

Discovering Causal Relations in Semantically-Annotated Probabilistic Business Process Diagrams

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GCAI-2018: 4th Global Conference on Artificial Intelligence
Luxembourg City, Luxembourg, September 18-21, 2018

Agenda

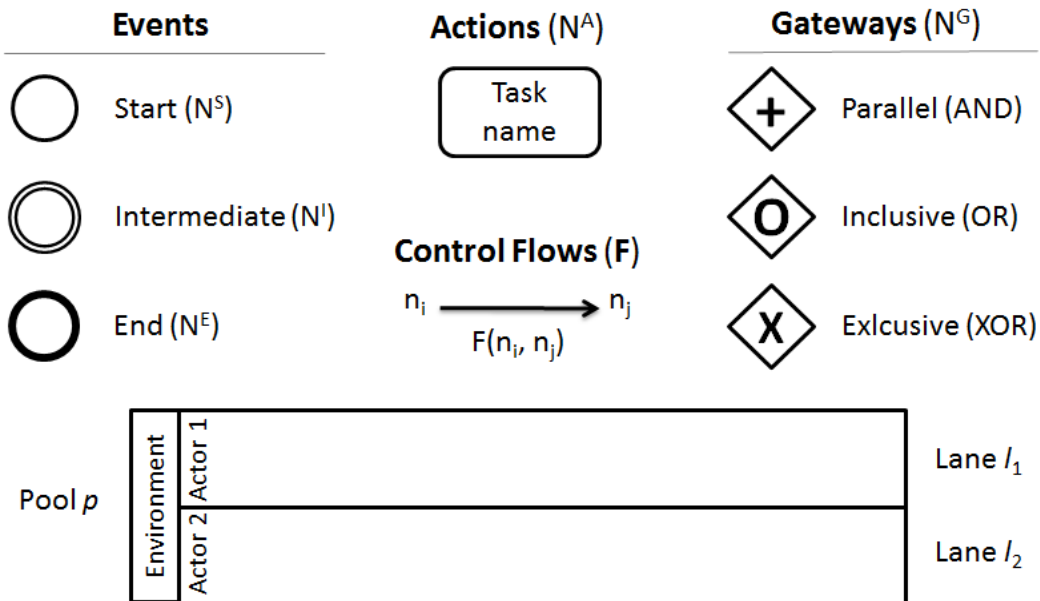
- ▶ Business Process Diagrams
- ▶ Probabilistic BPMN normal form
- ▶ Semantic Descriptors
- ▶ A probabilistic and semantic process instance
- ▶ Causal Learning
- ▶ Decision Making
- ▶ Conclusions








Business Process Diagrams

- ▶ Business Process Modeling and Notation (BPMN)
 - ▶ Alternative sequences of tasks and events.
- ▶ Stochastic BPMN
 - ▶ Based on Continuous Time-Markov Chains
 - ▶ Probability of observing a given event or task at time t .
- ▶ Probabilistic BPMN normal-form
 - ▶ Based on Bayesian Networks
 - ▶ How likely is to observe an event or a task B given that another one A occurs
- ▶ The goal: discovering causal dependencies between non-consecutive events/tasks.

