How Much Event Data Is Enough?

A Statistical Framework for Process Model Discovery

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Processes and Events

Automated control
of business processes

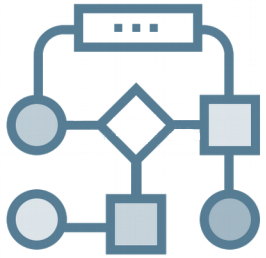
Recording of process
execution information

Event logs:
- Timestamps
- Case IDs
- Activity IDs
- …

The Question of Process Discovery

Event log

Discovery



Process model

Efficiency of process discovery becomes increasingly important

Pervasiveness of data sensing/logging

- => Large-scale event logs
- Tuning a large range of parameters of discovery algorithms
- => Repeated, exploratory analysis
- Software-as-a-Service solutions for process discovery
- => Online handling of event logs

A View on Related Work

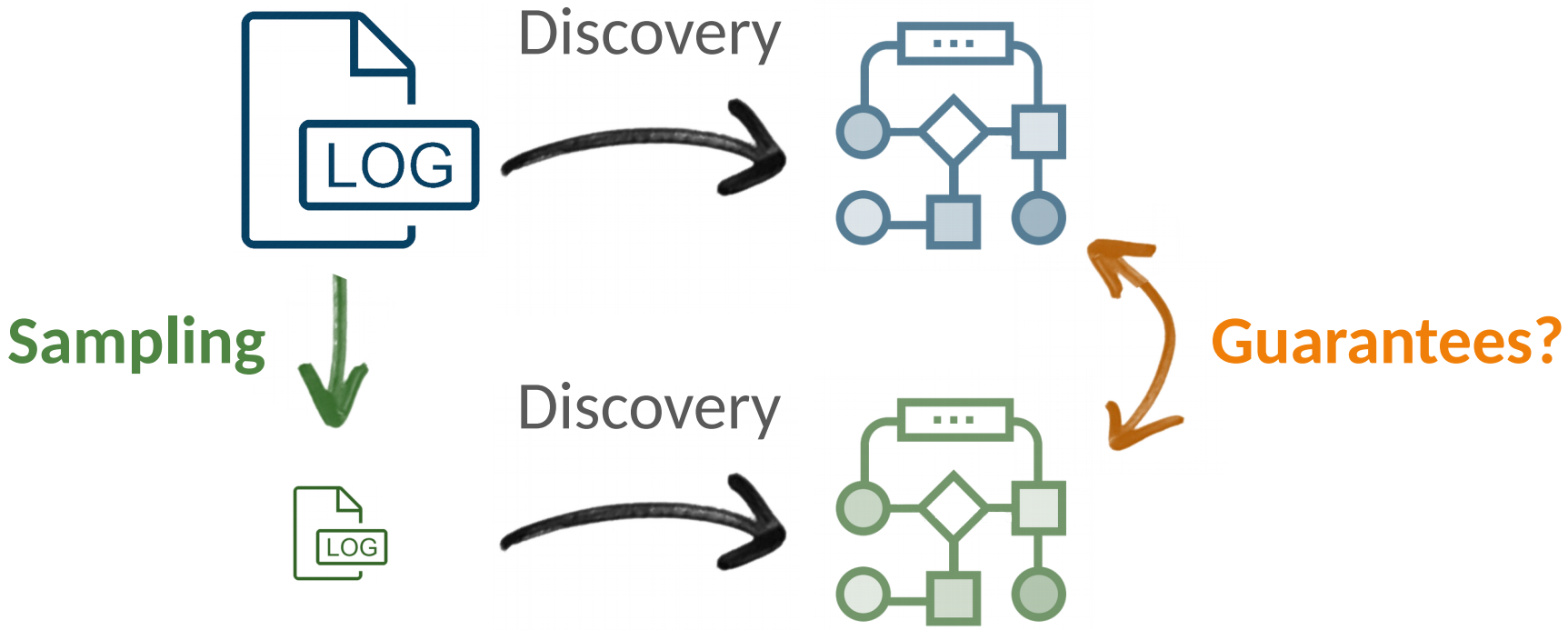
Plethora of discovery algorithms [Augusto et al. 2017]

Striving for scalability

- By divide-and-conquer: Decompose the discovery problem [van der Aalst & Verbeek 2015]
- By parallelization and distribution [Wang et al. 2015, Evermann 2016]

Recently: Idea of sampling event data [Busany & Maoz 2016]

Daring the Gap



How to determine how much of an event log to use to discover a process model?

