end{array}$	0.83 0.88 0.75 0.75	0.81 0.96 0.76 0.74	1.0 0.83 0.85 10.85
	Log metrics	C P S	$1.0 \\ 0.9 \\ 0.3$	$0.31 \\ 0.42 \\ 0.31$	0.59	$1.0 \\ 0.98 \\ 0.31$	1.0 0.95 0.31	1.0 0.88 0.32	0.26 0.0 0.26	$0.48 \\ 0.94 \\ 0.3$	$0.48 \\ 0.91 \\ 0.29$	1.0 0.97 0.31	0.75 0.96 0.3	$1.0 \\ 0.74 \\ 0.31$	$0.15 \\ 0.0 \\ 0.24$	0.2 0.0 0.29	1.0 0.78 0.29	1.0 0.91 0.31	0.43 0.86 0.3	0.2 0.0 0.28	0.72 0.88 0.3	0.41	$ \begin{array}{c} 0.3 \\ 0.81 \\ 8 \\ 0.3 \end{array} $
HM	Model metrics	B_p B_r S_p S_r	1.0 1.0 1.0 1.0	1.0 0.98 0.97 0.97	0.94 30.92 0.96 0.86	1.0 1.0 1.0 1.0	0.9 0.98 0.93 0.97	0.97 0.97 0.97 1.0	0.87	1.0 0.98 1.0 1.0	0.96 0.95 0.96 0.96	1.0 1.0 1.0 1.0	1.0 1.0 1.0 1.0	0.97 0.97 0.96 0.92	0.96 0.98 1.0 0.86	0.97 1.0 1.0 0.9	1.0 1.0 1.0 1.0	1.0 1.0 1.0 1.0	0.99 0.99 0.97 0.91	0.6 1.0 0.91 0.94	0.92	0.76 0.94 0.85 0.85	50.81 40.96 50.76 50.74
	Log metrics	P S	0.9 0.3	0.83	0.78	0.98	0.86	0.9	0.86	$0.74 \\ 0.93 \\ 0.31$	0.9	0.97	0.93 0.3	0.92	0.87	0.85 0.93 0.3	0.78 0.29	0.91 0.31	0.9	0.0	0.93	0.23	0.29



Current applications of ProDiGen

SoftLearn

Is being used to discover the workflow that represents the learning path followed by the learners during the course

SoftLearn

SoftLearn demo Web Page

tec.citius.usc.es/SoftLearn



Conclusions

- Genetic algorithm for process discovery guided by completeness, precision and simplicity
- New criteria for precision and simplicity
- Recombination guided by heuristics
- Heuristics Miner's solution is incorporated to the initial population

Great performance



THANKS FOR YOUR ATTENTION

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ProDiGen

tec.citius.usc.es/SoftLearn/ProDiGen.html

SoftLearn demo Web Page

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