Enhancing Declare Maps Based on Event Correlations

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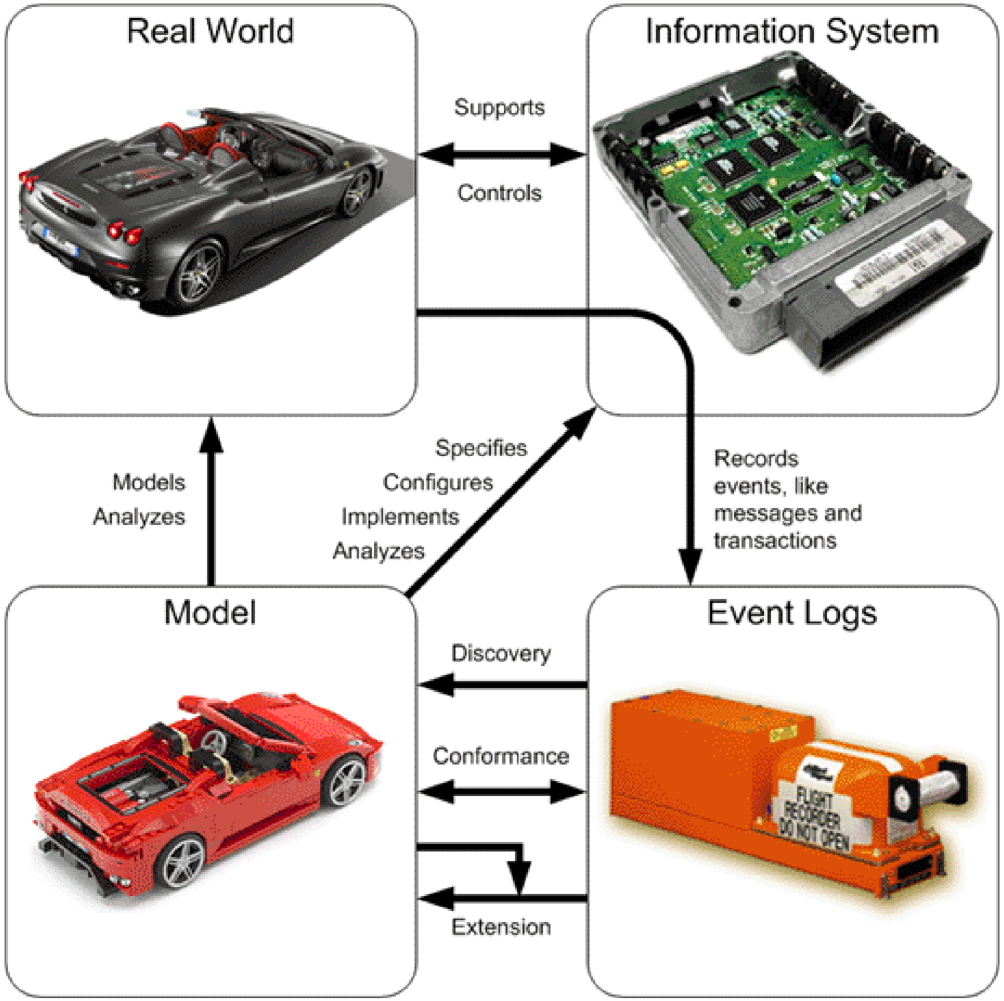
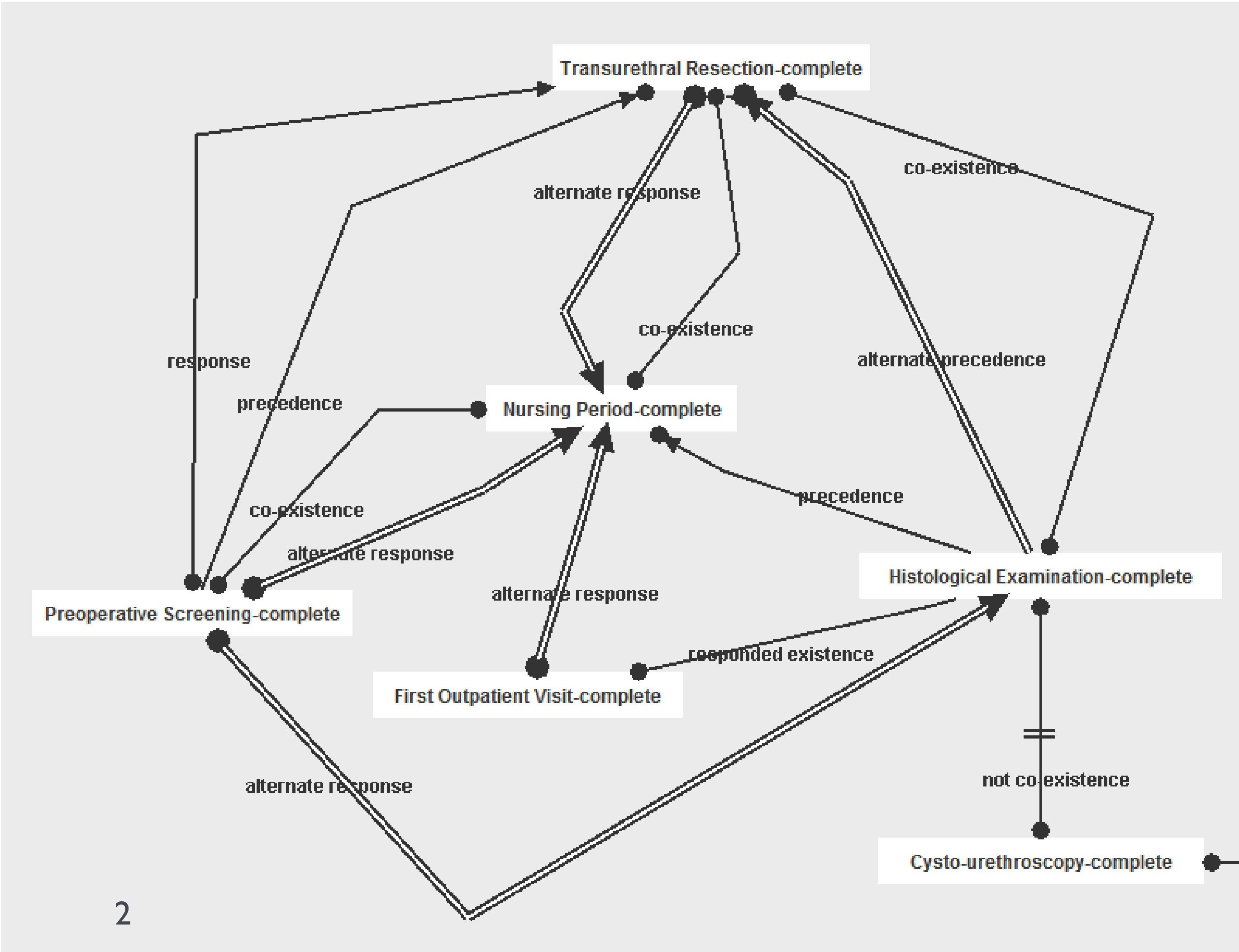
Process mining

