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Leading-edge, open-source process mining

Accurate and Reliable What-If Analysis of Business Processes: Is it Achievable?

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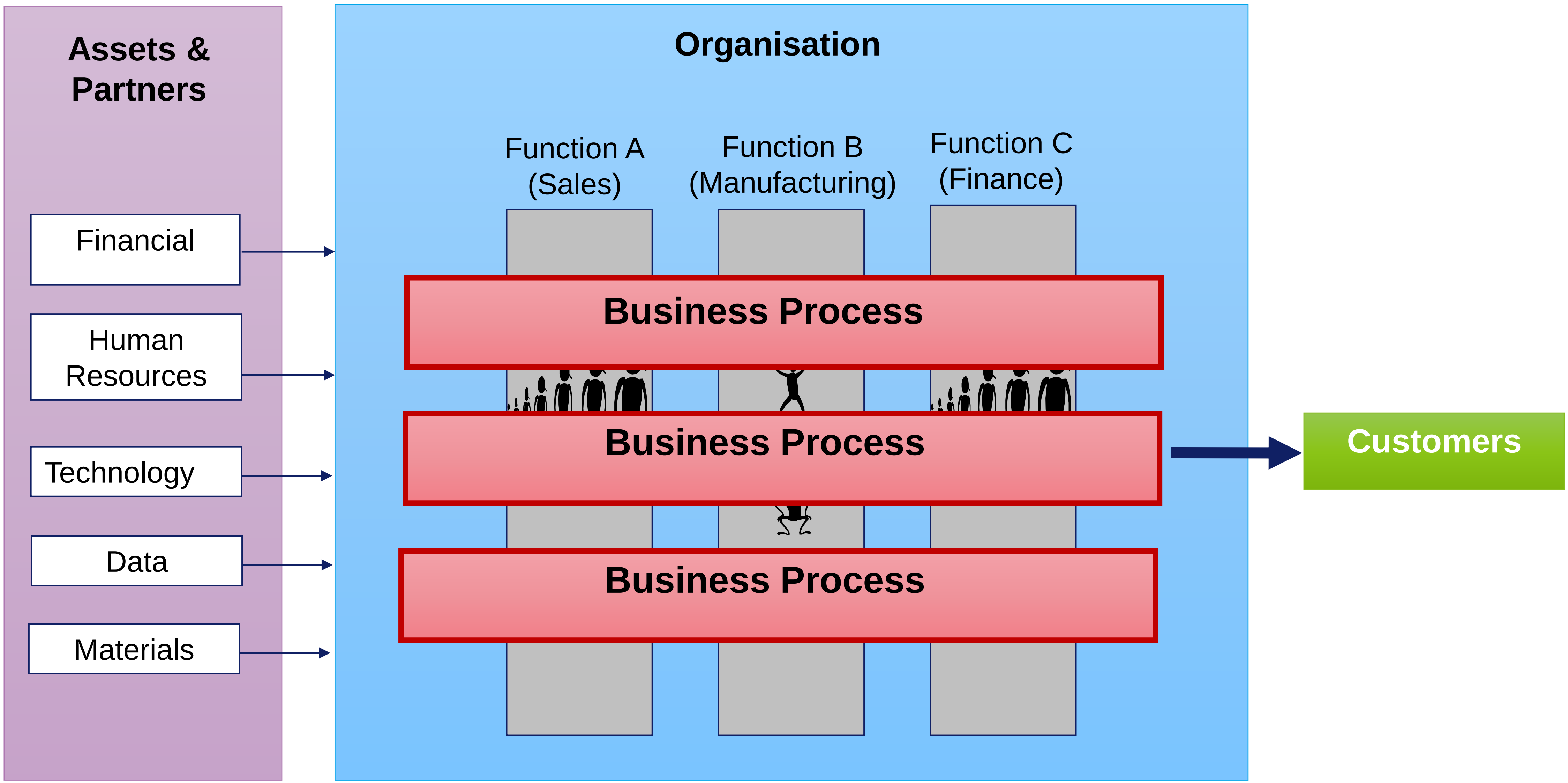
With contributions by Manuel Camargo and Oscar González-Rojas


Issue delivery receipt
Load truck
Package products
Issue invoice
Prepare shipment
Schedule payment
Schedule delivery
Check & confirm PO
Unload truck
Notify shipment
Obtain PO confirm.
Match incoming payment
Check Invoice
Request PO change

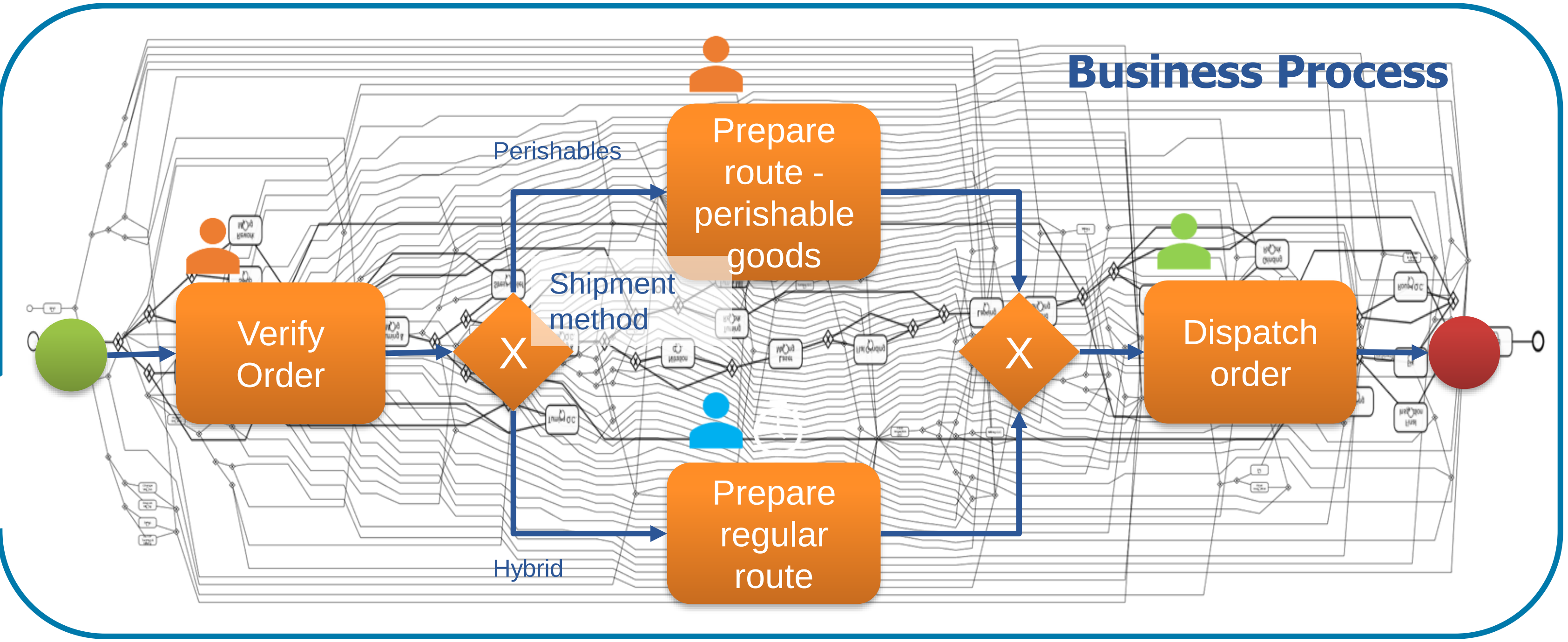
Business processes




PO received
Check & confirm PO
Package products
Load truck
Notify shipment
Issue invoice
Match payment
Payment made
PO issued
Obtain PO confirm.
Schedule delivery
Unload truck
Issue delivery receipt
Check invoice
Schedule payment
Goods arrived

