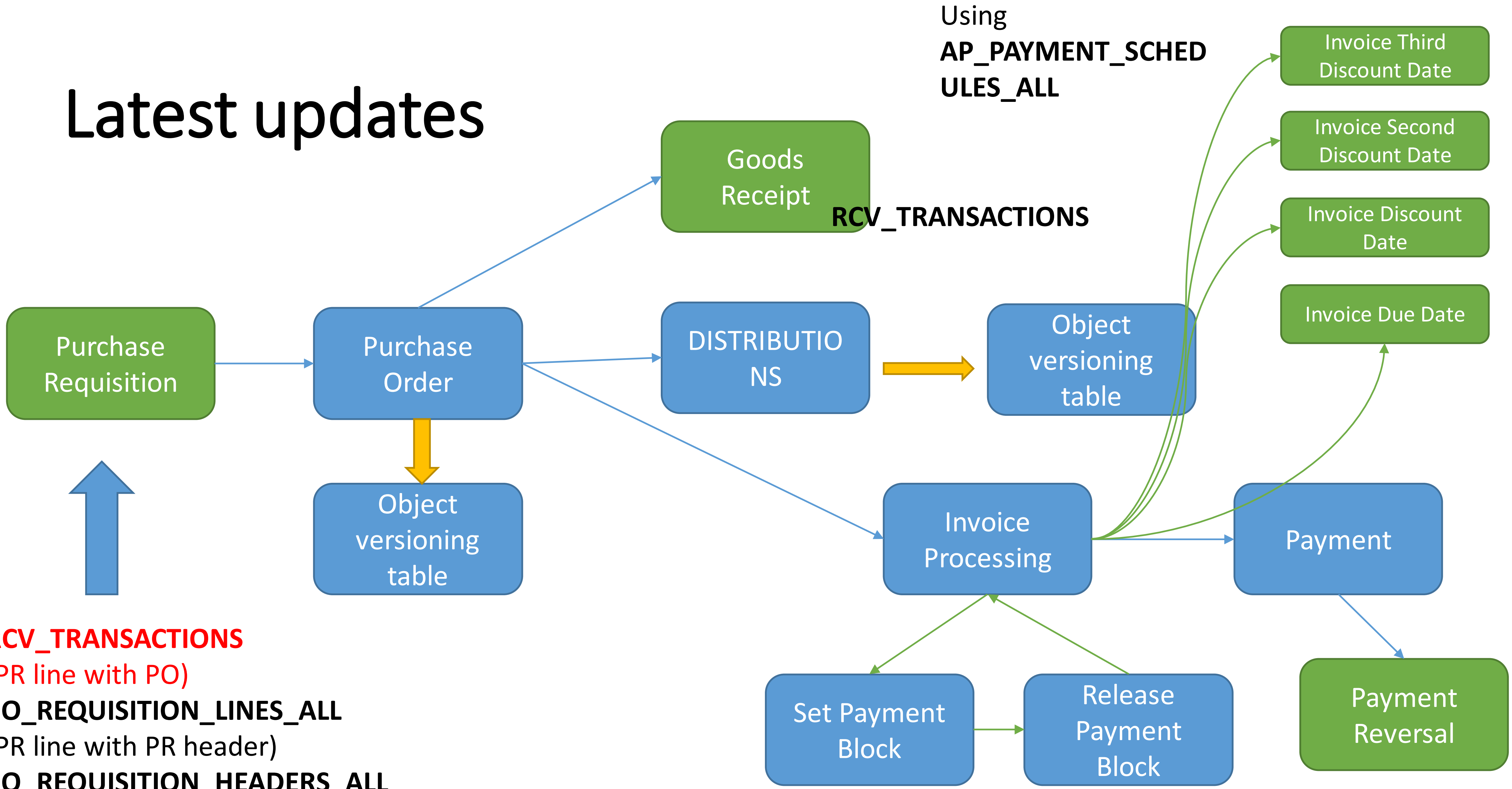
Latest updates



RCV_TRANSACTIONS
(PR line with PO)
PO_REQUISITION_LINES_ALL
(PR line with PR header)
PO_REQUISITION_HEADERS_ALL
(PR header with info about PR)