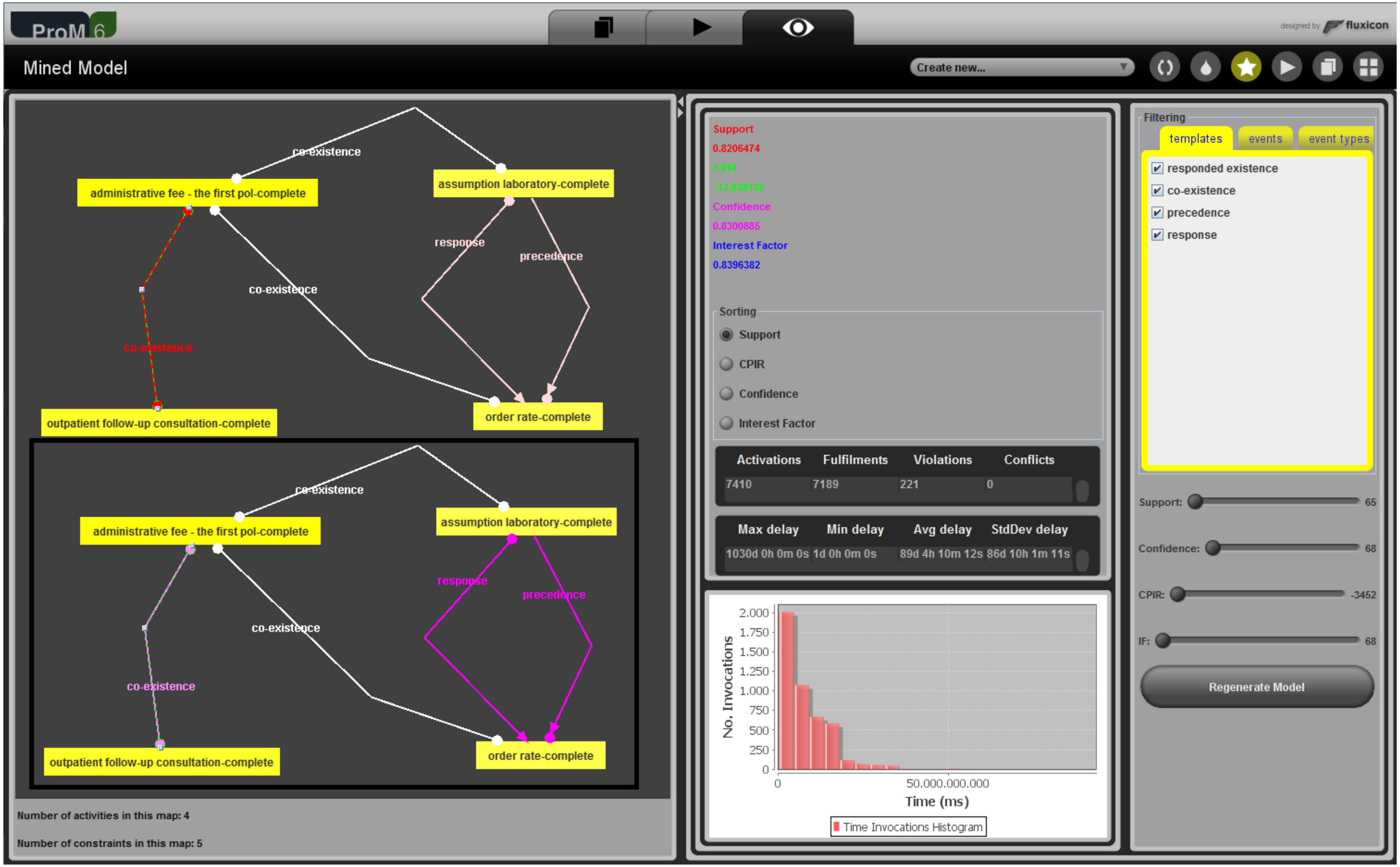


www.processmining.org

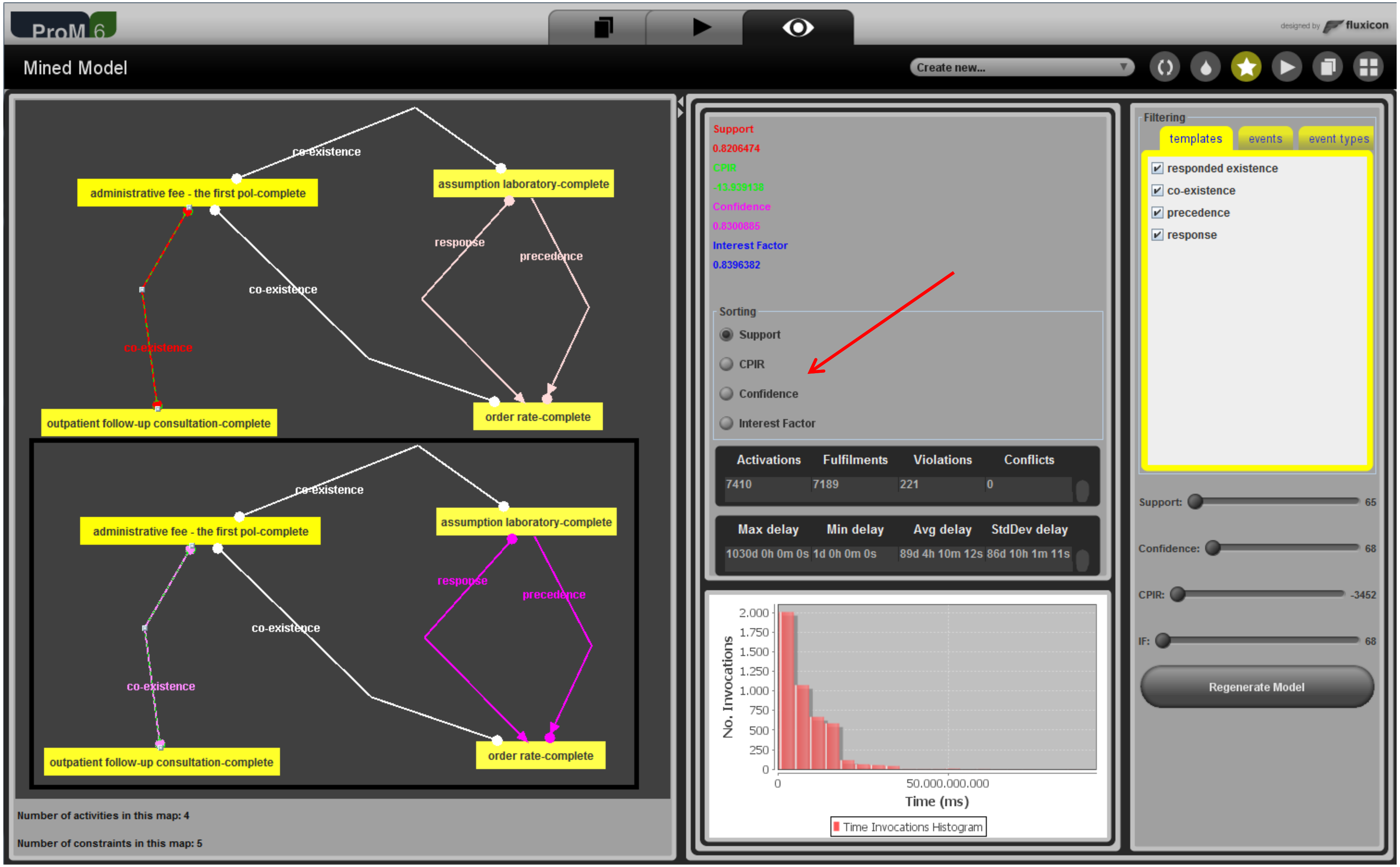
An example of Declare model



Declare Maps: a TomTom like visualization