Agenda

Background and Related Work on Process Discovery

A Statistical Framework for Process Discovery

- Log sampling
- Framework definition

Instantiating the Framework

- For control-flow discovery
- For performance discovery

Experimental Results

Log Sampling

- We want to stop when new information is unlikely
  - Log L, sampled Log $L' \subseteq L$
  - Trace abstraction function Ψ(ξ)
  - boolean predicates γ(L' ,ξ)
    - γ(L' ,ξ) ⇔ $\Psi(\xi) \notin \bigcup \Psi(\xi')$
    - γ(L' ,ξ) ⇔ d($\Psi(\xi), \bigcup \Psi(\xi')$) > ε

- $L' \subseteq L$ is (δ, ε, Ψ)-discovery sufficient if for newly sampled trace ξ:
  - P(γ(L',ξ) = 1) < δ

This is our Stopping criteria!

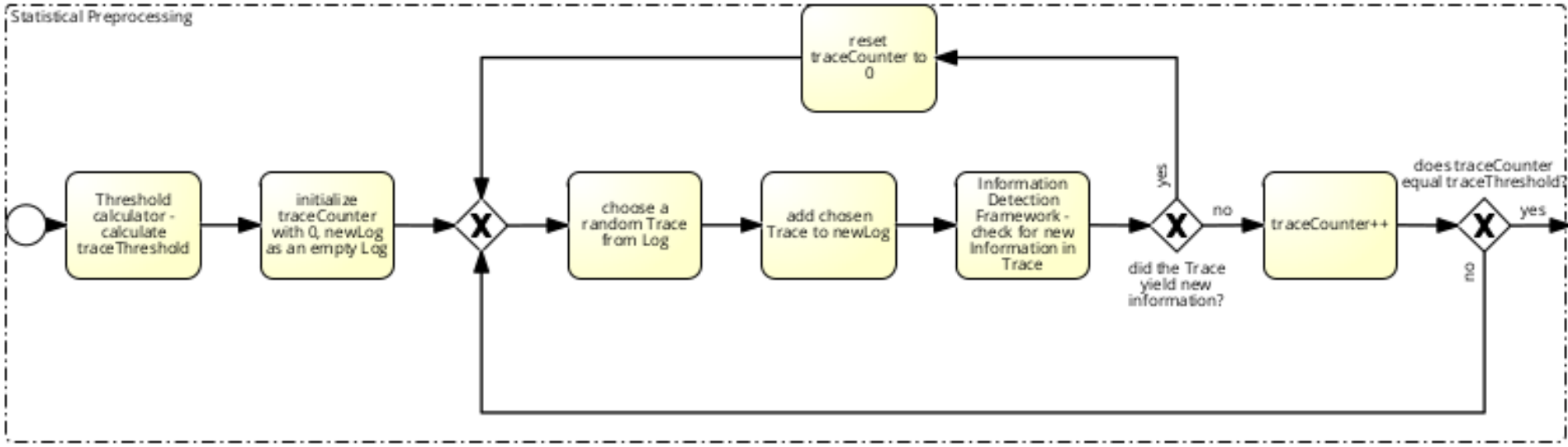
Minimum Sample Size

- „The longer we see no new information, the more likely it is that we have seen everything we need“
  - Each consecutive Trace Sampling until new Information is a binomial trial (parameters p, k, N)
    - Interval estimation can compute bounds for unknown p
    - rearranging interval for N, setting k=0, and p=δ we can compute smallest N for which p<δ holds
- BILD DER FORMEL
- For α=0.01 and δ=0.05 => N_min=128
  - After 128 consecutive trials without new information we stop

Sampling as multiple Binomial Trials

Trace #	Activities	New Info?	New binTrial?	Stop Sampling
1	A,B,C	Yes	Yes	No (1)
2	A,B,C	no	No	No (2)
3	A,B,D	Yes	Yes	No (1)
4-120	A,B,D	no	no	No (117)
121	A,B,E	Yes	Yes	No (1)
122-250	A,B,E	no	no	Yes (128)

Framework


Statistical Preprocessing
reset traceCounter to 0
Threshold calculator - calculate traceThreshold
initialize traceCounter with 0, newLog as an empty Log
choose a random Trace from Log
add chosen Trace to newLog
Information Detection Framework - check for new Information in Trace
yes
no
did the Trace yield new information?
traceCounter++
does traceCounter equal traceThreshold?
yes
no

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Control-Flow Perspective

A notion of “new control-flow information”

- New activity
- New directly-follows dependency
- New initial or final activity

Trace	New Information
A, B, C	Activity, Start, End, DF
A, B, D	Activity, End, DF
B, C, C	Start, DF
A, B, C, C	-

What about frequencies?