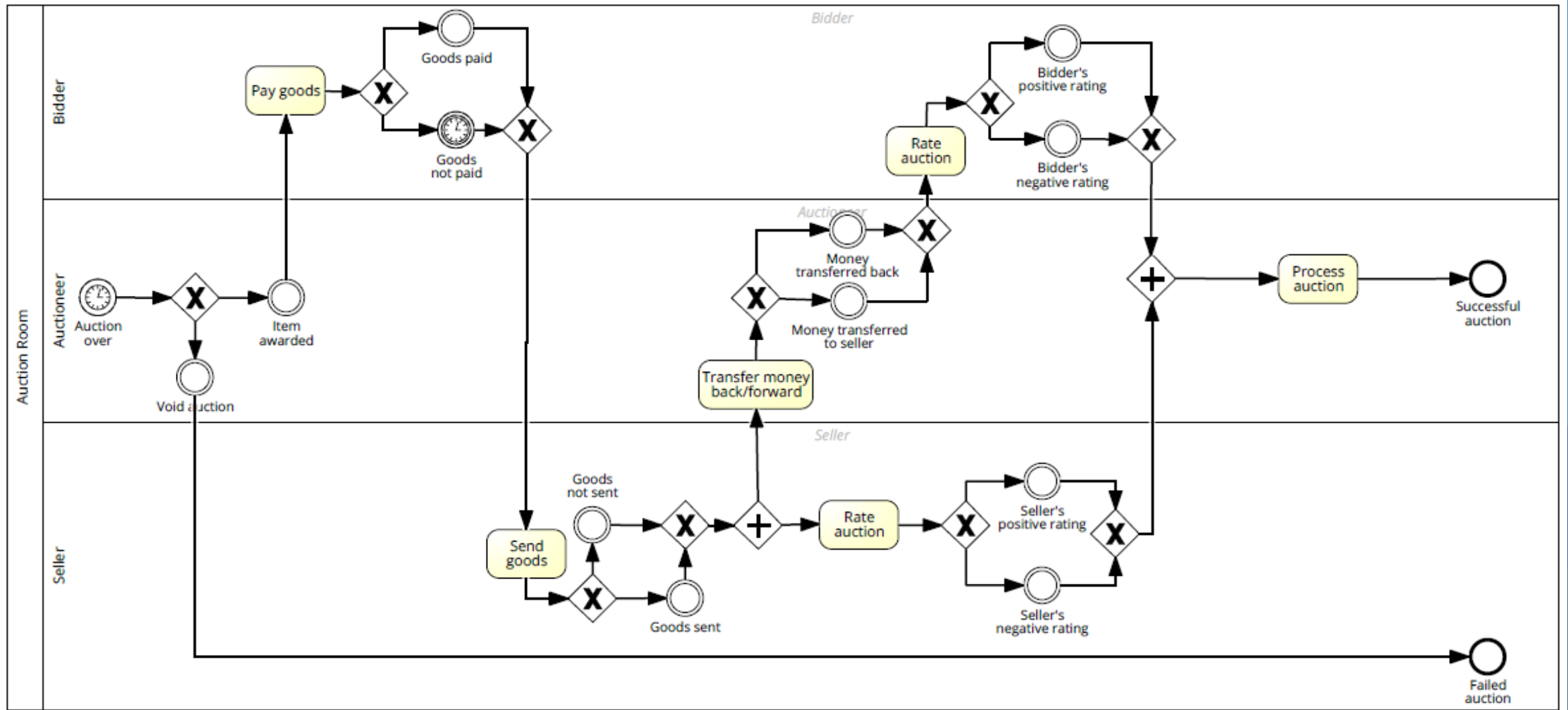
The BPMN normal form

- ▶ Business Process Diagram: $W = \{P, L, N, F\}$
- ▶ Lanes represent agent roles.
- ▶ DAG (G_N)