Using the reversal information in
AP_INVOICE_PAYMENTS_ALL

Application of object-centric process mining

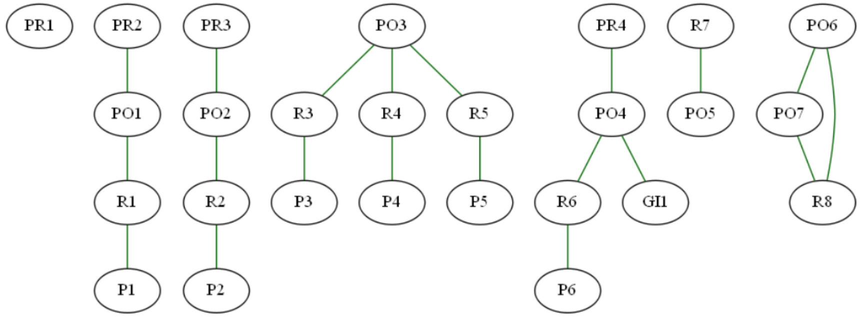
- Resolution of convergence/divergence issues:
  - More reliable frequency numbers
  - More reliable performance numbers
- Improving the machine learning applications:
  - Quality of the prediction (MAPE, RMSPE) of the remaining time, thanks to considering different interactions between objects
  - Quality of other machine learning tasks, such as anomaly detection (for example, in another case study on P2P we identified automatically maverick buying and post-mortem changes to purchase requisitions).

Convergence / Divergence Issues: the main reason behind the adoption of object-centric process mining

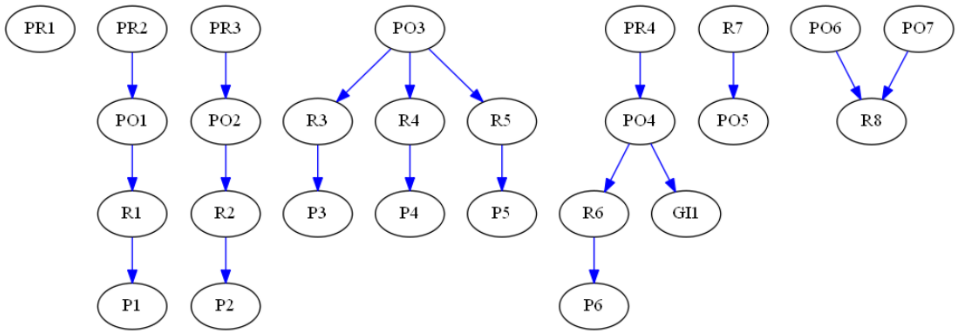
	ORDER	VENDOR	INVOICES	DISTR	REQ	PAYMENT	INVPAY
ORDER	0 35	0 1	0 4288	0 6303	0 4299	0 0	0 0
VENDOR	0 2751	0 0	0 31111	0 0	0 0	0 0	0 0
INVOICES	0 36	1 1	0 296	0 0	0 0	0 34	0 343
DISTR	1 1	0 0	0 0	0 0	0 0	0 0	0 0
REQ	1 14	0 0	0 0	0 0	0 0	0 0	0 0
PAYMENT	0 0	0 0	1 297	0 0	0 0	0 0	1 297
INVPAY	0 0	0 0	0 297	0 0	0 0	0 4	0 296