- Determine on sample (no guarantee on δ-similarity)
- Changes in relative frequencies are “new information”

Performance Perspective

Focus on cycle time of a process, a fine-grained numerical value

A notion of “new cycle-time information”

- Cycle time is more than ε-different
- Measuring granularity:
  - Per complete process
  - Per individual activities

A (30 ms), A (30 ms), A (30 ms)
A (30 ms, A (30 ms)

A (30 ms), A (10 ms)
A (5 ms) A (25 ms)

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Setup

Datasets

- BPI Challenge 2012
  - Loan/overdraft applications
  - >262k events of >13k traces
- BPI Challenge 2014
  - Incident management at Rabobank Group ICT,
  - >343k events of >46 traces

Discovery algorithm

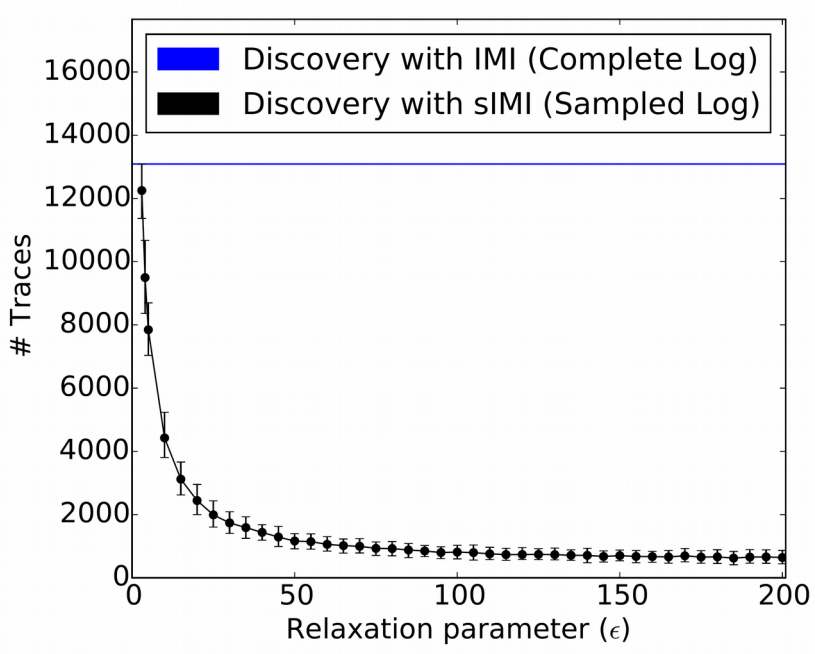
- Inductive Miner Infrequent [Leemans et al. 2013]
- Noise threshold set to 20%

Approach implemented as a ProM plugin (@Github)