“What-If” Business Process Analysis

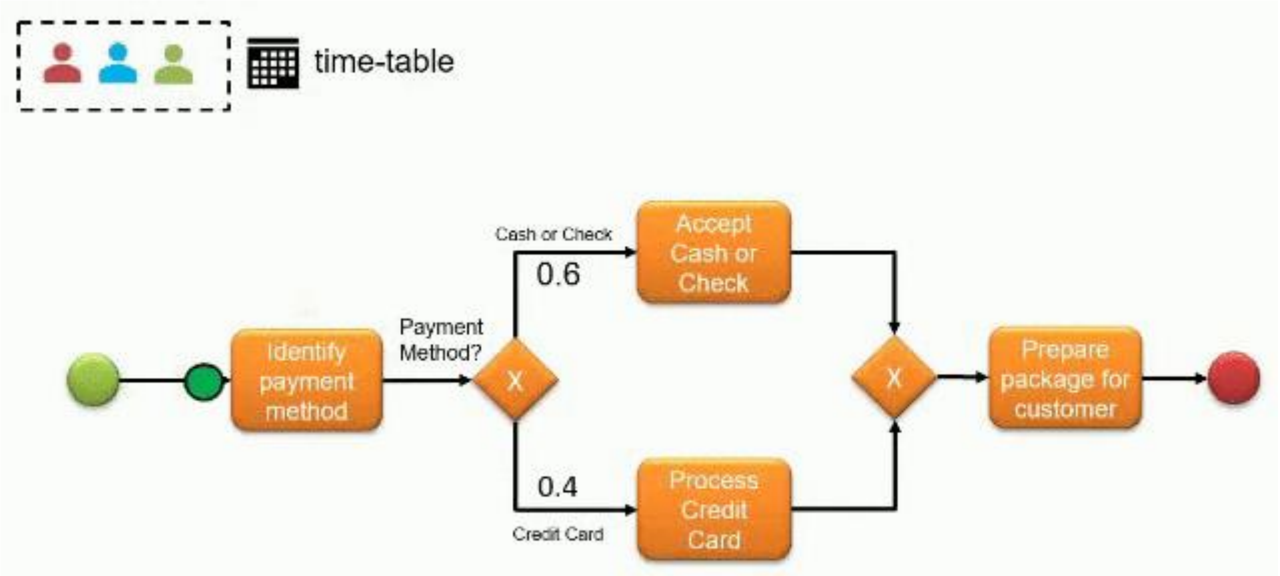
- ➢ Reallocate resources
- ➢ Automate tasks
- ➢ Parallelize activities
- ➢ Modify the sequence flow
- ➢ Increase de process demand



Process Managers(s)
Business Analyst(s)

How to determine if a given process change would improve a business process, and by how much?