Declare Maps: a TomTom like visualization



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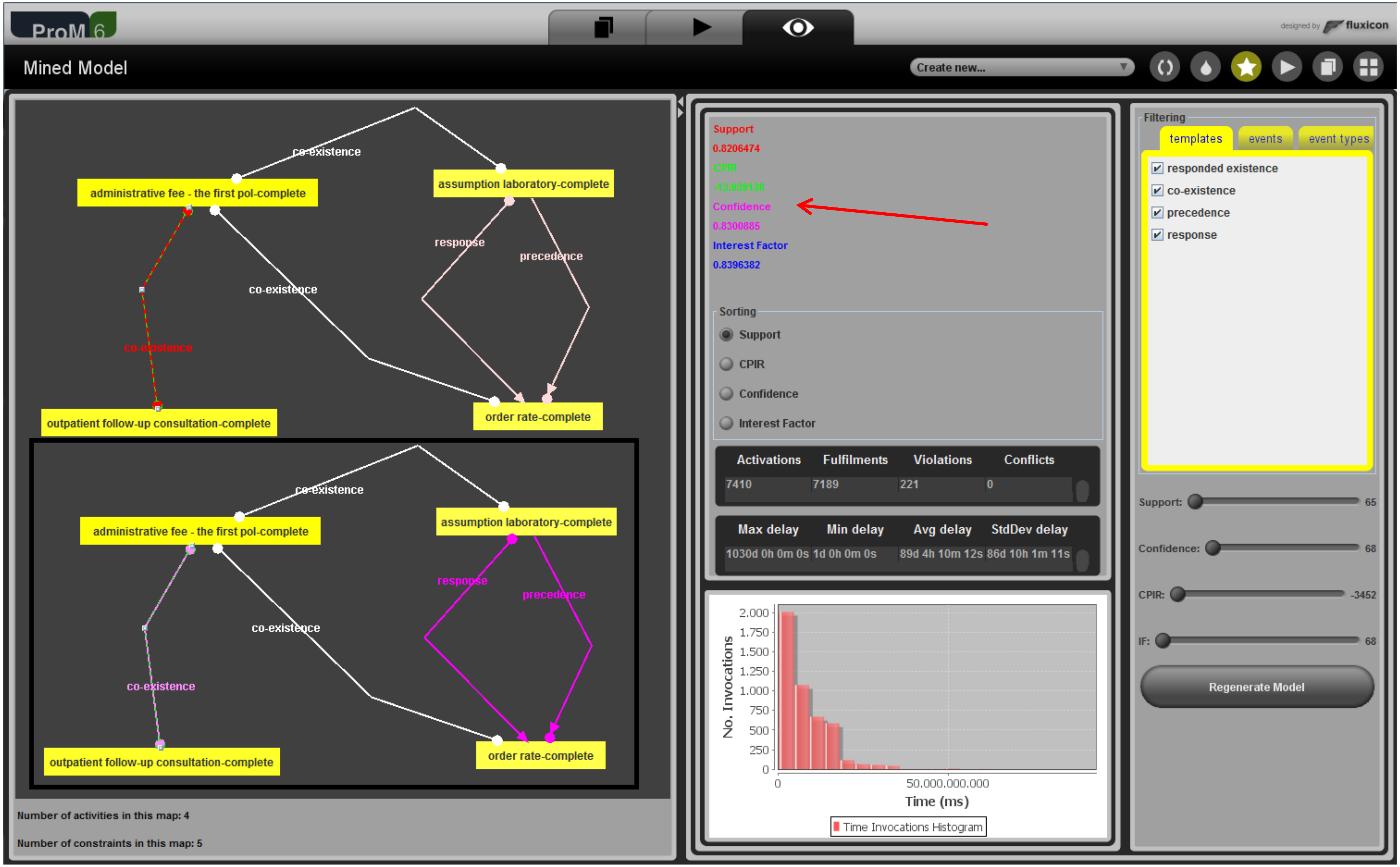