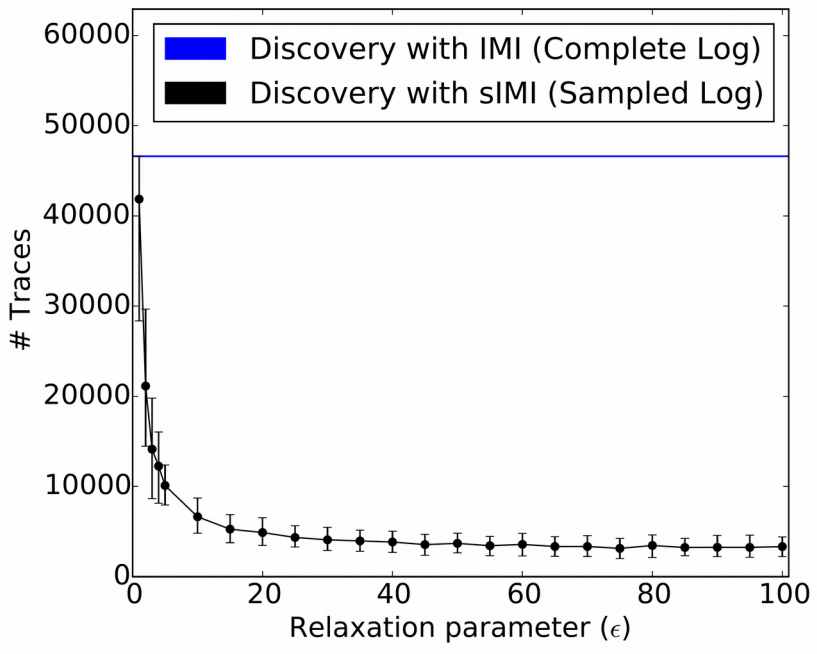
Measures

- Pre-processing effectiveness: #traces sampled
- Actual efficiency: runtime, memory footprint

