Information (Computational) Systems in the Big-Data Era
Eindhoven University of Technology, 14 May 2012

Process Mining in Complex Domains

joint work with Antonella Guzzo and Luigi Pontieri

Gianluigi Greco
University of Calabria

An Application Domain

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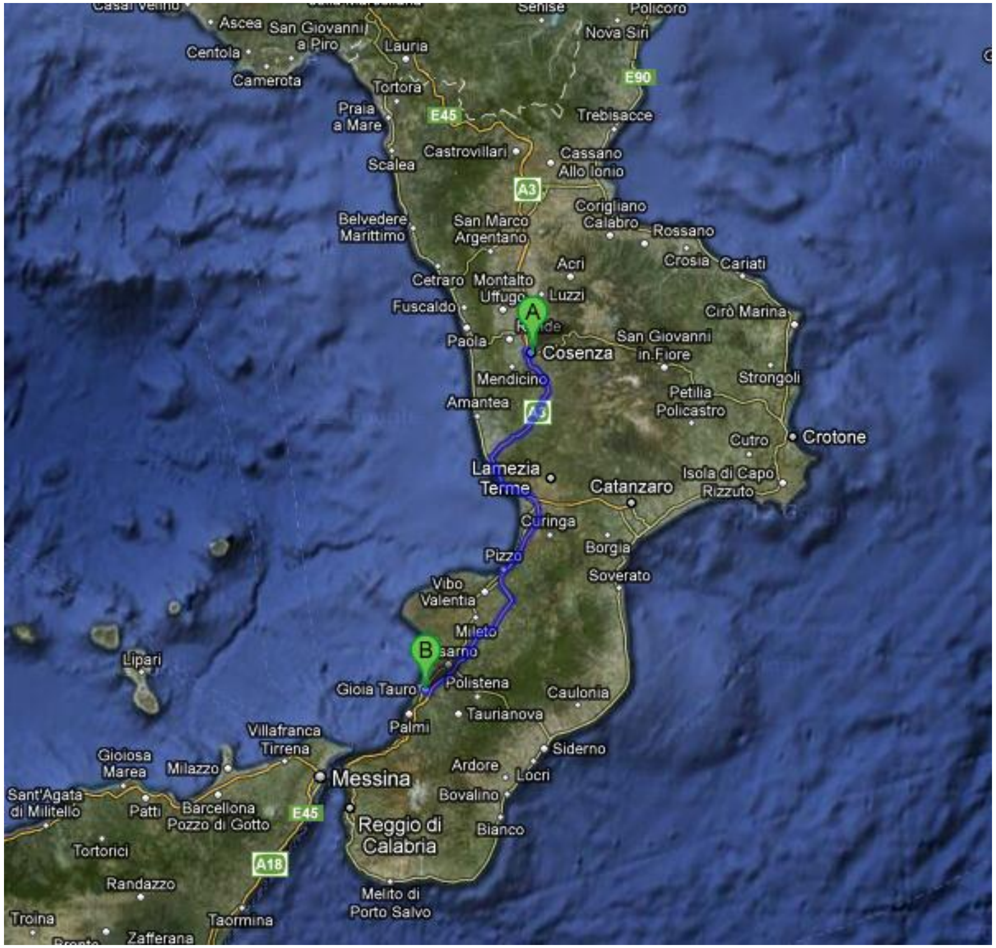
Gioia Tauro

- Italian harbor acting as a maritime freight hub (about 4 millions of containers per year).
  - Berth planning
  - Routing
  - …
  - Yard planning



Yard Planning

- The mission is to offer high quality of service to the navigation lines, while reducing the overall cost of internal logistic processes.
- Critical performance measures are
  - *the latency time* elapsed when serving a ship (where, typically, a number of containers are both discharged off and charged on), and
  - *the overall costs* of moving the containers around the yard.
- A key factor impacting on both these measures is the number of "*house-keeping*" moves that are applied to the containers.

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Minimize house-keeping moves