Using graph-based features to improve machine learning tasks

Ev.ID	Activity	Timestamp	Purch.Req.	Purch.Ord.	Goods Issues	Invoices	Payments
e1	Create Purchase Requisition	2021-03-20 10:30	['PR1']				
e2	Close Purchase Requisition	2021-03-20 14:00	['PR1']				
e3	Create Purchase Requisition	2021-03-21 09:30	['PR2']				
e4	Create Purchase Order	2021-03-22 14:59	['PR2']	['PO1']			
e5	Invoice Receipt	2021-03-25 11:00		['PO1']		['R1']	
e6	Perform Payment	2021-03-30 11:58				['R1']	['P1']
e7	Create Purchase Requisition	2021-04-01 09:15	['PR3']				
e8	PR Formal Approval	2021-04-01 10:15	['PR3']				
e9	Create Purchase Order	2021-04-02 17:00	['PR3']	['PO2']			
e10	Change Purchase Requisition	2021-04-03 10:00	['PR3']				
e11	Invoice Receipt	2021-04-05 15:00		['PO2']		['R2']	
e12	Perform Payment	2021-04-15 09:27				['R2']	['P2']
e13	Create Purchase Order	2021-04-17 14:29		['PO3']			
e14	Invoice Receipt	2021-04-28 10:00		['PO3']		['R3']	
e15	Perform Payment	2021-04-30 15:00				['R3']	['P3']
e16	Invoice Receipt	2021-05-28 10:01		['PO3']		['R4']	
e17	Perform Payment	2021-05-30 15:17				['R4']	['P4']
e18	Invoice Receipt	2021-06-28 10:01		['PO3']		['R5']	
e19	Perform Payment	2021-06-30 15:29				['R5']	['P5']
e20	Create Purchase Requisition	2021-07-01 11:15	['PR4']				
e21	Create Purchase Order	2021-07-02 09:38	['PR4']	['PO4']			
e22	Invoice Receipt	2021-07-09 16:00		['PO4']		['R6']	
e23	Goods Issue	2021-07-11 10:30		['PO4']	['GI1']		
e24	Perform Payment	2022-05-15 09:00				['R6']	['P6']
e25	Invoice Receipt	2022-05-20 12:00				['R7']	
e26	Create Purchase Order	2022-05-20 15:00		['PO5']		['R7']	
e27	Create Purchase Order	2022-06-01 09:17		['PO6']			
e28	Create Purchase Order	2022-06-02 11:48		['PO7']			
e29	Create Invoice	2022-06-05 09:00		['PO6', 'PO7']		['R8']	



Object Interaction Graph (detection of high number of interactions between objects of different types, e.g., maintenance contracts)



Object Creation Graph (logical order between the objects, e.g., detecting easily maverick buying)

Using graph-based features to improve machine learning tasks (prediction)

- We considered a common prediction task (prediction of the total throughput time) in four different settings:
    - Only the features related to the lifecycle of an object are considered
    - Lifecycle features + Features extracted from the object interaction graph
    - Lifecycle features + Features related to object interaction graph + creation graph
    - Lifecycle features + Features related to int.+creation+continuation graph

Using graph-based features to improve machine learning tasks (prediction)

MAPE

Event Log	S1-t	S2-t	S3-t	S4-t
Order Management log	**54%**	55%	55%	55%
SAP ERP IDES instance - O2C log	53%	36%	28%	**27%**
SAP ERP IDES instance - P2P log	147%	134%	132%	**129%**
Recruiting Process	45%	45%	44%	**43%**

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_i - F_i}{A_i}\right|$$

RMSPE

Table 8: Prediction error (RMSPE) of the lifecycle duration in the four experimental scenarios S1-t, S2-t, S3-t, and S4-t (lower is better).

Event Log	S1-t	S2-t	S3-t	S4-t
Order Management log	**0.14D**	0.15D	0.15D	0.15D
SAP ERP IDES instance - O2C log	3.63D	3.14D	2.85D	**2.79D**
SAP ERP IDES instance - P2P log	0.14D	0.12D	**0.11D**	0.13D
Recruiting Process	0.82D	0.82D	0.82D	0.82D

$$RMSPE = \frac{\sqrt{\sum_{i=1}^{n}(A_i - F_i)^2}}{n}$$

Using graph-based features to improve machine learning tasks (anomaly detection)

- Considering graph-based features also improves the chances to correctly detect anomalies, for example:
  - Maverick Buying
  - Post-Mortem Changes to Purchase Requisitions (SAP)

Table 7: Amount of variance explained by the first (1C) and the first two (2C) components in the four experimental settings S1, S2, S3 and S4 (lower is better).

Event Log	**S1**		**S2**		**S3**		**S4**	
	1C	2C	1C	2C	1C	2C	1C	2C
Order Management log	87%	95%	83%	96%	**74%**	**90%**	**74%**	**90%**
SAP ERP IDES instance - O2C log	88%	97%	86%	95%	87%	94%	**85%**	**93%**
SAP ERP IDES instance - P2P log	**59%**	96%	99%	99%	85%	97%	77%	**95%**
Recruiting Process	63%	92%	60%	91%	**58%**	**90%**	**58%**	**90%**