

VU Business Intelligence II

Replication Study: Mining Behavioral Patterns for Conformance Diagnostics

Group Member:

- Khalifa Nikzad (12437813)
- Fatemehsadat Sepehrihosseini (12350114)
- Aziz Massomi (12244794)
- Shogofa Nawrozi (12314943)
- Irdi Kuka (12407107)

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Paper Overview – Context

- Process mining compares real executions (logs) with process models
- Deviations are common in real-life processes
- The challenge:
How can we detect and explain deviations in a meaningful way?

Paper Overview: Problem & Idea

- Problem:
 - Many deviations
 - Hard to explain them clearly
- Authors' idea:
 - Use **behavioral constraints**
 - Automatically discover patterns that explain deviations
- Key novelty (simple):
 - Not only *detect* deviations
 - Also *explain* them in a structured way

Paper Overview: How It Works

- Input:
 - Process model
 - Event log
- Steps:
 - Generate candidate constraints
 - Check which constraints hold
 - Minimize constraints
 - Use them to explain deviations

What do we mean by a Constraint?

- A **constraint** is a **rule about how activities should happen** in a process.
- It describes **expected behavior**, not a single trace.
- Constraints are used to:
 - detect deviations
 - explain why a process execution is wrong

Simple example

- Activity A: Send fine
- Activity B: Pay fine

Constraint:

“If Send fine happens, then Pay fine should eventually happen.”

If this rule is broken → we found a **deviation**.

Role of Constraints in the Evaluation

Table 4 — Performance

- Constraints are treated as **candidates**
- The system:
 - generates many possible rules
 - removes invalid and redundant ones
- Goal: measure **scalability and runtime**

Table 5 — Diagnostics

- Constraints are used as **explanations**
- The system checks:
 - which constraints are violated
 - how many deviations are explained
- Goal: measure **explanation quality**

Key idea

- Table 4 → How expensive is it to find rules?
- Table 5 → How useful are these rules to explain deviations?

Evaluation Setup in the Paper

- Two datasets:
 - Road Fines (RF)
 - BPI-15
- Different constraint sizes:
 - $k = 2, 3, 4$
- Two template sets:
 - ALL templates
 - Γ -invariant (SCALABLE) templates
- **Paper evaluates:**
 - Runtime & scalability (Table 4)
 - Diagnostic quality (Table 5)

Replication Setup & Experience

What the authors provided

- Executable Python implementation
- Event logs and constraint libraries in JSON format

How we replicated the experiments

- Used the same datasets and template repositories
- Ran the experiments for $k = 2, 3$, and 4
- Collected both performance and diagnostic outputs

Main challenges

- Experiments become very slow for larger k
- High memory and computation cost
- Careful setup was needed to avoid re-running expensive steps

Replication Results (Table 4)

- As k increases:
 - Number of constraints increases rapidly
 - Runtime increases strongly
- Γ -invariant templates:
 - Much faster
 - Much fewer constraints

ALL Templates							Γ -Invariant (SCALABLE) Templates				
DS	max k	#inst	tsat (s)	#sat	tmin (s)	#min	#inst	tsat (s)	#sat	tmin (s)	#min
RF	2	8531	1.25	1295	17.73	227	3386	0.27	511	15.67	141
RF	3	50075	8.46	19653	130.96	221	13772	1.34	1244	18.77	149
RF	4	683315	144.77	336991	3387.55	494	140420	12.55	21927	1204.22	464
BPI-15	2	9442	26.24	444	7.46	242	3763	4.09	148	1.85	109
BPI-15	3	49042	88.48	11147	104.36	1112	13663	20.86	170	2.37	109
BPI-15	4	555922	1798.74	221355	4 152.14	1953	115039	56.68	9632	1581.3	554

Replication Results (Table 5)

- Diagnostic behavior matches the paper
- More constraints → richer explanations
- Γ -invariant templates:
 - Slightly fewer explanations
 - Still good diagnostic quality

DS	Templates	dev	det k=2	det k=3	det k=4	mov	expl k=2	expl k=3	expl k=4	avg k=2	avg k=3	avg k=4
RF	ALL	995	994	995	995	4 489	4 448	4 489	4 489	3.8	4.29	9.73
RF	Γ (SCALABLE)	995	992	995	995	4 489	3 914	4 238	4 238	3.47	3.97	8.68
BPI-15	ALL	70	70	70	70	110	108	108	108	2.34	2.46	7.3
BPI-15	Γ (SCALABLE)	70	70	70	70	110	108	108	108	2.17	2.17	5.8

Additional investigation (beyond the paper)

- We intentionally kept the diagnostic verification step enabled during all runs
- This allowed us to measure **end-to-end execution cost**, not only discovery time
- We analyzed how this affects runtime across:
 - different k values
 - ALL vs Γ -invariant templates
- This highlights a practical trade-off between:
 - fast constraint discovery
 - full diagnostic execution

Conclusion & Limitations

Replication outcome

- We successfully replicated the quantitative evaluation (Tables 4 and 5)
- The main scalability and diagnostic trends reported in the paper were confirmed

Limitations and future work

- Experiments were run on different hardware
- Large k values lead to very long runtimes
- Future work could include:
 - applying the approach to new datasets
 - comparing with other conformance tools

Work Distribution

All members contributed to the project. We jointly suggested and selected the paper, read and discussed it, planned the replication approach, reviewed the results, and refined the final presentation. Primary responsibilities were:

- Aziz Massomi – Coordination, environment setup, and troubleshooting replication issues.
- Fatemehsadat Sepehrihosseini – High-level paper summary and writing up the technical approach.
- Khalifa Nikzad – Running the replication, organizing outputs, and trying extra experiments for more insights.
- Irdi Kuka – Analyzing results and comparing them with the paper's reported findings.
- Shogofa Nawrozi – Final slide structure, assignment requirement checks, and final presentation polishing.
- Link to repository: [GitHub](#)