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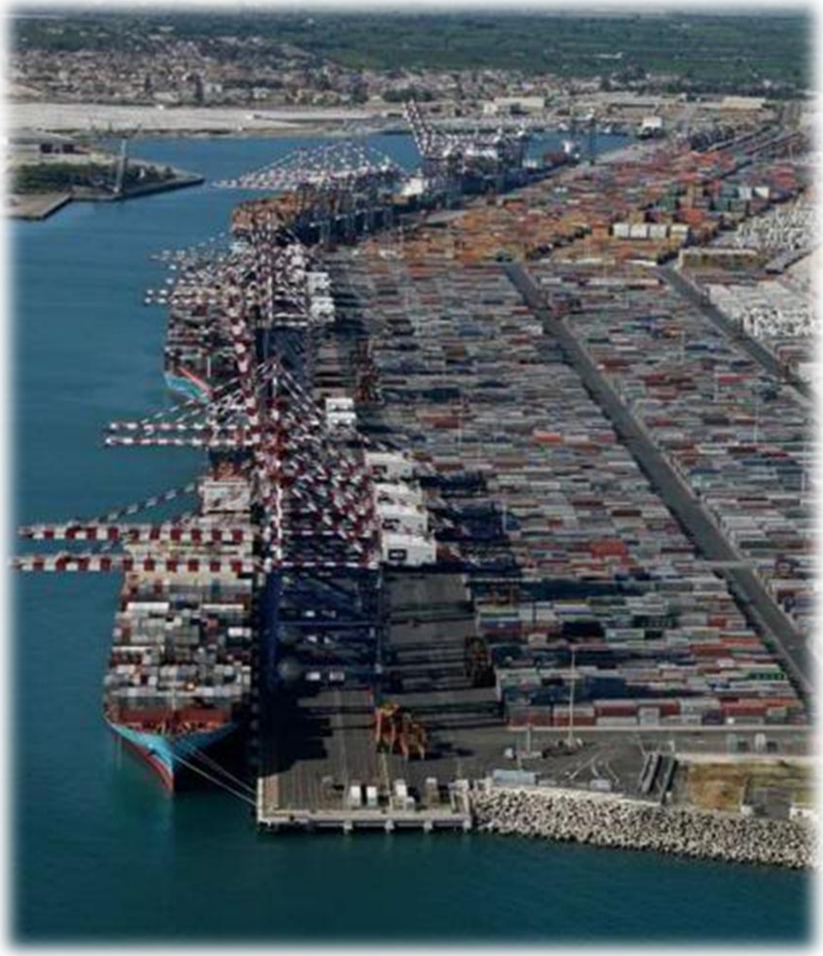
Understand the process, first!