Pre-Processing Effectiveness



BPI-2012

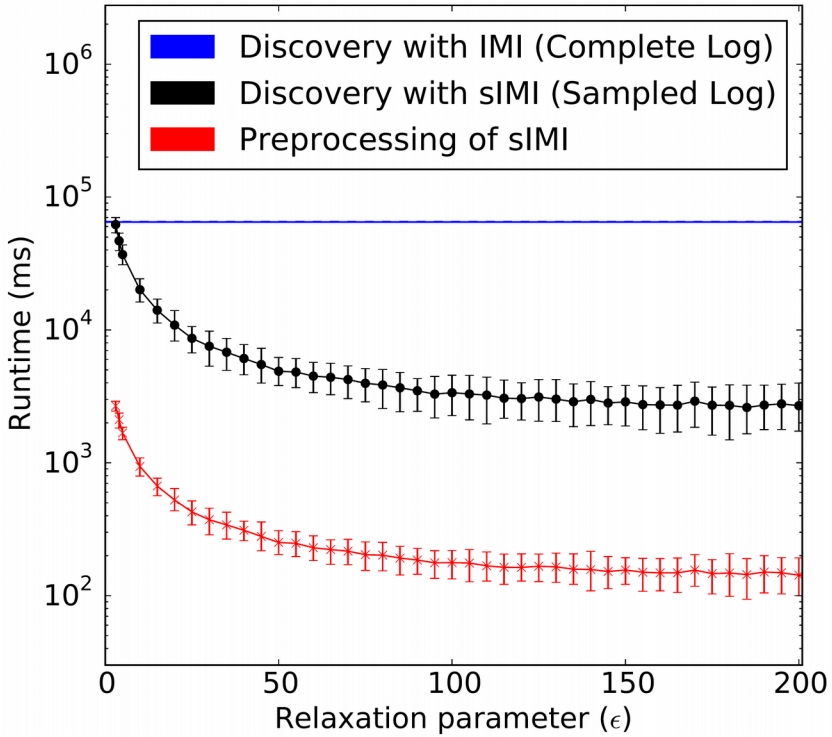


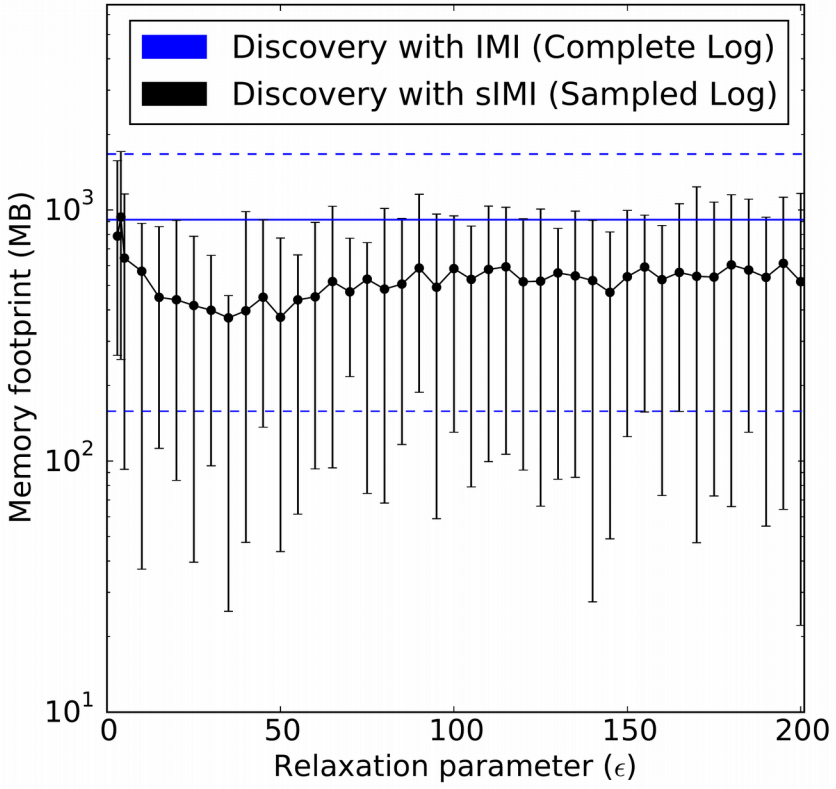
BPI-2014

Drastic reduction of number of traces considered for discovery

Trend is consistent for different datasets

Runtime and Memory Footprint

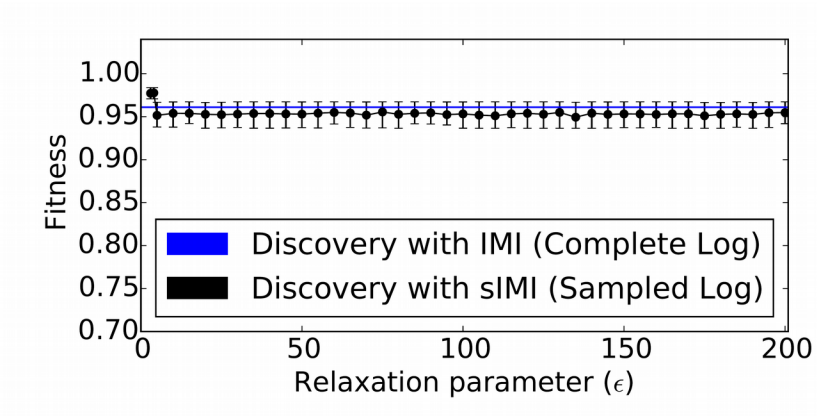


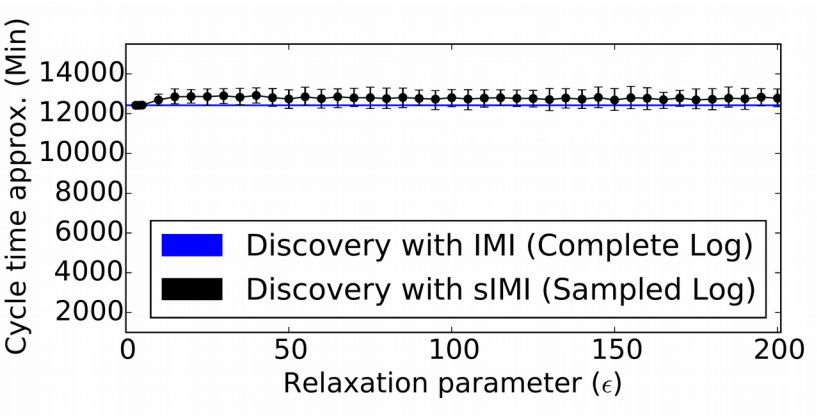


Pre-processing is efficient

Significant reduction of overall resource utilisation

Discovery Effectiveness





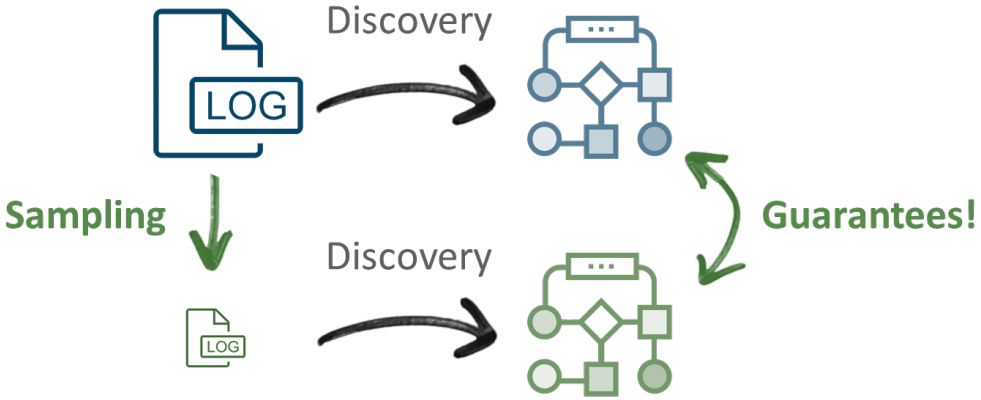
Negligible degradation of discovery quality