The Traditional Answer: Business Process Simulation



Cycle time

1h

Processing / Waiting times

Identify payment method 20 / 5 min

Accept Cash or Check 18 / 8 min

Process Credit Card 5 / 2 min

Prepare package for customer 10 / 5 min

Resource utilization

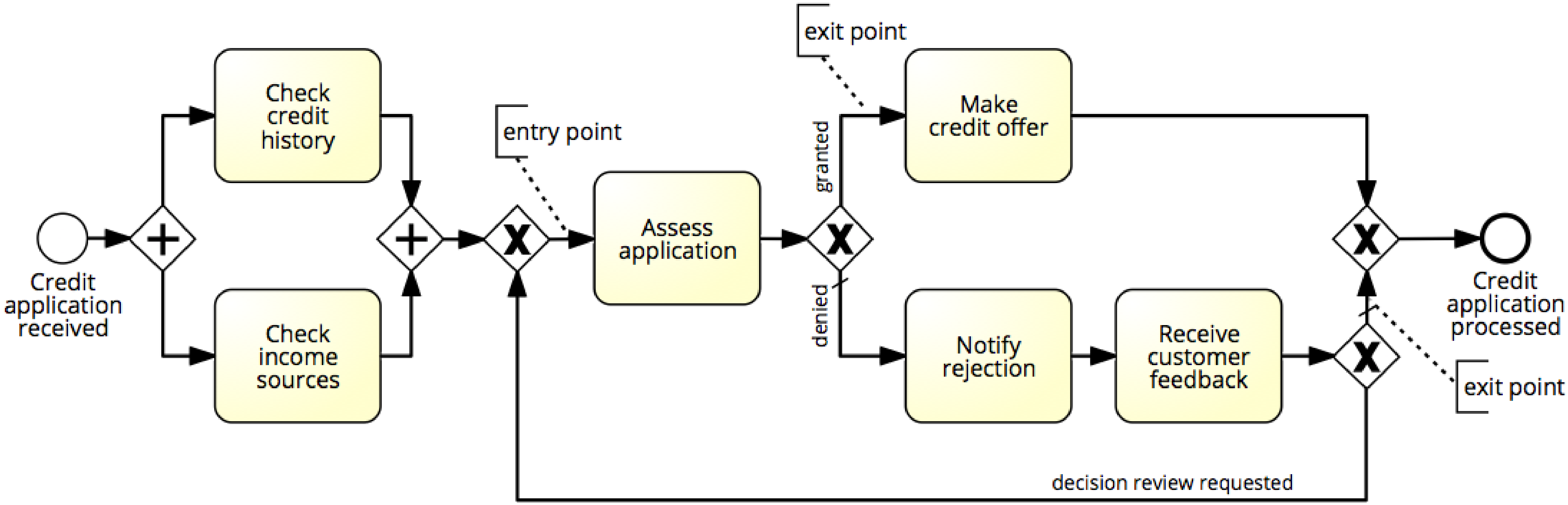
38 min

5 min

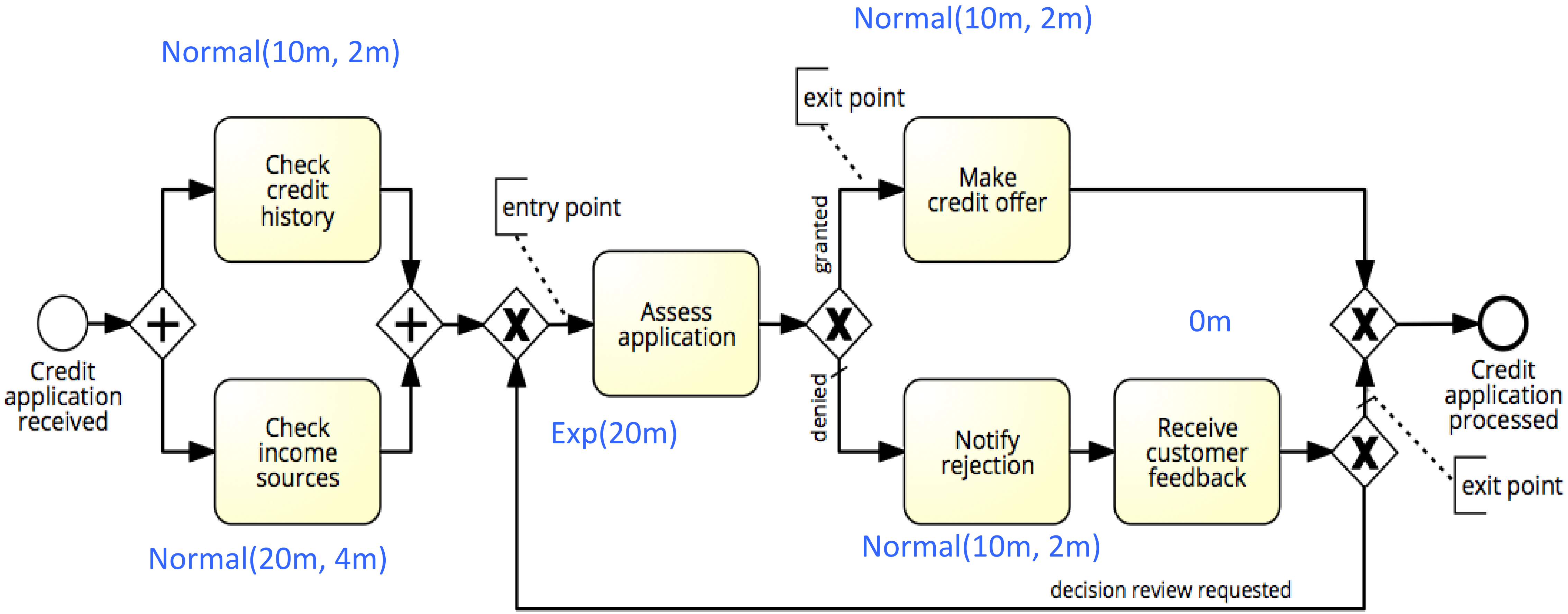
10 min

Costs x activity x resource …

Starting Point: Business Process Model

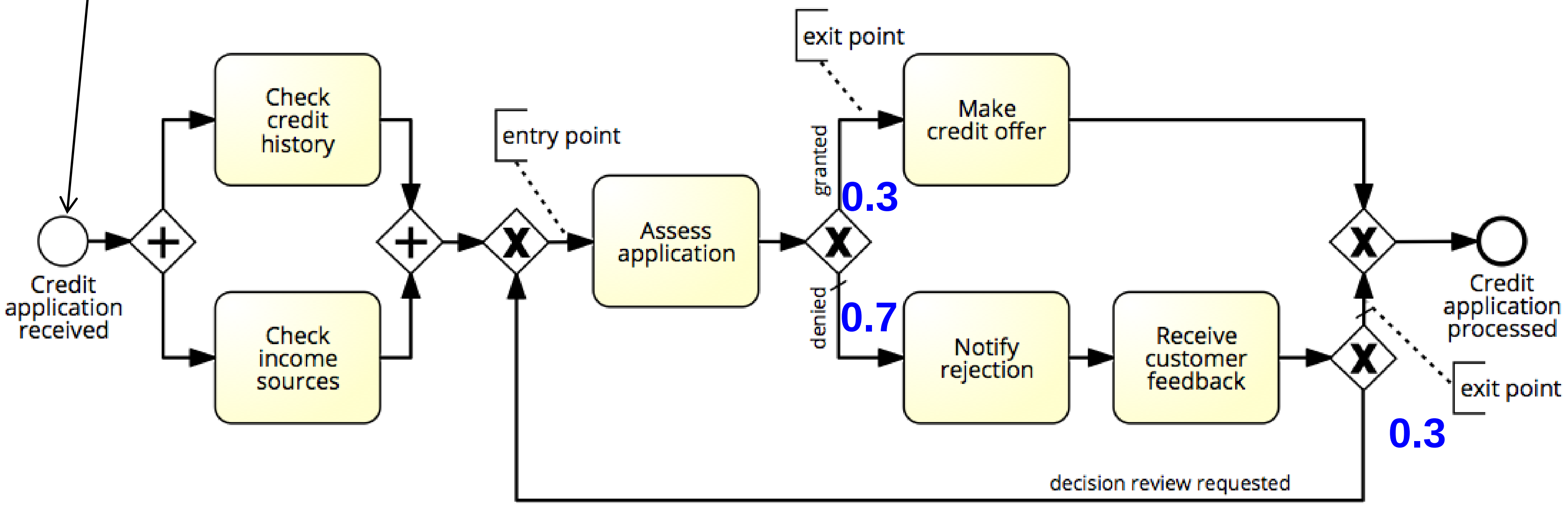


1. Specify Processing Times



2. Specify arrival process & branching probabilities

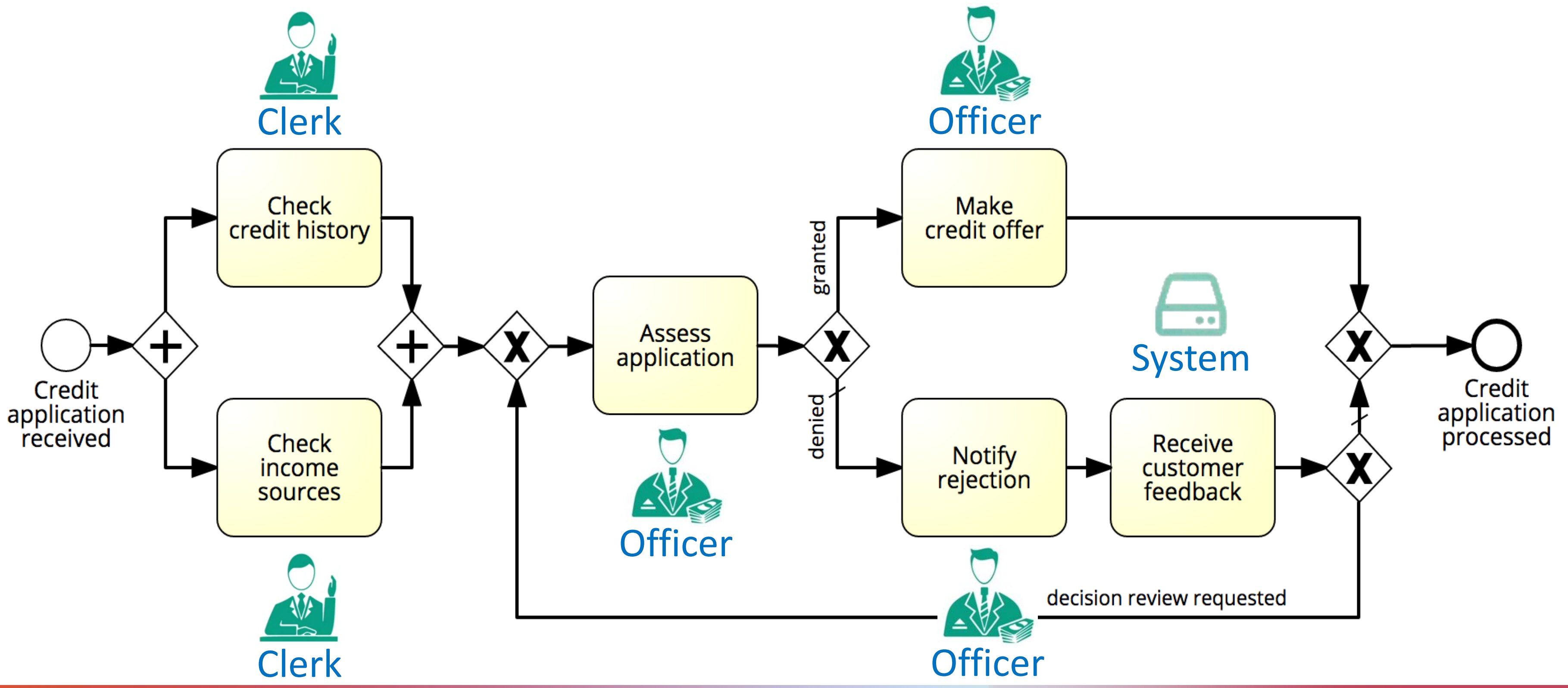
Arrival rate = 2 applications per hour
Inter-arrival time = 0.5 hour
Negative exponential distribution
From Monday-Friday, 9am-5pm



3. Specify resource pools & task-to-pool assignment

<u>Clerk</u>
€ 25 per hour
Mon-Fri, 9am-5pm

<u>Credit Officer</u>
€ 35 per hour
Mon-Fri, 9am-4pm



Business Process Simulation: Assumptions

The process model is authoritative (always followed to the letter)

- No deviations
- No workarounds

The simulation parameters accurately reflect reality

- …whereas in reality, they are often guesstimates

A resource only works on one task instance at a time / a task is performed by one resource

- No multi-tasking / no multi-resource tasks (teamwork)