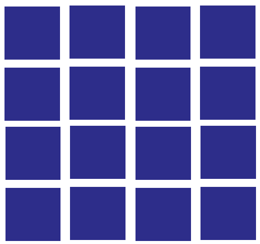
The yard

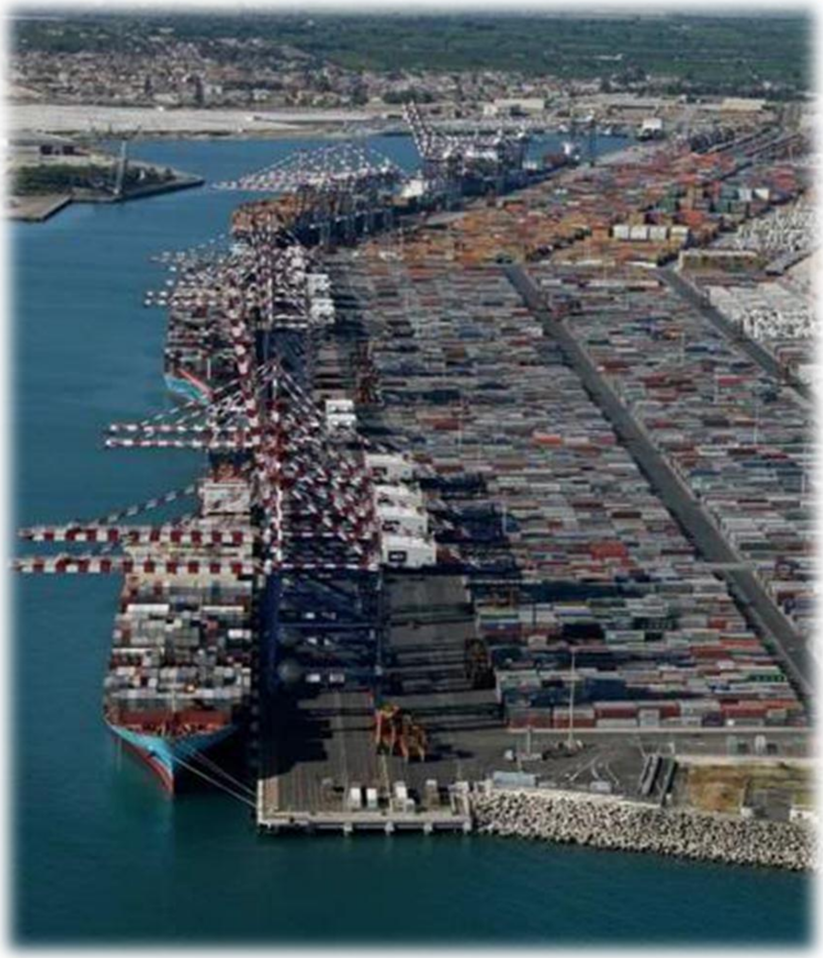
slot



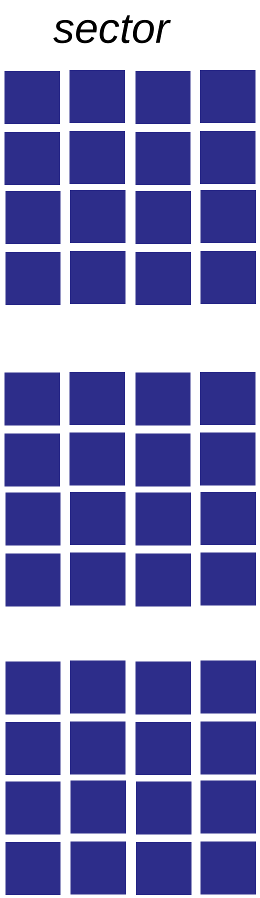
The yard

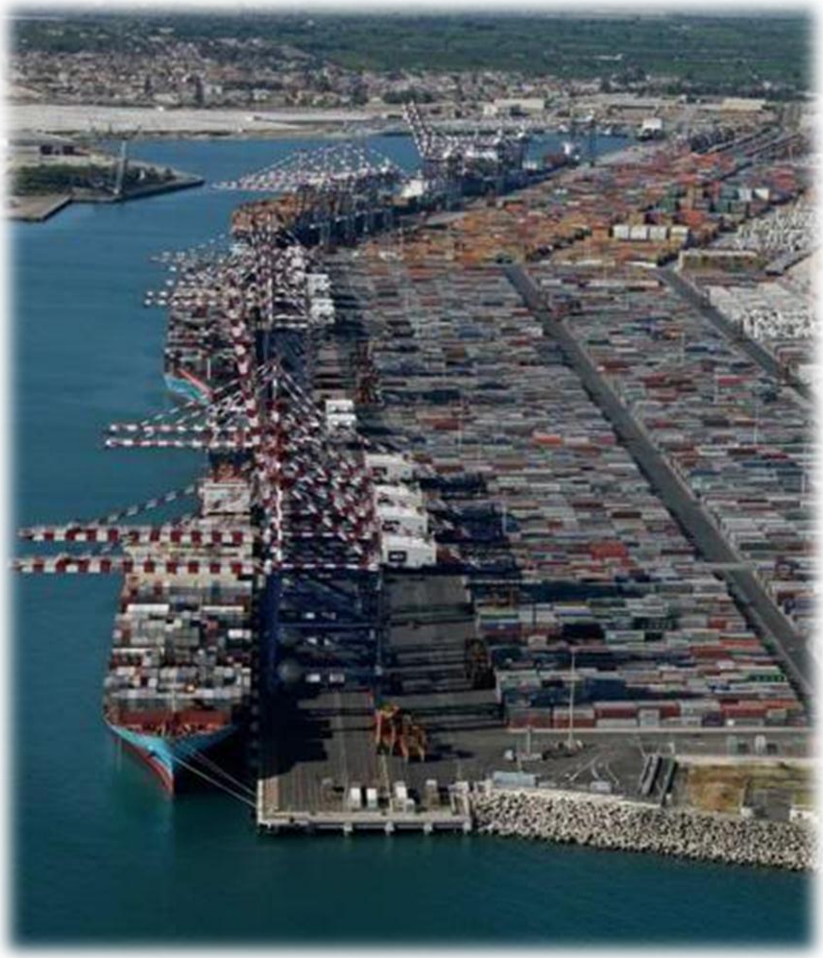
block



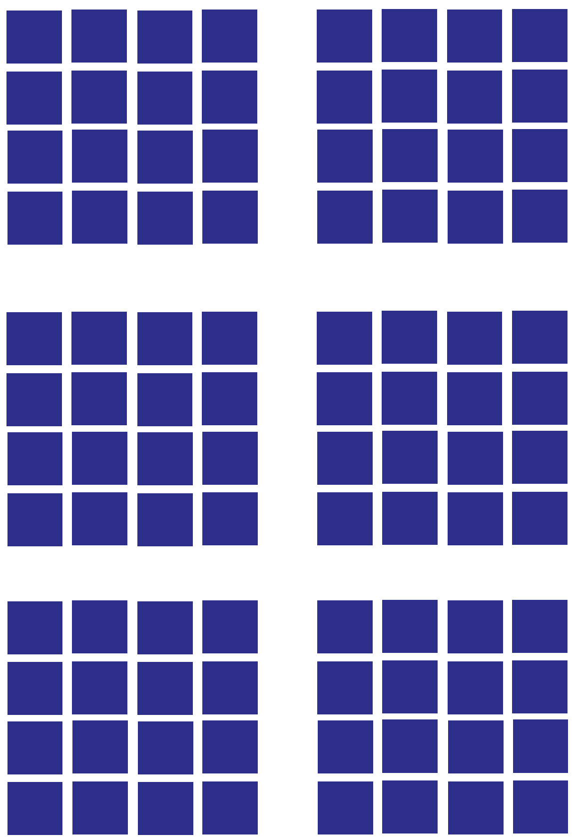


The yard





The yard

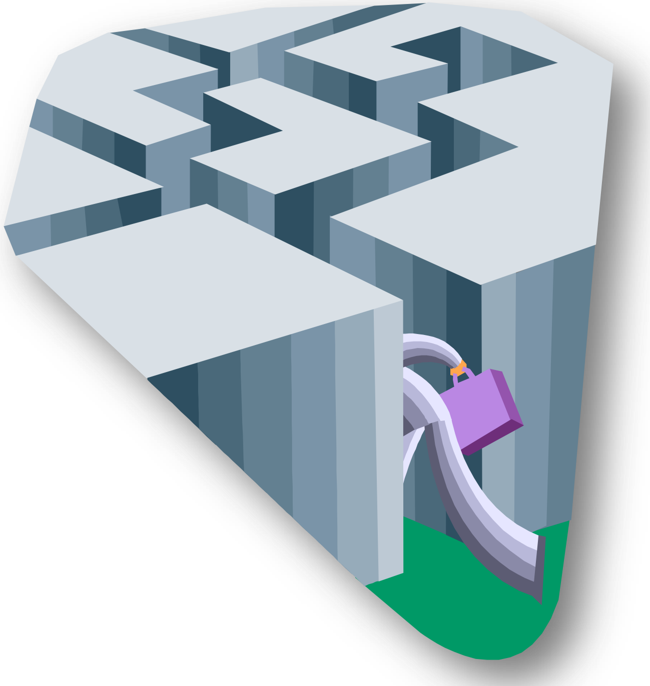


Life Cycle

- The container is initially unloaded from the ship, with the help of a crane
- It is first stocked within a zone near to the dock
- It is carried to some slot of the yard, via
  - cranes
  - straddle-carriers (a vehicle capable of picking and carrying a container, by possibly lifting it up)