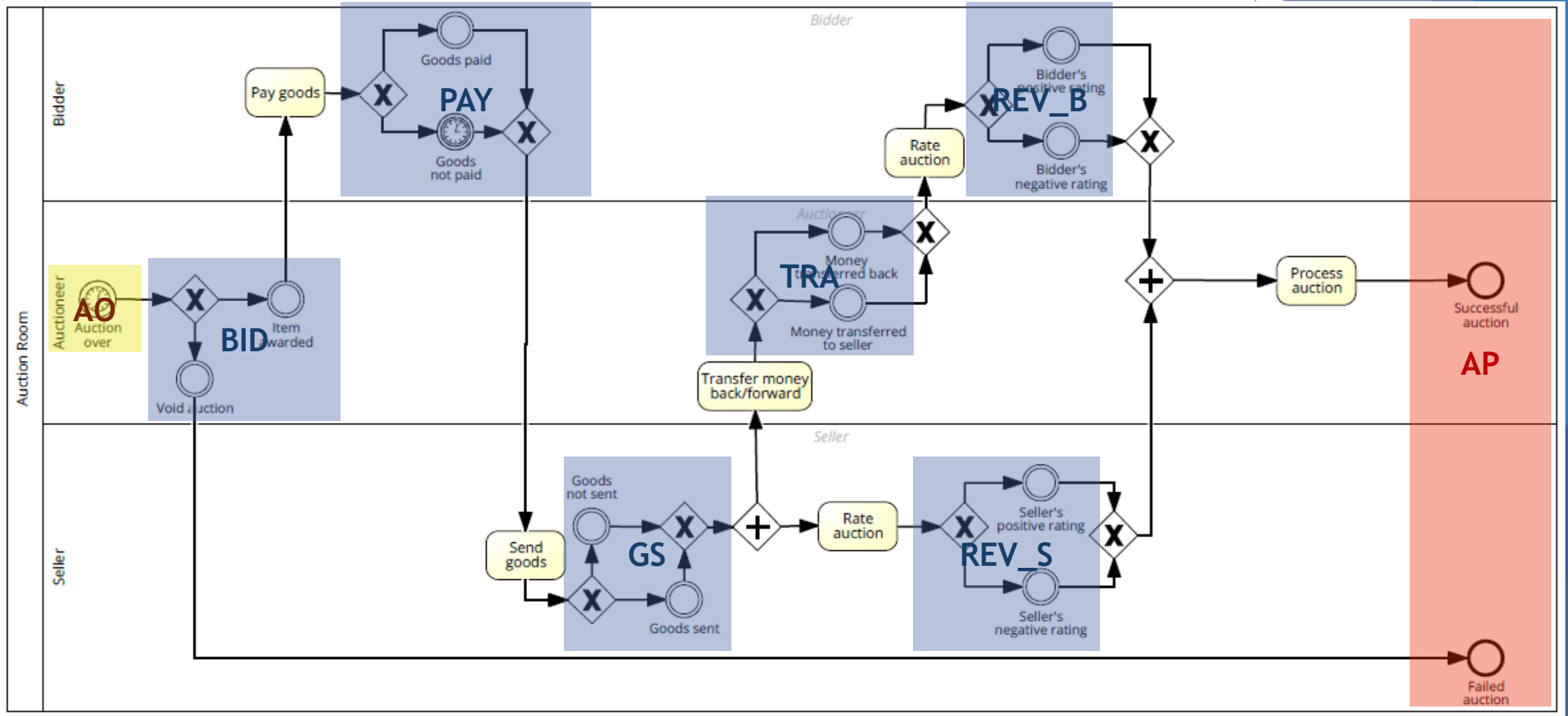


Structure		Mappings	In G'_N
Trigger	 $\rightarrow n_i$	$\text{map}(s, Z_s=\text{True})$ (1)	s
Outcome	$n_i \rightarrow$ 	$\text{map}(e_i, Z_E=e_i)$ (2)	e_1 (7d)
Event	$n_i \rightarrow$  $\rightarrow n_j$	$\text{map}(i, Z_i=\text{True})$ (3)	i
Actions	$n_i \rightarrow$  $\rightarrow n_j$	$\text{map}(a, X_a=\text{True})$ (6)	a
Split gateways	Decision	 $n_i \rightarrow$ n_{j-1} n_{j-2}	$\text{map}(i, Z_g=i)$ (4) g (7a)
	Alternative	 $n_i \rightarrow$ n_{j-1} n_{j-2}	n_i, n_j (see above) n_i, n_j (7c)
Merge gateways		 $n_{i-1} \rightarrow$ $n_{i-2} \rightarrow$ n_j	n_i, n_j (see above) n_i, n_j (7b)