Resources have robotic behavior (eager resources consume work items in FIFO mode)

- No batching
- No tiredness effects, no interruptions, no distractions beyond “stochastic” ones

Undifferentiated resources

- Every resource in a pool has the same performance as others

No time-sharing outside the simulated process

- Resources fully dedicated to one process

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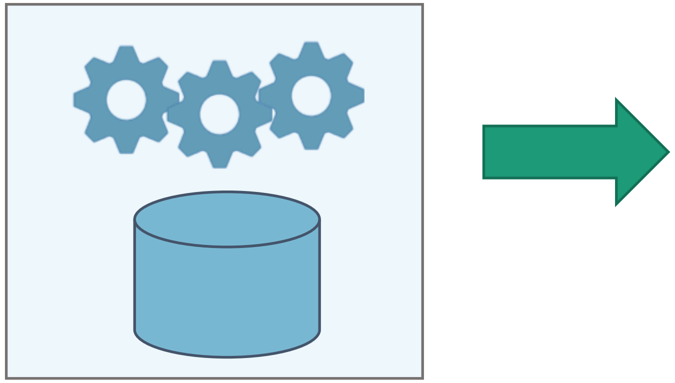
End Result

Business process simulations based on incomplete models, guesstimates, and simplifying assumptions are not faithful

→ adoption of business process simulation is disappointing

Data to the Rescue!

Enterprise System
(CRM, ERP, ...)



Event Log

Case ID	Timestamp	Activity	Resource	Loan goal	Requested amt	Offered amt
C001	18-10-2016	Check completeness	Sue	Mortgage	100 000	-
C001	19-10-2016	Check credit history	Sue	Mortgage	100 000	-
C001	19-10-2016	Calculate risk score	Bob	Mortgage	100 000	-
C001	20-10-2016	Make offer	Mike	Mortgage	100 000	70 000
C001	25-10-2016	Make offer	Mike	Mortgage	100 000	80 000
C002	20-10-2016	Check completeness	Sue	Car	15 000	-
C002	20-10-2016	Check credit history	Sue	Car	15 000	-
C002	22-10-2016	Calculate risk score	Elsa	Car	15 000	-
C002	24-10-2016	Reject application	Elsa	Car	15 000	-
C003	02-11-2016	Check completeness	Maria	Mortgage	30 000	-
C003	04-11-2016	Ask for additional data	Maria	Mortgage	30 000	-
C003	10-11-2016	Check credit history	Maria	Mortgage	30 000	-
...	...	...	...	...	...	...

Problem Statement

Given

- one or more business processes, for which we have:
  - one or more process specifications and/or
  - event logs generated by the execution of the processes on top of one or more information systems.
- one or more process performance measures of interest (e.g. cycle time, resource cost)
- One or more changes to the process (<u>interventions</u>)

Predict

- Predict the values of the process performance measures after the given interventions.

Non-Functional Requirements

Predictions accurate.

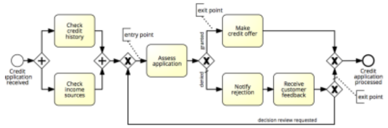
Accuracy may be measured e.g. via an error between the predicted and the actual performance measures after intervention.

Predictions should be accompanied by a reliability estimate. In most cases, the reliability is high.

Reliability could be captured, e.g. by confidence intervals

Data-Driven Business Process Simulation

Process Constraints or Process Model

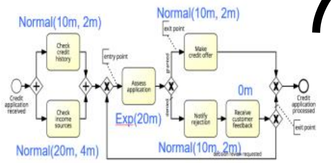


Process Change Specification

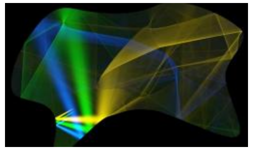
Case ID	Timestamp	Activity	Resource	Loan goal	Requested amt	Offered amt
C001	18-10-2016	Check completeness	Sue	Mortgage	100 000	-
C001	19-10-2016	Check credit history	Sue	Mortgage	100 000	-
C001	19-10-2016	Calculate risk score	Bob	Mortgage	100 000	-
C001	20-10-2016	Make offer	Mike	Mortgage	100 000	70 000
C001	25-10-2016	Make offer	Mike	Mortgage	100 000	80 000
C002	20-10-2016	Check completeness	Sue	Car	15 000	-
C002	20-10-2016	Check credit history	Sue	Car	15 000	-
C002	22-10-2016	Calculate risk score	Elsa	Car	15 000	-
C002	24-10-2016	Reject application	Elsa	Car	15 000	-
C003	02-11-2016	Check completeness	Maria	Mortgage	30 000	-
C003	04-11-2016	Ask for additional data	Maria	Mortgage	30 000	-
C003	10-11-2016	Check credit history	Maria	Mortgage	30 000	-
...	...	...	...	...	...	...