  - multi-trailers (a sort of train-like vehicle that can transport many containers
- At boarding time, the container is first placed in a yard area close to the dock
- Finally, it is loaded on the cargo by means of a crane

Challenges

- Logs from transactional systems
- Logs mix different usage scenarios
- Traces are stored at different level of details
- Noise
- Huge volume of data



Outline

- Application Domain
- Process Mining Approaches @UniCAL
- Another Challenge in Process Mining
- Formal Framework
- Implementation Issues

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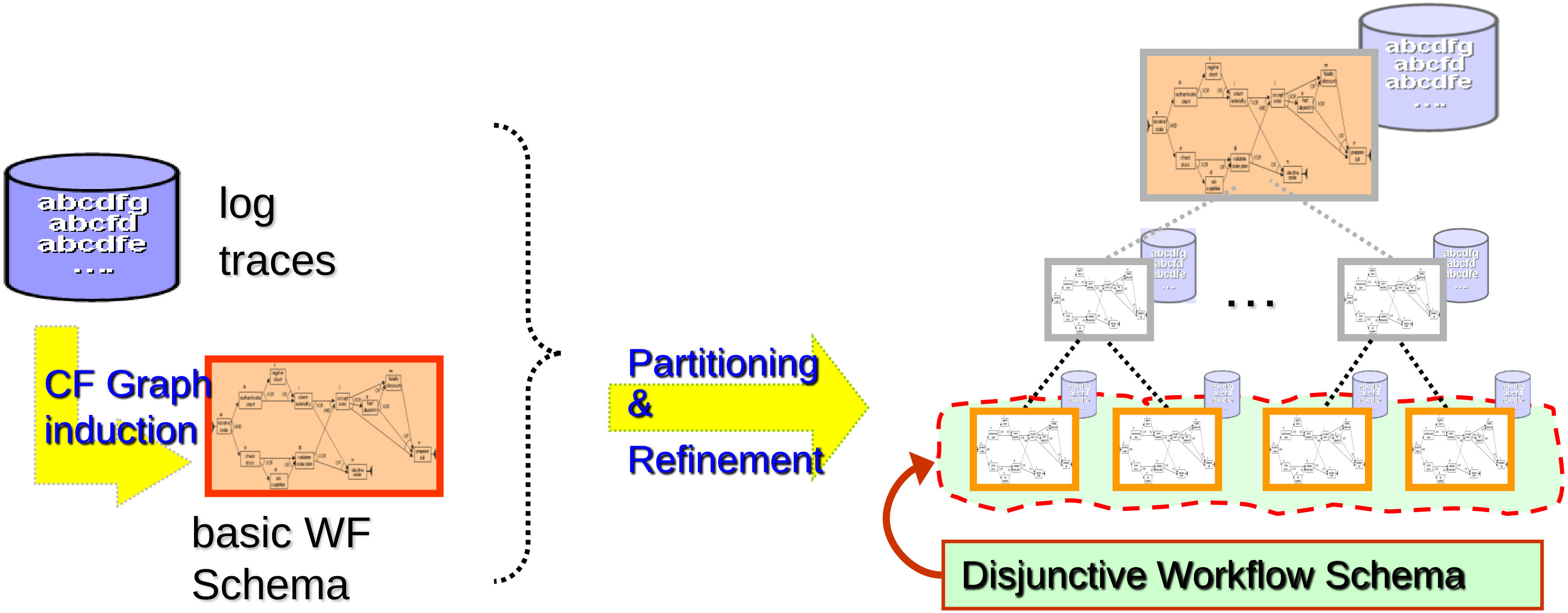
(1) Clustering