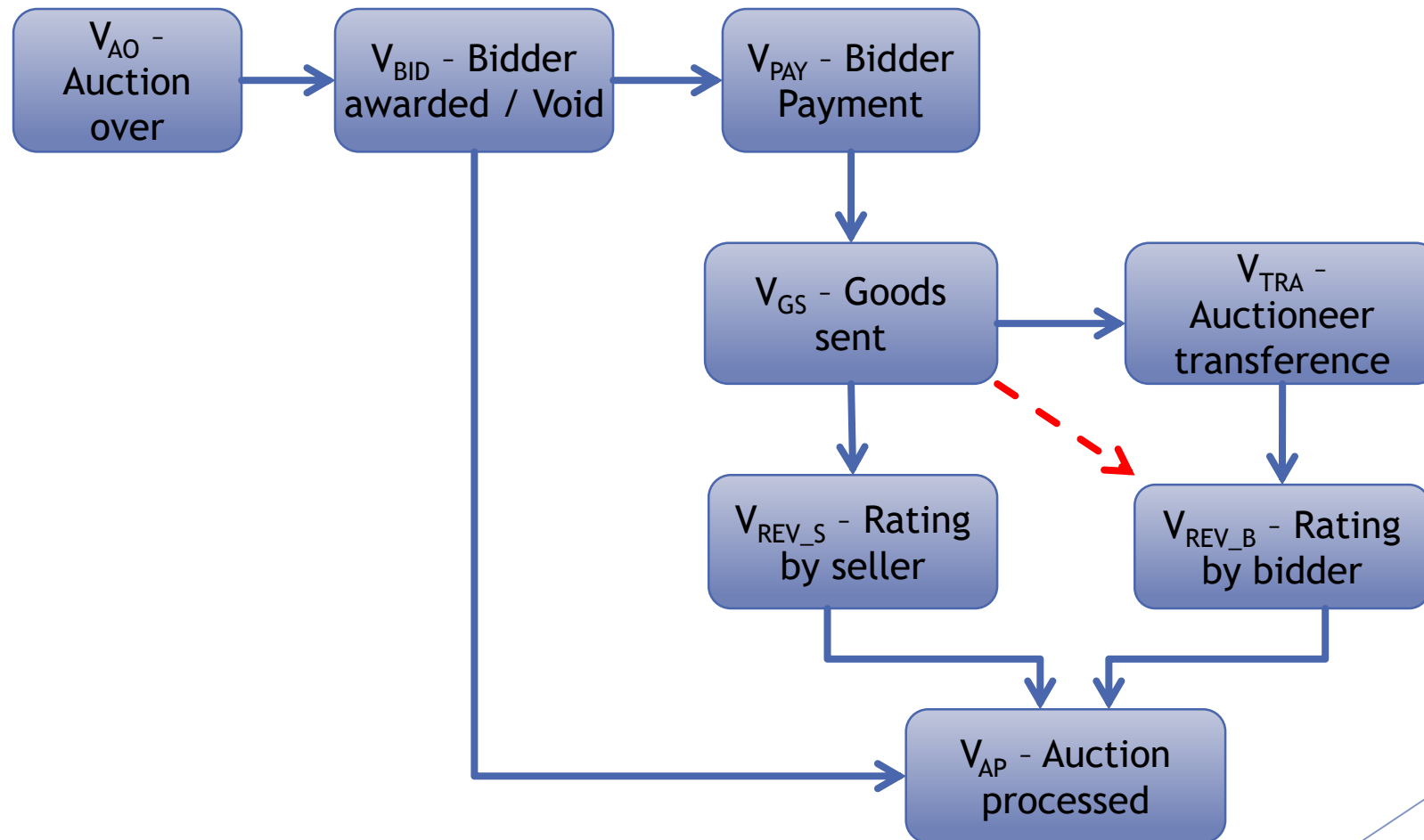
Processing an electronic auction (BPD)



Processing an electronic auction (BPD)



Processing an electronic auction (BN)



Semantic Descriptors

- ▶ A **semantic descriptor** $Ann(n, Q)$ is used for describing the meaning of lanes, events and tasks, where Q is a DL conjunctive query

$$Q = (s_1, \dots, s_n). \{T_1, \dots, T_m\}$$

$$T_i \begin{cases} \text{concept clauses (s rdf:type C)} \\ \text{relation clauses (s r s')} \end{cases}$$

- ▶ A **bridge descriptor** is a semantic descriptor $Ann(n, Q_B)$ such that its conjunctive query Q_B has a single distinguished variable $Dis(Q_B) = \{s_B\}$

No.	V_i	v_{ij}	Q_{ijl}
1	V_{BID}	?bidder	$Q_{BID}() = (?bidder). \{ ?a \text{ rdf:type :Auction.}$ $?a \text{ :awardedBidder ?bidder } \}$

A probabilistic and semantic process instance

- ▶ An instance of a process modeled through an annotated BPD W_D and compliant with a probabilistic normal form is represented by a tuple $I_W = \langle \pi_i, \bar{v}_i \rangle$.

- ▶ Example of a void auction: $I_{\text{auction}} = \langle \pi_{\text{void}}, \bar{v}_{\text{void}} \rangle$

$$\pi_{\text{void}} = \{?a : \langle \text{things/auction_003} \rangle, ?seller : \langle \text{people/john} \rangle\},$$

$$\bar{v}_{\text{void}} = \{V_{AO} = \text{TRUE}, V_{BID} = \text{FALSE}, V_{AP} = \text{TRUE}, V_{PAY} = \text{FALSE}, V_{GS} = \text{FALSE}\}.$$