Event Log

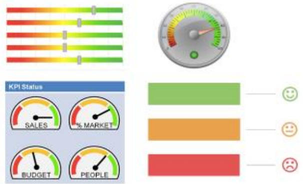
Simulation Model Learner



Simulation Model

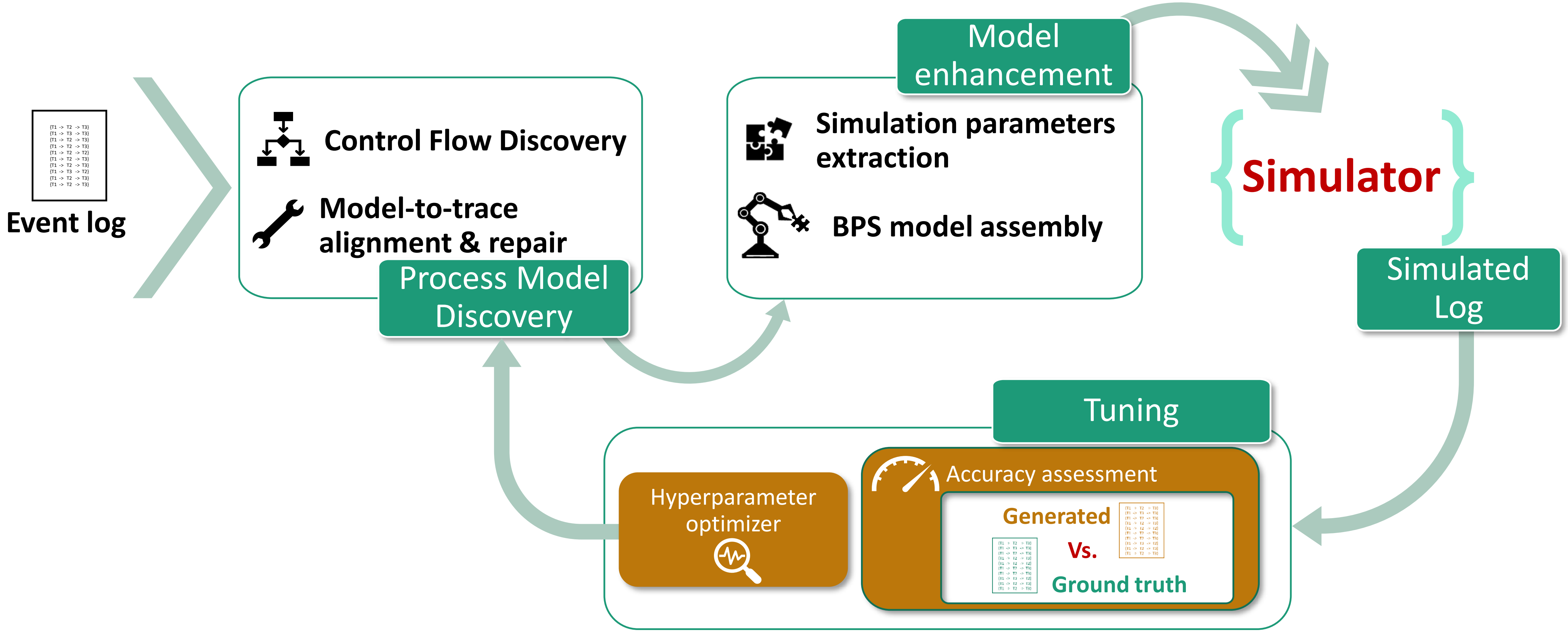


Simulation Engine



Predicted Performance Profile & Reliability Estimate

SIMOD: Simulation Model Discovery from Event Logs



https://github.com/AutomatedProcessImprovement/Simod

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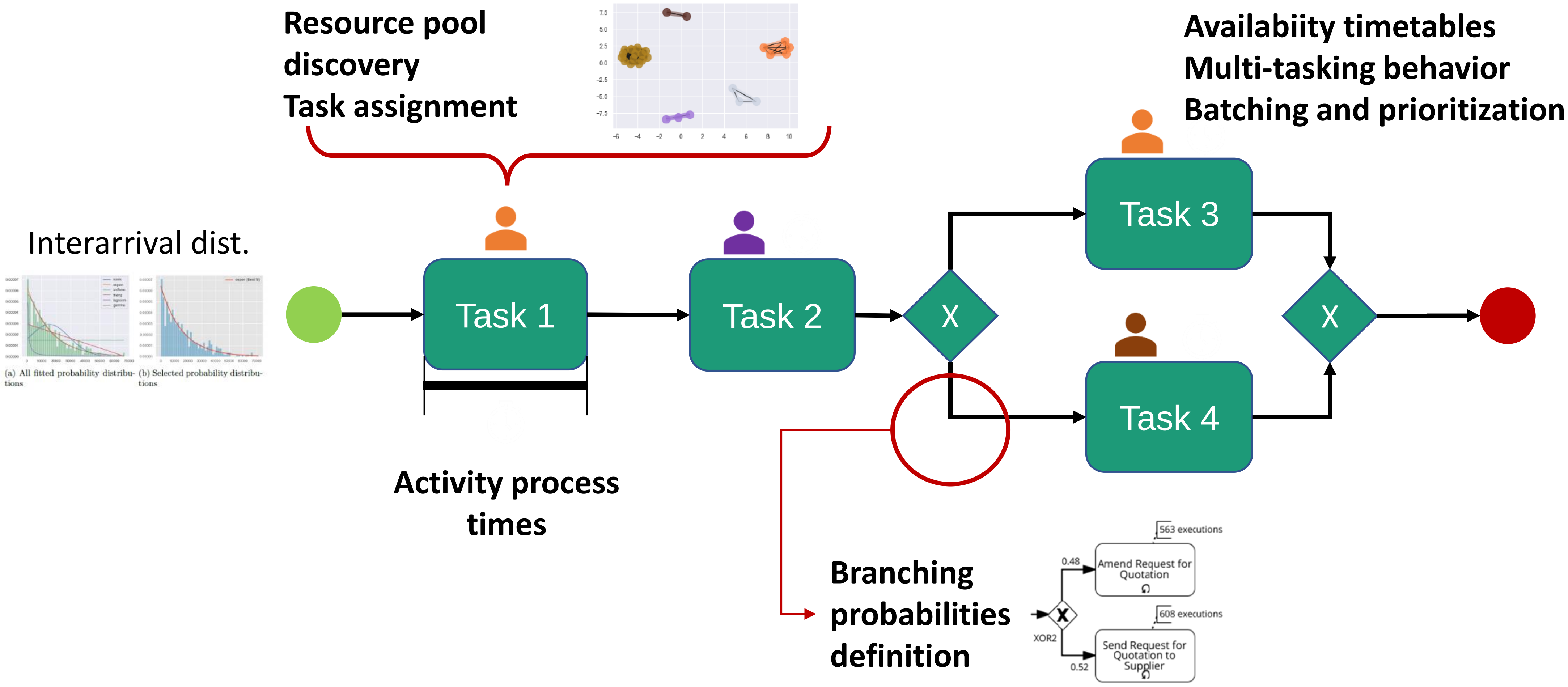
Simulation Parameters Discovery



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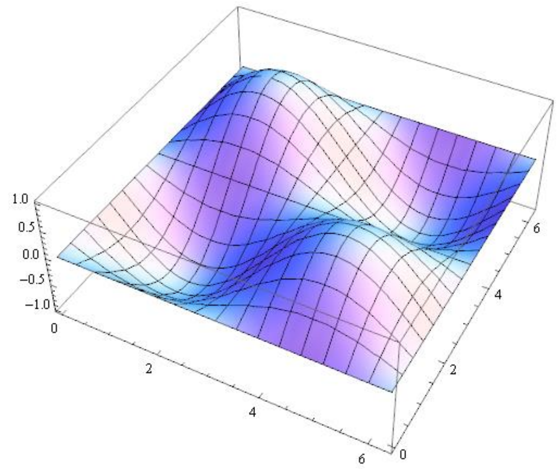
Hyper-Parameter Tuning



Phase	Category	Variable
	Control flow discovery	Parallelism threshold (ε)
		Filtering threshold (η)
		Parameters for log repair
	Simulation parameters discovery	Thresholds for resource pool discovery
		Parameters for fitting temporal distributions

Optimal alignment of complete bipartite graph Test Log x Simulation Log weighted by Damerau-Levenshtein (DL) distance, with penalty for temporal mismatch

Test Fold of Event-Log

{T1 -> T2 -> T3}
{T1 -> T2 -> T3}
{T1 -> T2 -> T3}
{T1 -> T2 -> T3}
{T1 -> T2 -> T3}
{T1 -> T2 -> T3}
{T1 -> T2 -> T3}
{T1 -> T2 -> T3}
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{T1 -> T2 -> T3}
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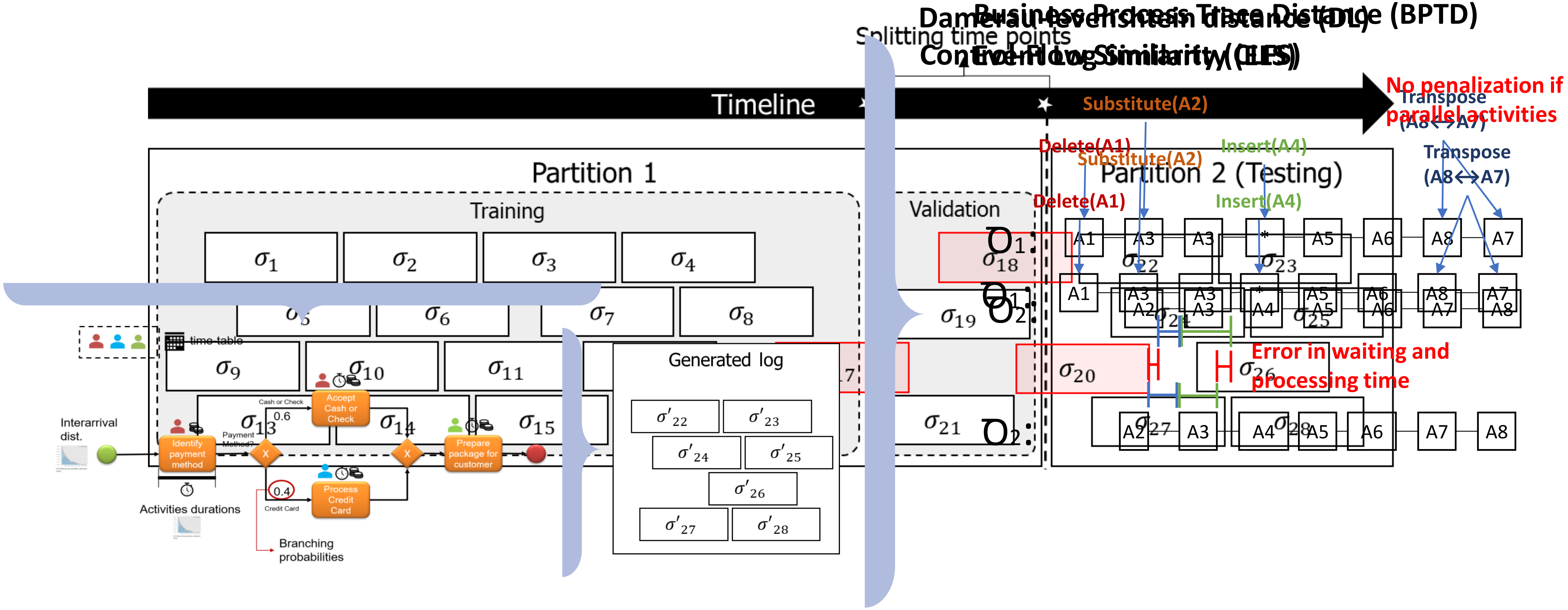
{T1 -> T2 -> T3}