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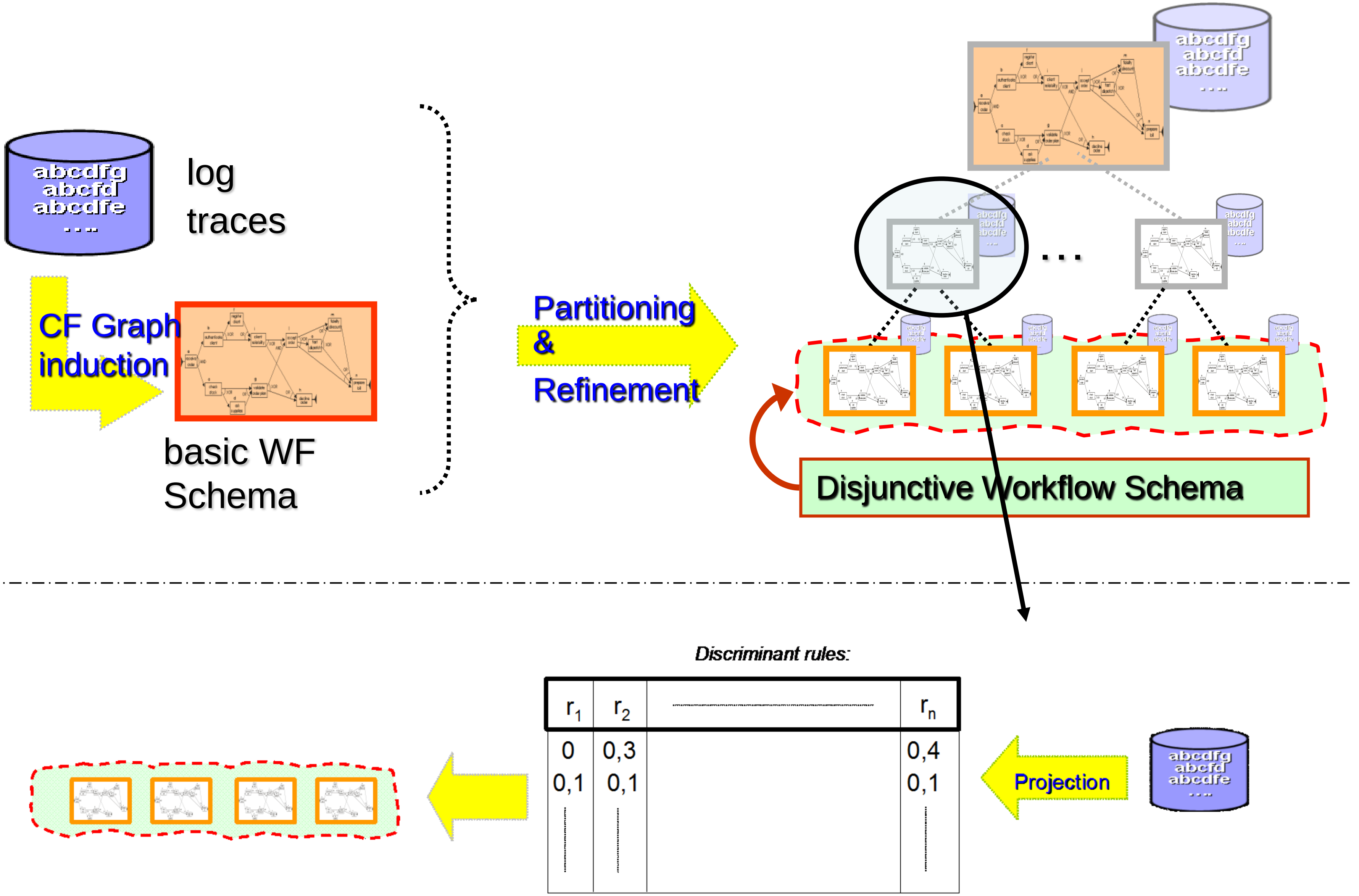
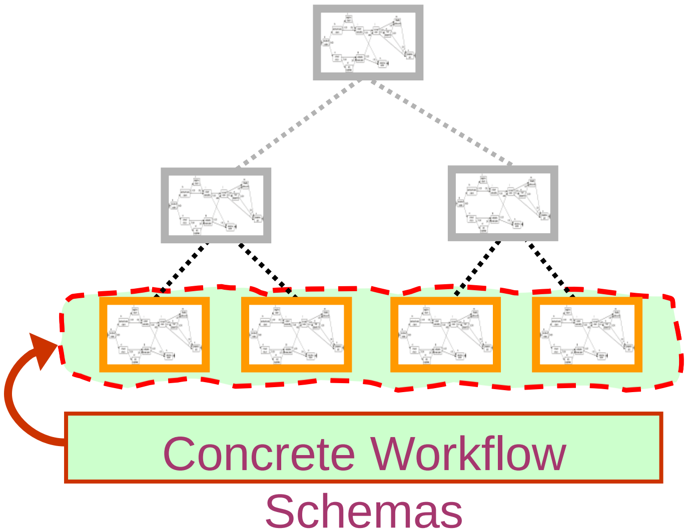