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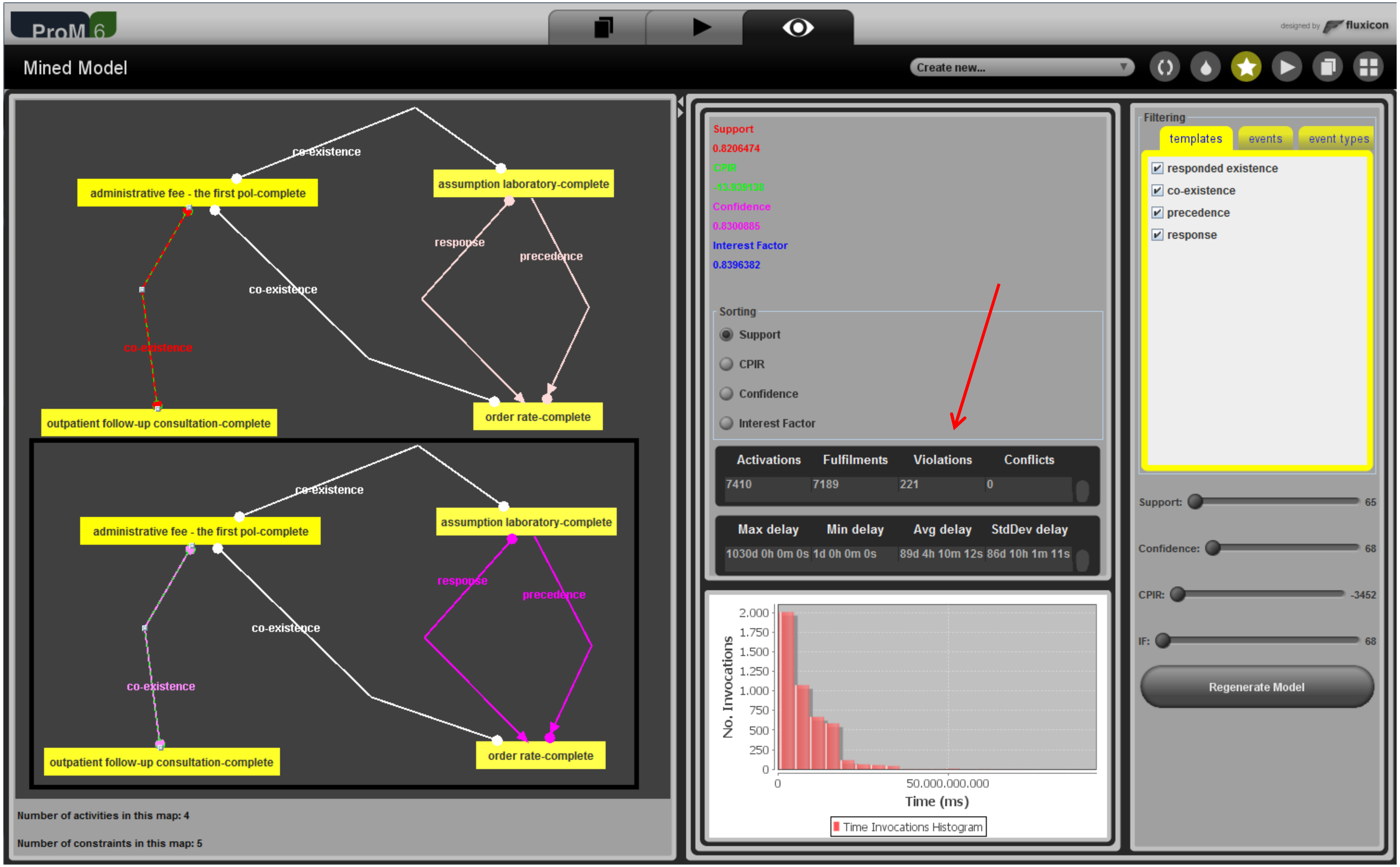