Simulated Log

SIMOD: Empirical Evaluation Procedure



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SIMOD: Evaluation Results

Discover simulation model → Simulate model 10 times → Evaluate Similarity (mean string-edit distance & timed-string edit distance)

Dataset	Control-Flow Similarity (string-edit distance)	Temporal Similarity (timed-string edit distance)
Call centre	0.37	0.41
Pharmacy customer service	0.29	0.30
Purchase-to-Pay	0.55	0.57
Make-to-order manufacturing	0.65	0.69
Academic credentials recognition	0.32	0.29
Insurance claims handling	0.39	0.43
Loan Origination	0.41	0.42

We can try to fill in the glass

- Discover and add batching behavior to simulation models
- .. prioritization
- … timers and external factors (not explicit in the data)
- etc.

Or perhaps we should look for another paradigm….

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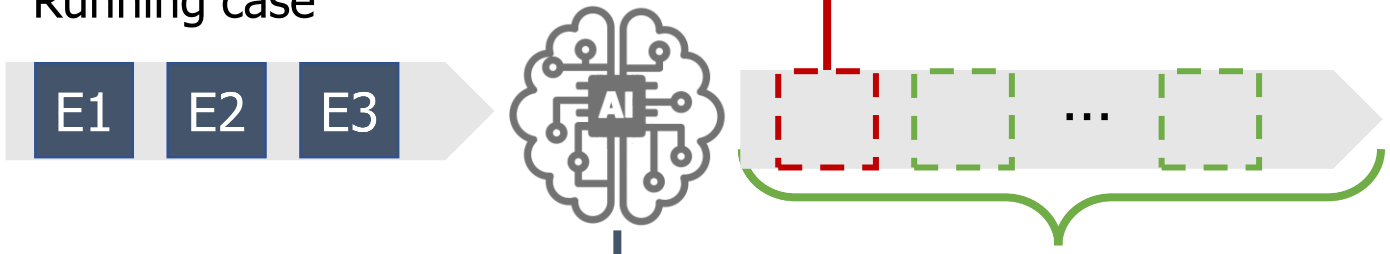
Generative Deep Learning Models of Business Processes

What is the next activity for this case?
When is this next activity going to take place?

Running case



How is going to continue this case until it is finished?
How long is this case still going to take until it is finished?

Generate a set of traces (event log)

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Generative Deep Learning Models of Business Processes