(2) Abstraction

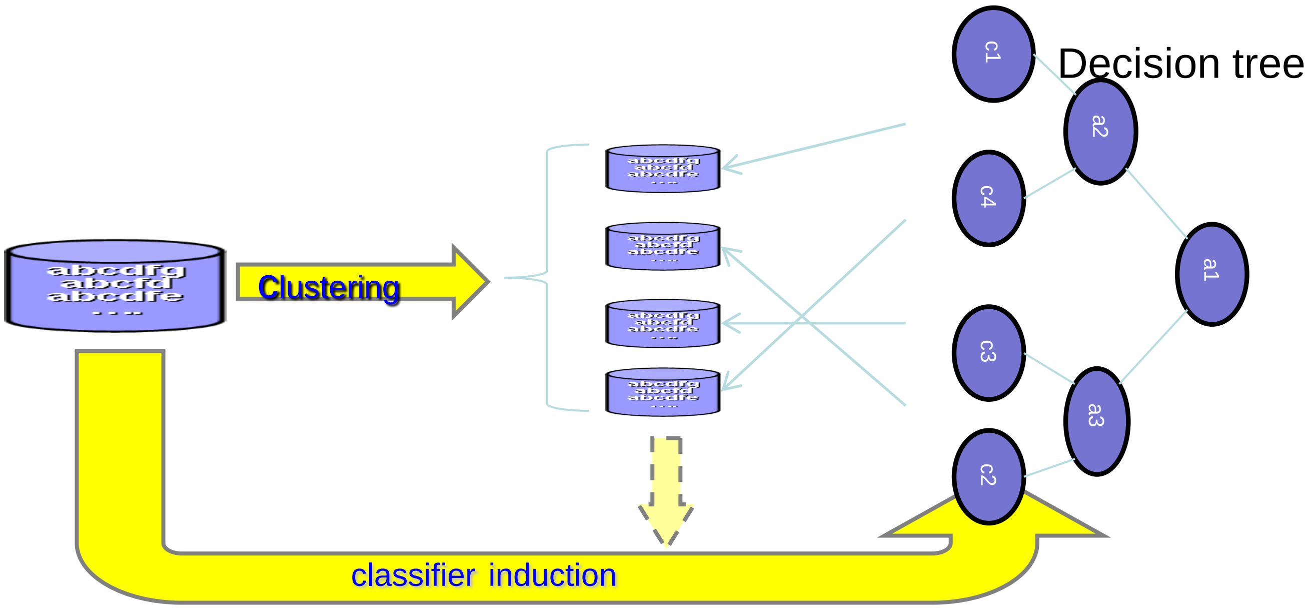


- The tree describes the process behavior at different level of details
- At the highest level of detail (leaves of the tree), the schemas could be used to support the design of concrete workflow models
- At lower levels, the schemas are abstract views over heterogeneous behaviors, which could support analysis and monitoring tasks

- Basic Idea:
  1) The hierarchy is restructured bottom-up at different levels
  2) Produce an abstraction dictionary

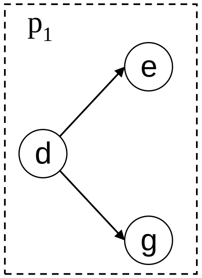
(3) Classification

- Basic idea:
  - find a comprehensive representation for the process, describing both structural and non-structural aspects
  - A rule-based classifier is induced to discriminate among given structural clusters, based on process/task data
  - help interpreting/predicting the different ways of executing the process, based on properties of process/task instances

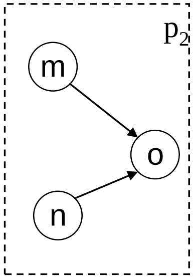


(4) Outlier Detection

- Structural patterns are identified



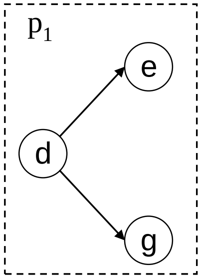
fork s-pattern



join s-pattern

(4) Outlier Detection

- Structural patterns are identified
- They are co-clustered with the traces, based on what an extent these latter support them
- Mark as outlier each trace *t* such that either
  - *t* has not been assigned to any cluster
  - *t* belongs to a cluster whose cardinality is “appreciably smaller” than the average cluster size



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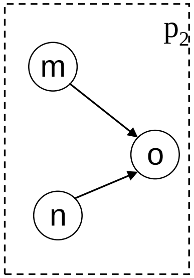