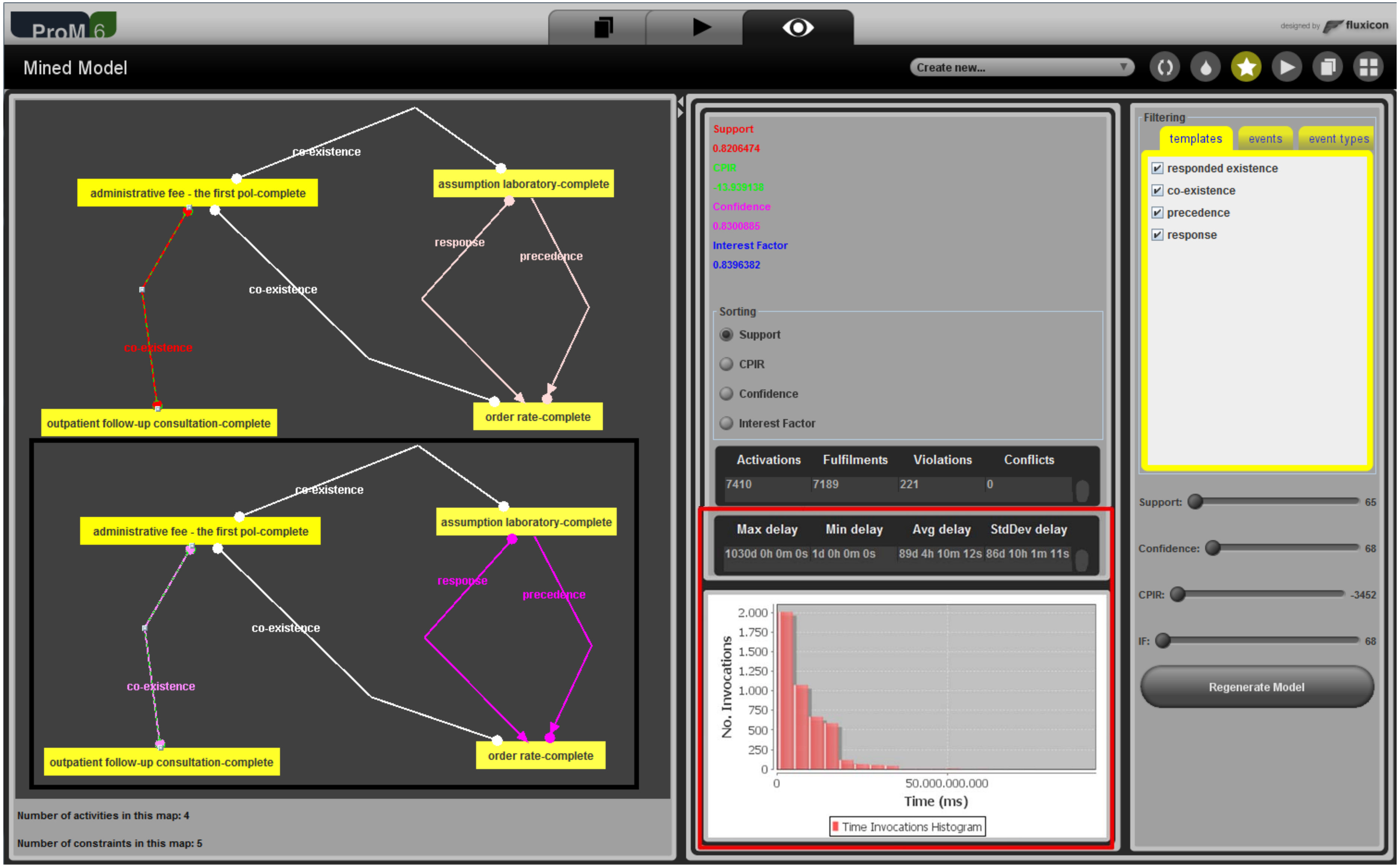
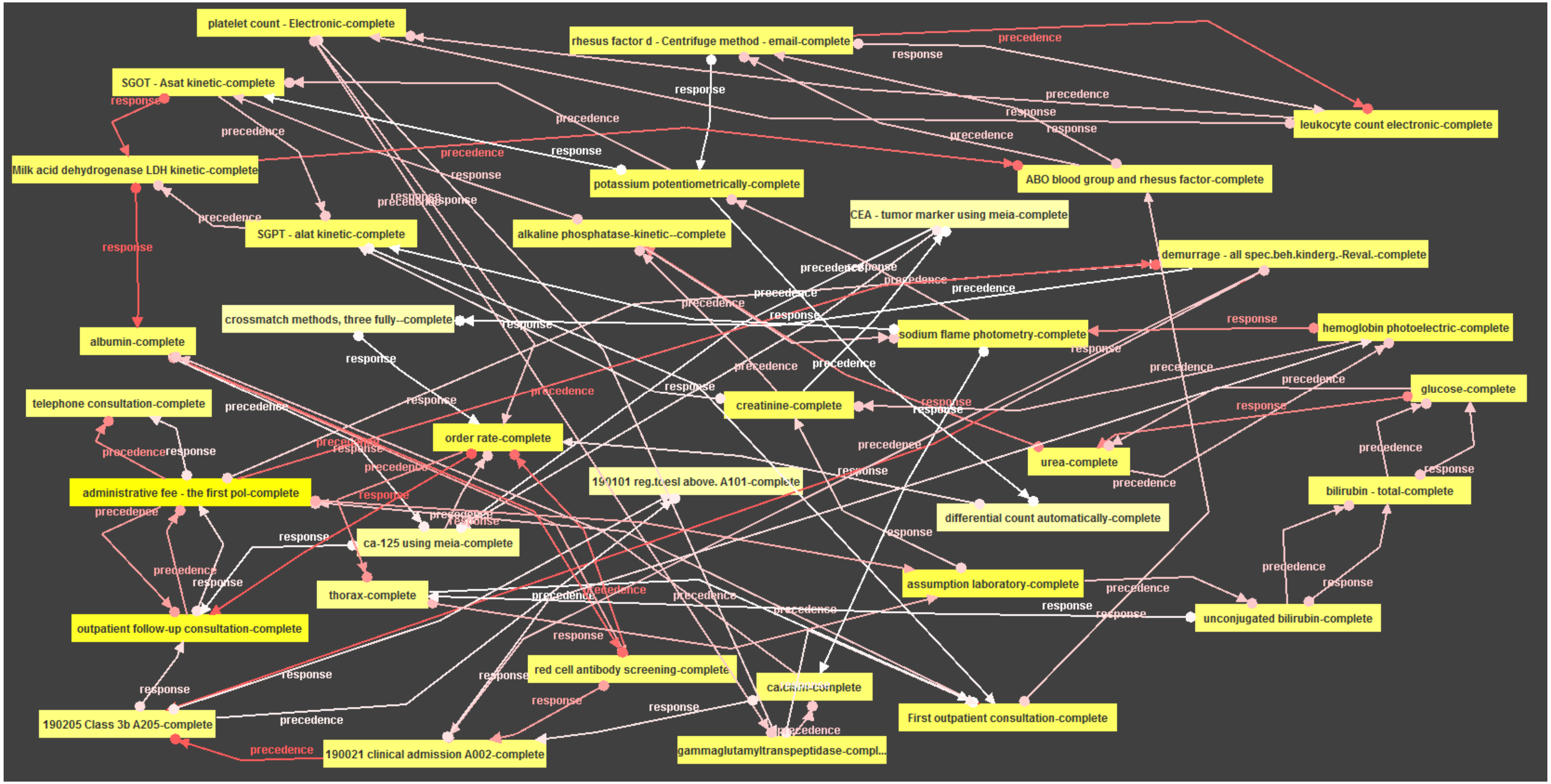