Event log

Pre-processing

Discrete features

- Embedded dimensions
- N-grams extraction
- Discovery of roles

Continuous features

- Timestamp relativization
- Scaling

Model selection & Training

Architecture selection

- Specialized
- Shared
- Concatenated

Training with examples of size 0

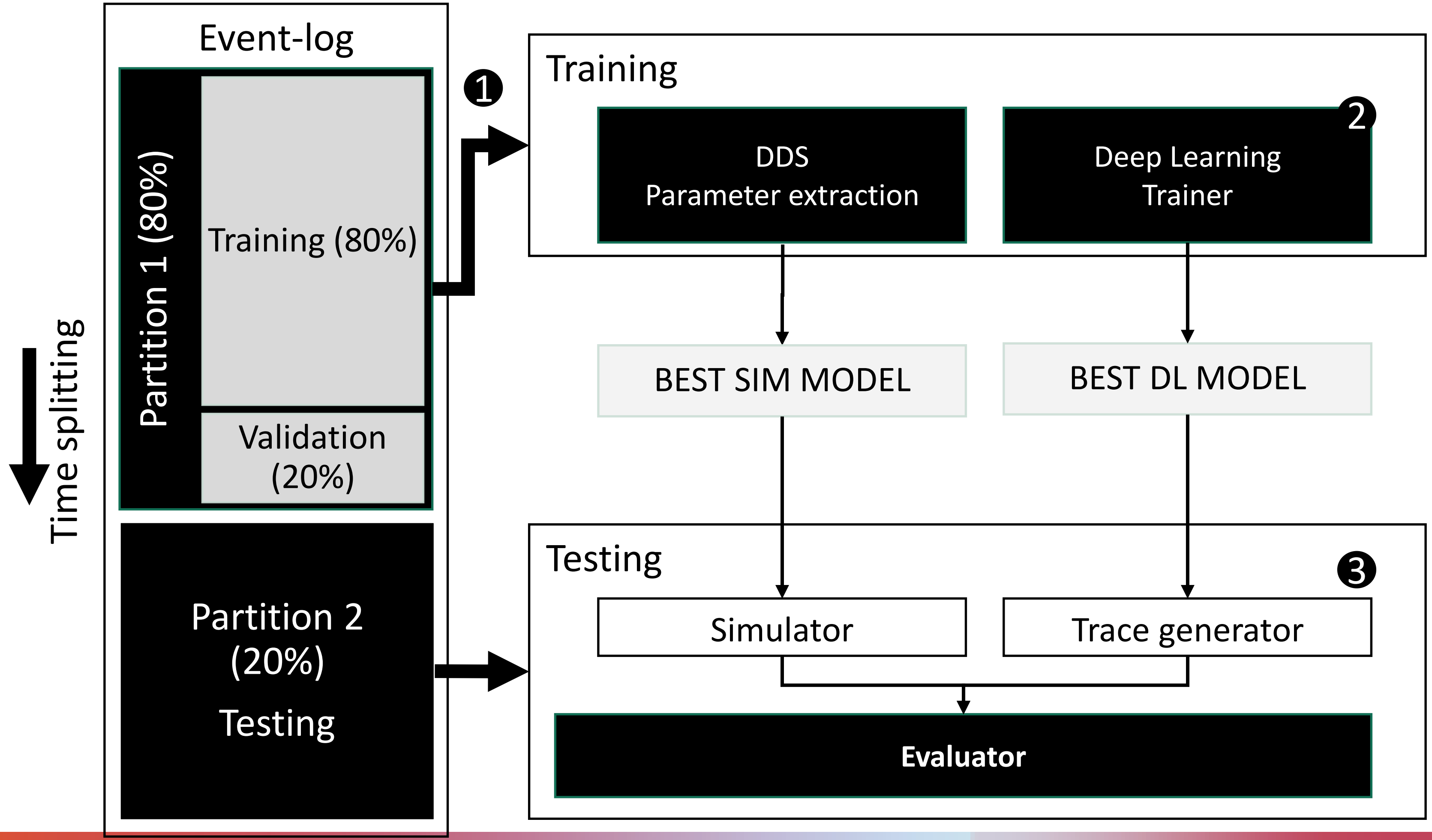
Generation & Assessment

Selection method

- Arg. Max
- Random choice

Accuracy assessment

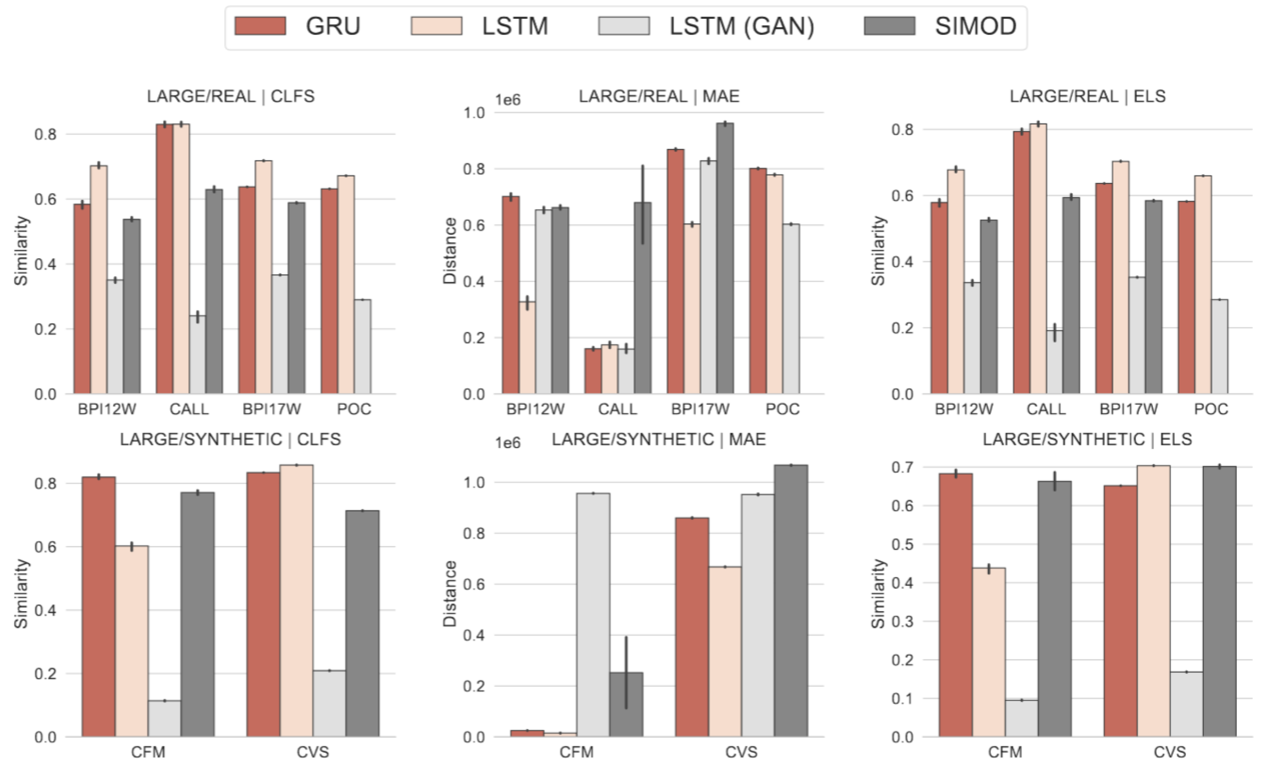
Data-Driven Simulation (DDL) vs Deep Learning (DL) Generative Models



Evaluation Results

- DDS Models (SIMOD) and DL models have comparable performance w.r.t. control-flow similarity (CLFS)
- DL models sometimes clearly outperform DDS models on temporal metrics (MAE, ELS)

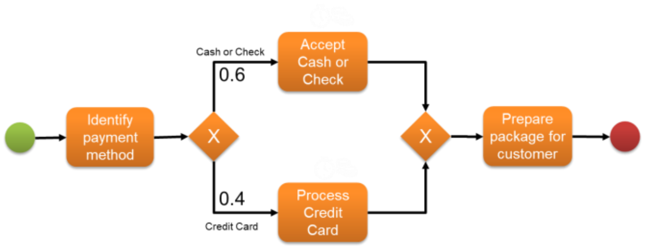
Could we combine them?

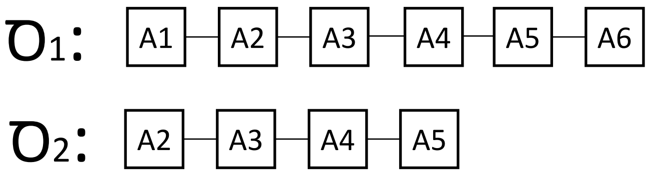


Data-Driven (Discrete Event) Simulation	Generative Deep Learning Methods
- May take as input a process specification (helps with interpretability)	- No interpretable process specification
- Takes into account resource constraints	- Does not explicitly take into account resource constraints
- Models the case creation process via a probability distribution	- Learns the case arrival process from data (univariate or multivariate models)
- Assumes undifferentiated resources with robotic behavior	- May capture differentiated resources and robotic behavior
- Models resource availability as calendars (possibly discovered from historical data)	- Models resource availability via neural networks that may capture non-linear availability functions
- Branches are selected using branching probabilities	- Branching behavior modeled via neural networks (e.g. LSTM) that may capture complex relations
- Provides a natural mechanism for capturing the effect of changes to the process	- Does not have a mechanism for capturing the effect of changes to the process