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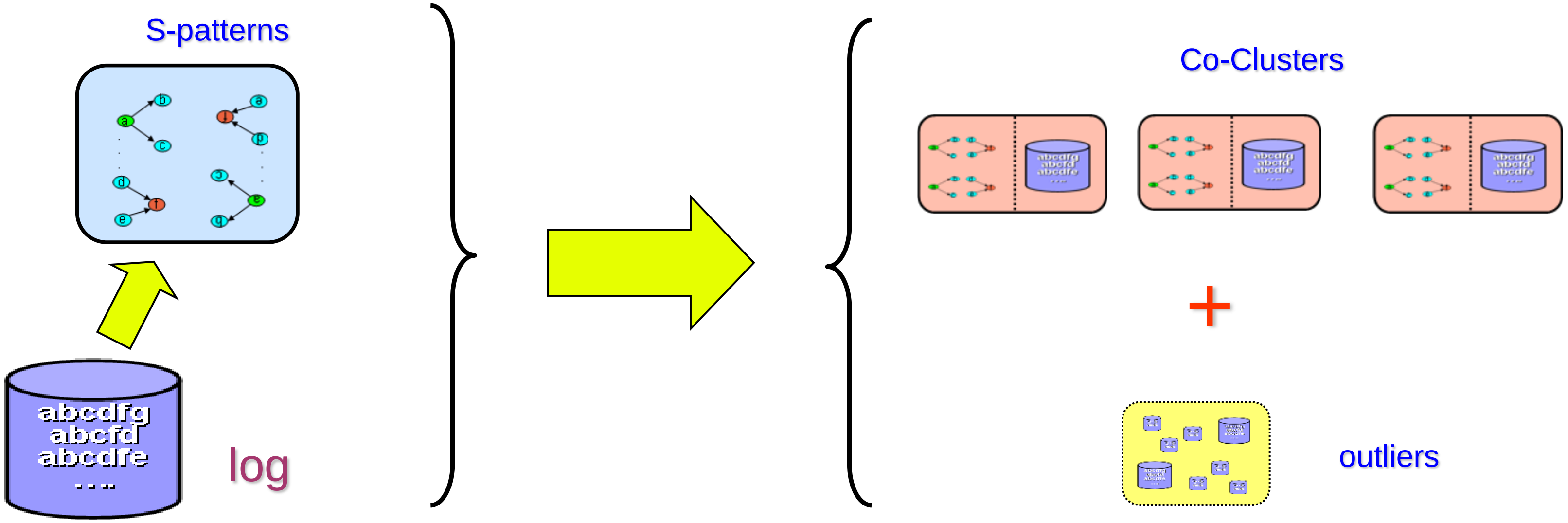

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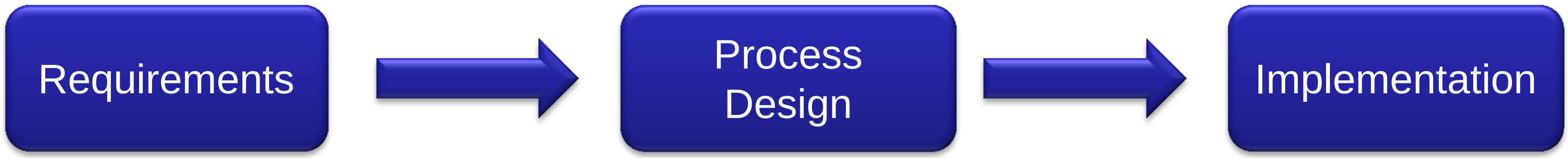

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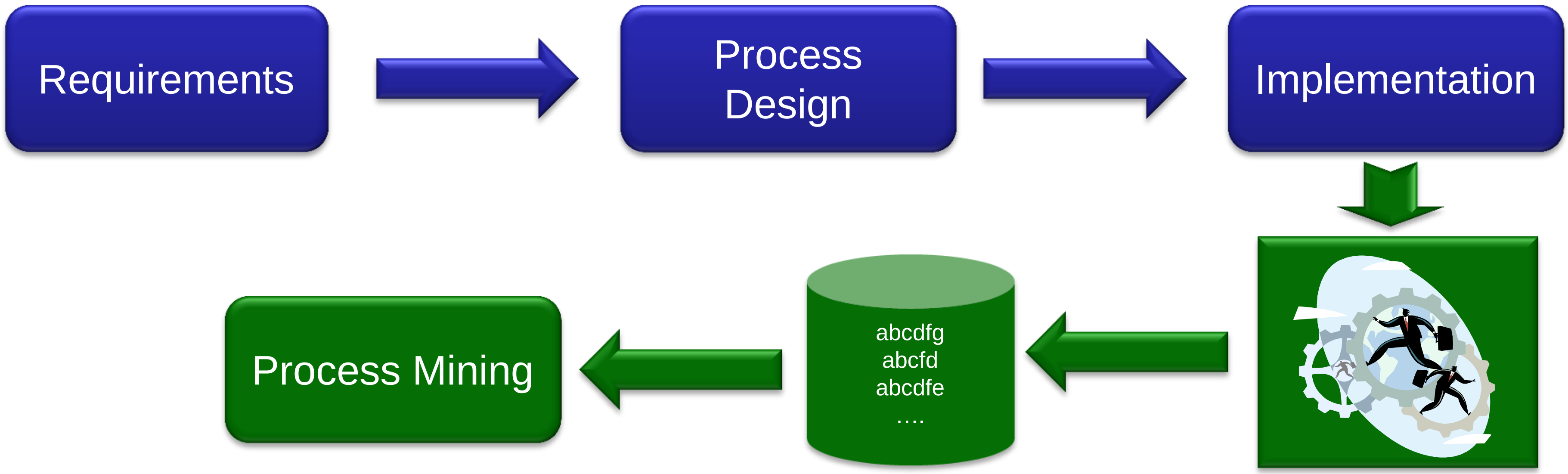