Declare Maps: a TomTom like visualization



Spaghetti Declare



Addressing the problem of too many constraints

- Removing non-interesting constraints
  - Filter out non-interesting constraints based on activation support
  - Filter out redundant constraints "dominated" by other constraints
  - Filter out redundant constraints through transitive reduction
  - Filter out redundant constraints through reduction rules

- Guiding the discovery process with a-priori knowledge
  - Conceptual groupings: discovering inter- and intra-group constraints
  - Repair an existing Declare map with info retrieved from the log

F.M. Maggi, J.C. Bose, and W.M.P. van der Aalst
A Knowledge-Based Integrated Approach for Discovering and Repairing Declare Maps In CAiSE 2013

Addressing the problem of too many constraints (taking the data perspective into consideration)

- Considering interesting only those constraints between events that are highly correlated
  - constraints involving activities are interesting only if they share some common (data) elements of a process
    - **Example:** an *insurance claim process* could include a *claim application* and *filling in a questionnaire for feedback*. These two portions of the process sharing no or very few attributes (there are not significant correlations between them)
  - A constraint is considered satisfied only if some common attributes of the events involved in the constraint share the same value
    - **Example:** constraint *response(A,B)*;
      trace <A(x=1), B(x=1)> SATISFIED
      trace <A(x=1), B(x=2)> VIOLATED

Through correlations you can also…

- Disambiguate events
  - **Example:** trace <*A,B,C,B*>, *response(A,B)* (ambiguous) <*A(x=1),B(x=2),C,B(x=1)*> (can be disambiguated)
    - Disambiguation of events facilitates a correct association of events involved in a constraint and helps in *performance analysis* of a process
- Improve diagnostic capabilities
  - *Outliers*
    - **Example:** correlation *A.x* = *B.x* holds for 98% of the fulfillments of *response(A,B)*. The 2% of the activations where the correlation does not hold may potentially be outliers
  - *Discriminatory correlation patterns*
    - **Example:** if A and B are executed by the same department the response time between A and B is "Fast"
- Define conceptual groupings of activities
  - **Example:** activities involving all events that are executed in the same location as one conceptual group
    - Such conceptual groupings of activities can be used for guiding the discovery of Declare maps towards results that are more significant from an application domain point of view