- For control-flow fitness
- For the cycle time approximation

Conclusions

Framework for statistical process discovery

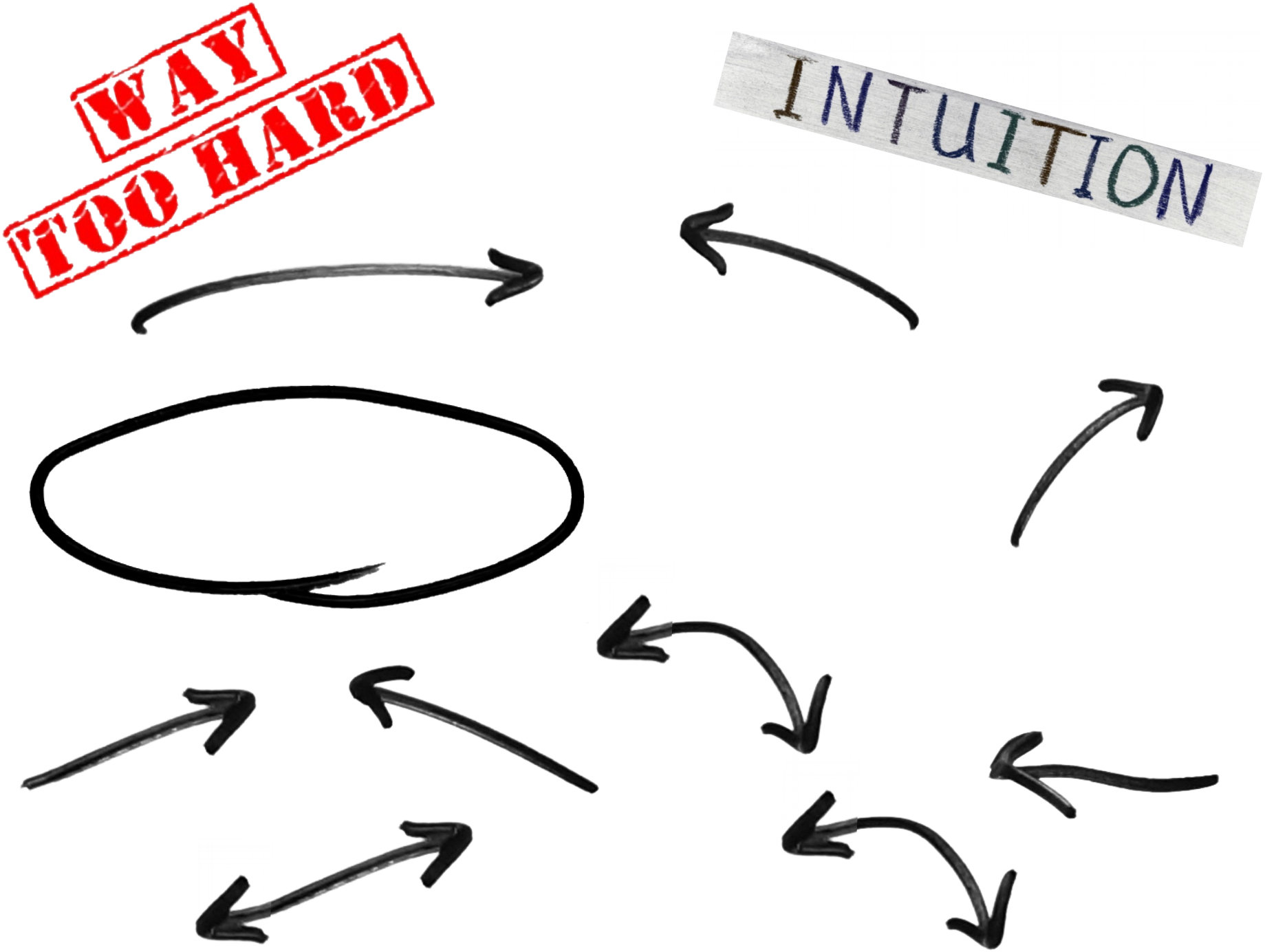
- Sample an event log
- Guarantees on the
- introduced error



Instantiation for control-flow and performance aspects

Next: Additional model perspectives

Thank you!


WAY
TOO HARD
INTUITION