Structural Learning

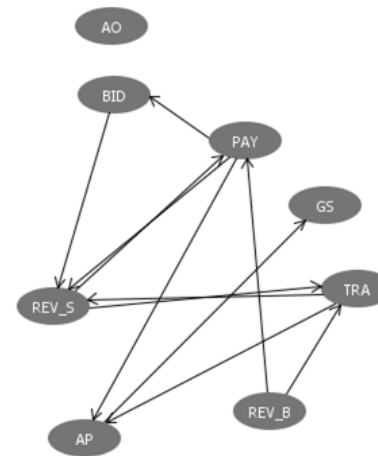
- Structural learning on 1,000 instances based on a probabilistic distribution: 10 folds cross-validation (80% - 20%)

Cases	AO	BID	PAY	GS	TRA	REV_B	REV_S	AP	Comment
5%	TRUE	FALSE	FALSE	FALSE				FAILURE	Void auction
4%	TRUE	?bidder	FALSE	FALSE				FAILURE	Bidder doesn't pay item
4%	TRUE	?bidder	FALSE	FALSE			NEG	FAILURE	Bidder doesn't pay item. Seller rates negatively.
5%	TRUE	?bidder	TRUE	FALSE	BIDDER	NEG		FAILURE	Bidder pays, Seller doesn't send the item. Bidder rates negatively.
65%	TRUE	?bidder	TRUE	TRUE	SELLER	POS	POS	SUCCESS	Item sold. Rating POS-POS.
8%	TRUE	?bidder	TRUE	TRUE	SELLER	NEG	POS	SUCCESS	Item sold. Rating NEG-POS.
6%	TRUE	?bidder	TRUE	TRUE	SELLER	POS	NEG	SUCCESS	Item sold. Rating POS-NEG.
3%	TRUE	?bidder	TRUE	TRUE	SELLER	NEG	NEG	SUCCESS	Item sold. Rating NEG-NEG.

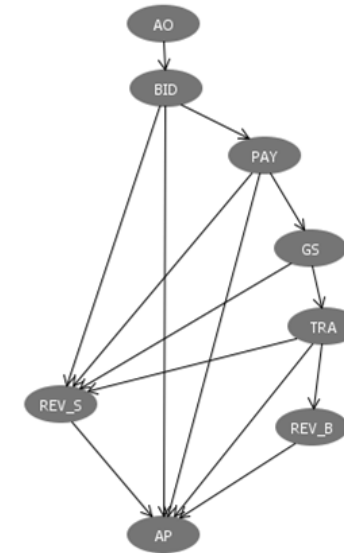
- 87% of the instances classified correctly: causal relations are not encoded in temporal precedence.

Causal Learning

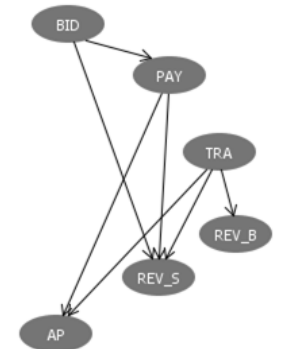
- ▶ a) Inferred Causation (IC*) discovered 5 new valid arcs and 2 new undirected arcs.
- ▶ b) Temporal precedence was used for directing these 2 arcs.
- ▶ c) A compact model with only the 7 arcs discovered by IC*.
- ▶ 100% instances classified correctly with b) and c)



(a)



(b)



(c)

Decision Making

- ▶ The variable ?bidder in the bridge descriptor is used for selecting instances associated to a specific bidder.
- ▶ A *bad bidder* can be discovered by comparing his probabilistic distribution ($\langle \text{people}/\text{tom} \rangle$) against the overall behavior (?bidder).

	Enriched Model		Compact Model	
A posteriori probability	?bidder	$\langle \text{people}/\text{tom} \rangle$?bidder	$\langle \text{people}/\text{tom} \rangle$
$P(AP = \text{SUCCESS} BID = ?bidder)$	0.9142	0.3924	0.8715	0.3912
$P(REV_S = POS BID = ?bidder)$	0.8431	0.3091	0.8614	0.2939
$P(PAY = TRUE BID = ?bidder)$	0.9153	0.3888	0.9153	0.3888

Conclusions

- ▶ IC* discovered new causal relationships that improved process development prediction.
- ▶ Temporal precedence was used for redirecting undirected arcs.
- ▶ **Future Work**
 - ▶ Normalization of BPDs by supporting cycles.
 - ▶ Using semantic annotations for generating traces from Linked Data.

Thank you for your attention

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