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Categorization of correlations

Barros, G. Decker, M. Dumas, F. Weber ***Correlation Patterns in Service-Oriented Architectures*** In FASE 2007

- Property-based correlation
  - events are classified based on a function operating on their attributes
  - **Example:** all claim applications referring to an amount greater than 1000 euros are grouped together
- Reference-based correlation
  - two events are correlated if an attribute of the first event (identifier attribute) and an attribute of the second event (reference attribute) have the same value
- Moving time-window correlation
  - two events are correlated if they occur within a given duration of one another (e.g., one hour)

- We use an extended definition of reference-based correlation
  - events are correlated if there is a function connecting an attribute of the first event with an attribute of the second event ***(this function can include not only equality but also operators such as greater than, less than, and not equal to)***
  - **Example:** an event of producing a document is correlated to an event of checking it if the resource that produces the document is different from the resource that checks it

How to get correlations

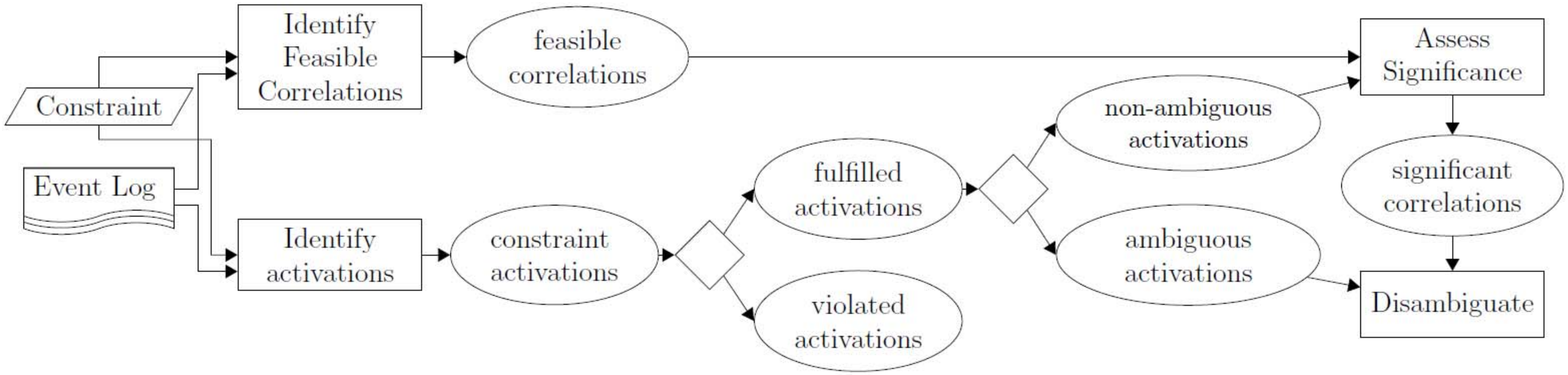
- Correlations can be
  - provided by a domain expert

  - automatically derived from event logs

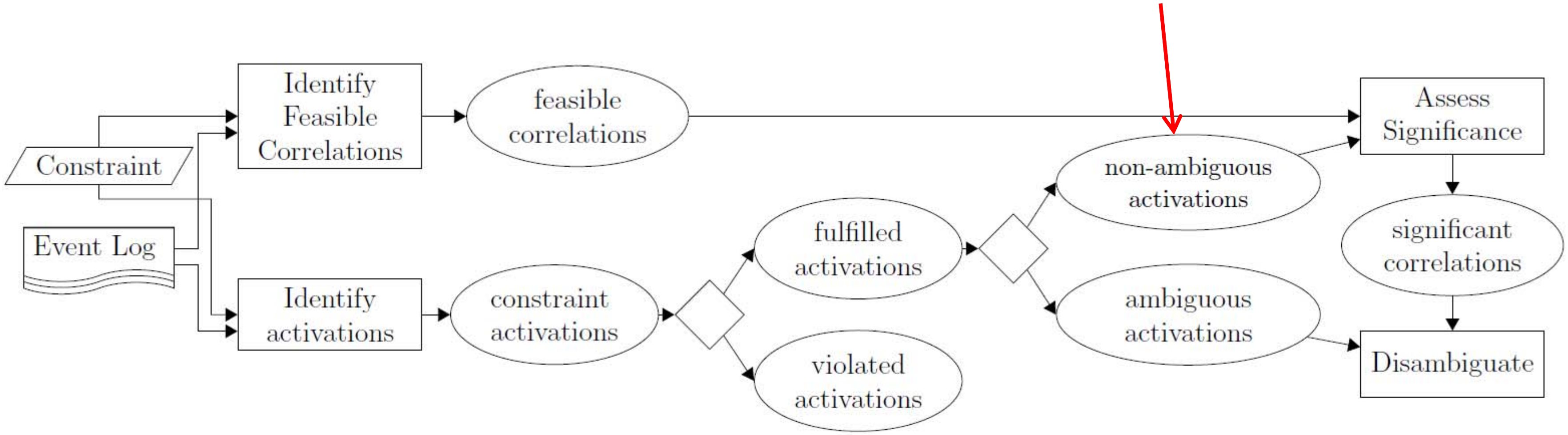
Discovering correlations from event logs (preamble)

- The XES standard for event logs allows for events having attributes
- Attributes can be comparable (feasible) or not
  - **Examples:** in an insurance claim process, attribute *amount claimed* is comparable to *amount issued*, but not to *location*.
  - *If a priori knowledge about the domain is available*, we can use that knowledge to identify/group attributes that are comparable.
  - *In the absence of prior domain knowledge*, we consider attributes having the same data type to be comparable.