DeepSimulator: Hybrid Learning of Business Process Simulation Models

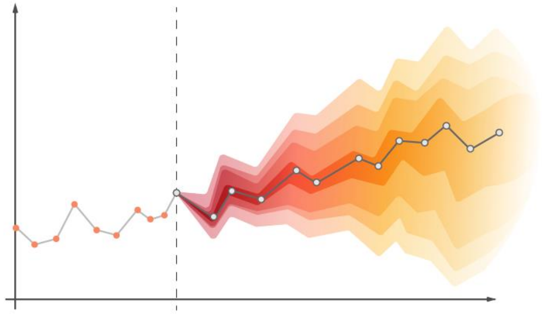
Phase 1

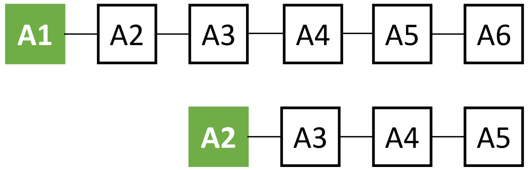




Discovering a process model to generate traces

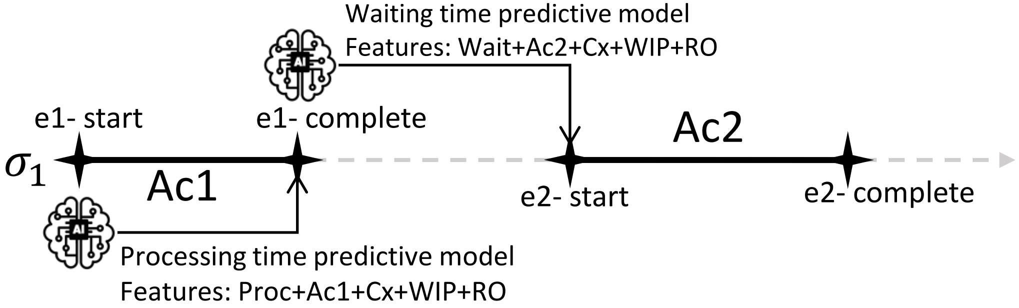
Phase 2

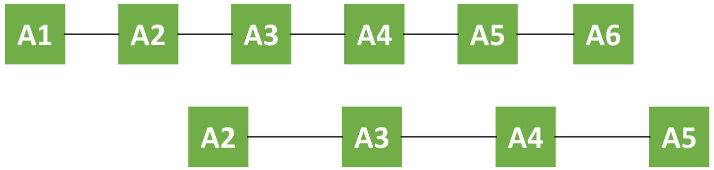




Learning a time series generator to determine when each trace starts

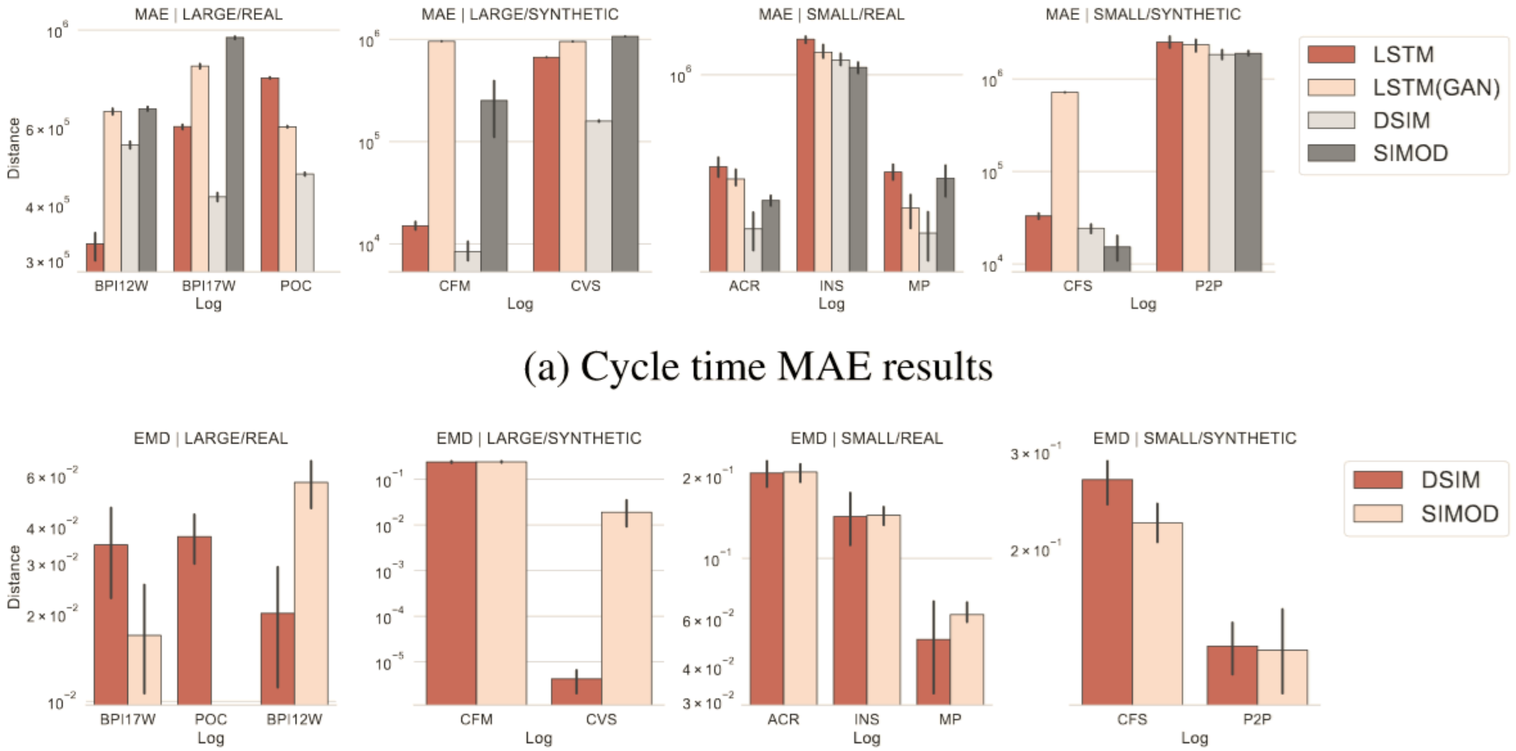
Phase 3





Deep-learning the processing time and waiting time of each activity in a given trace

EXP1 – Replicating "As-is" behavior

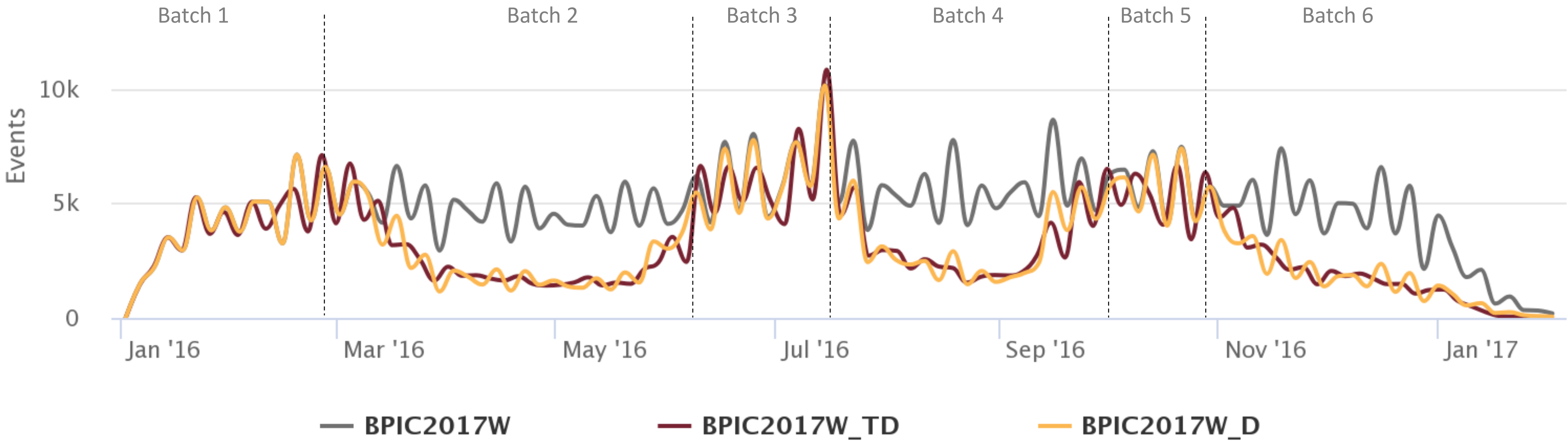


(a) Cycle time MAE results

(b) Earth Mover's Distance (EMD) results

Deep Simulation generally outperforms classical DDS in temporal measures

EXP2 – What-If the number of cases increases?



- **DeepSimulator can better estimate the impact of changes in the demand in settings where such changes have been previously observed in the data.**

EXP3 – What-If We Add an Never-Before-Seen Activity

	Log	MAE		EMD		DTW	
		SIMOD	**DSIM**	**SIMOD**	**DSIM**	**SIMOD**	**DSIM**
Scenario 1	*Version 1*						
	BPI17W	971151	***417572***	***0.02222***	0.03593	***3185***	3647
	BPI12W	660211	***534341***	0.11295	***0.04853***	515	***458***
	CVS	1489252	***467572***	0.03213	***0.00001***	3380	***849***
	Version 2						
	BPI17W	895524	***290980***	0.06438	***0.03218***	4528	***3431***
	BPT12W	550266	***524995***	0.25888	***0.22003***	726	***507***
	CVS	540112	***246159***	0.15674	***0.05708***	2453	***1967***
Scenario 2	**Log**	**MAE**		**RMSE**		**SMAPE**	
		AS-IS	**WHAT-IF**	**AS-IS**	**WHAT-IF**	**AS-IS**	**WHAT-IF**
	CFM	***7155***	17546	***22006***	33137	***0.15629***	0.28762
	CVS	***283061***	1040344	***357717***	1052255	***0.31972***	1.84601

- **The accuracy of DeepSimulator degrades when evaluated in a previously unobserved scenario (new task is added to the process)**

Wrap-Up

- There’s a long road ahead to constructing accurate and reliable simulation models from event logs
- Combination of deep learning techniques & simulation promising, but need to be further researched to become practically usable for what-if analysis
  - Extensions needed to support a wide range of interventions / changes
  - Extensions needed to provide reliability estimates (for what-if analysis)
  - More validation in large-scale scenarios

References

Limitations and pitfalls of traditional BP simulation

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Data-Driven Simulation and Deep Learning

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