Discovering correlations from event logs

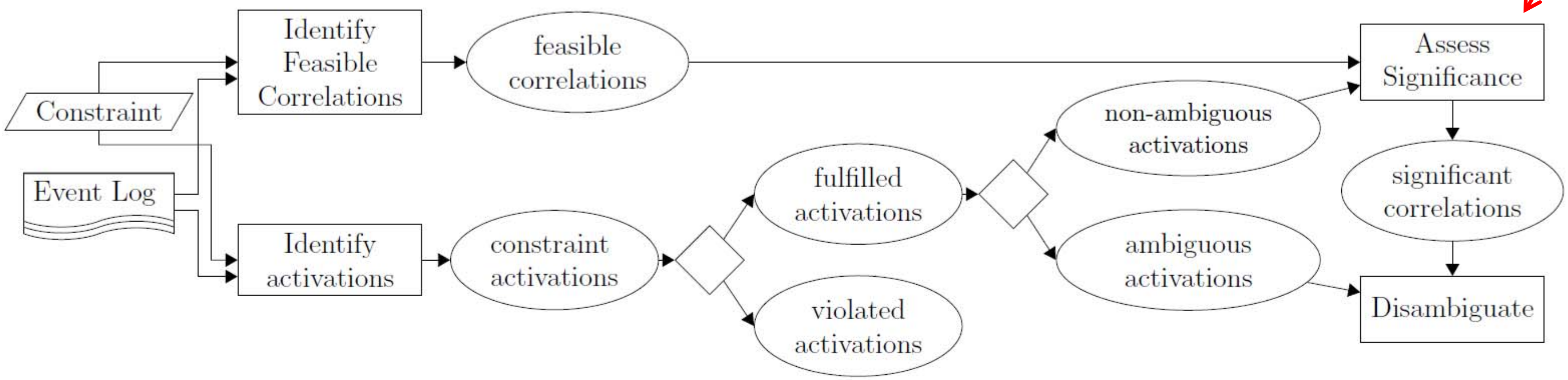


Discovering correlations from event logs



- Non-ambiguous activations
  - A fulfilled activation is non-ambiguous if there is only one possible target that can be associated to it
  - **Example:** for *response(A,B)*, the activations in traces <A,C,B> and <A,A,C,B> are <u>non-ambiguous</u> whereas the activations in traces <A,B,C,B> and <A,A,B,B> are <u>ambiguous</u>

Discovering correlations from event logs



- Correlation support
  - ratio between the number of non-ambiguous activations in which that correlation is true and the total number of non-ambiguous activations
  - We consider a feasible correlation as *significant* if its support is greater than a (user-specified) threshold

Discovering discriminant correlations

- *Step 1: Class Labeling*
  - **Example:** One can consider all the *fulfilled* activations of a constraint and classify them as *slow*, *medium* and *fast* based on their response time
- *Step 2: Feature Extraction and Selection*
  - The attributes of the events involved in a constraint are considered as primitive features for finding discriminatory patterns
- *Step 3: Discovering Discriminatory Patterns*
  - Discovery of the patterns over the features, which are strongly correlated to the class label (e.g., slow, medium and fast)
    - Standard data mining techniques, i.e., decision tree learning and association rule mining

Case study (BPI Challenge 2011)

- A = First outpatient consultation; B = administrative fee - the first pol; E = rhesus factor d - Centrifuge method; F = red cell antibody screening

constraint	support (constr.) (%)	#non-ambig. inst.	#ambig. inst.	**correlation**	support (correl.) (%)	degree of disambig-uation(%)
response (A,B)	57.39	517	559	A.org:group = B.org:group	94.00	57.96
				A.Producer code = B.Producer code	93.61	61.53
precedence (E,F)	54.85	603	932	E.time:timestamp = F.time:timestamp	100.00	96.45

Case study (BPI Challenge 2011)

constraint	correlation	#constraints			
		supp=30	supp=35	supp=40	supp=45
response(A,B)	⟨⟨ *no correlation* ⟩⟩	371	286	225	125
	A.org:group = B.org:group	229	180	163	114
	A.Producer code = B.Producer code	100	85	83	71
precedence(A,B)	⟨⟨ *no correlation* ⟩⟩	458	403	352	261
	A.org:group = B.org:group	274	249	240	237
	A.Producer code = B.Producer code	113	106	104	104

Conclusions and Future Work

- Motivation
  - Declarative process maps discovered from event logs without any consideration for event and case attributes tend to result in inaccurate and incomprehensible results.
- Contribution
  - We exploited the data present in event logs to discover process maps only showing relevant and accurate constraints.
  - We proposed a means of discovering significant correlations that exist between events and use these correlations to
    - *prune constraints*
    - *disambiguate event associations*
    - provide additional *diagnostic information*
  - We evaluated our approach using real-life logs
- Future work
  - extend the approach to also cover constraints involving multiple activities and negative relations
  - study the trade-off between completeness and efficiency of mining
  - evaluate our approach using more case studies