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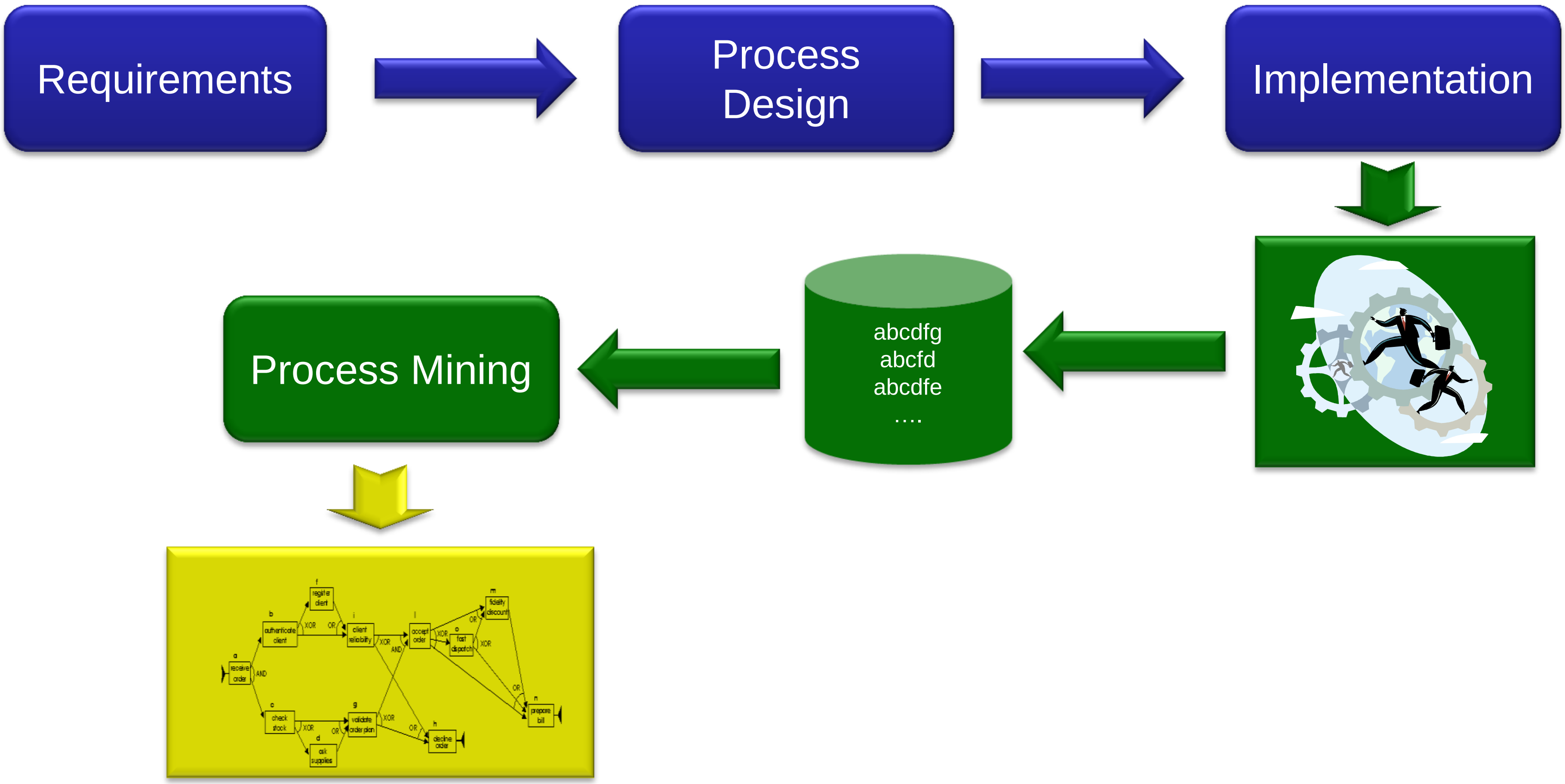

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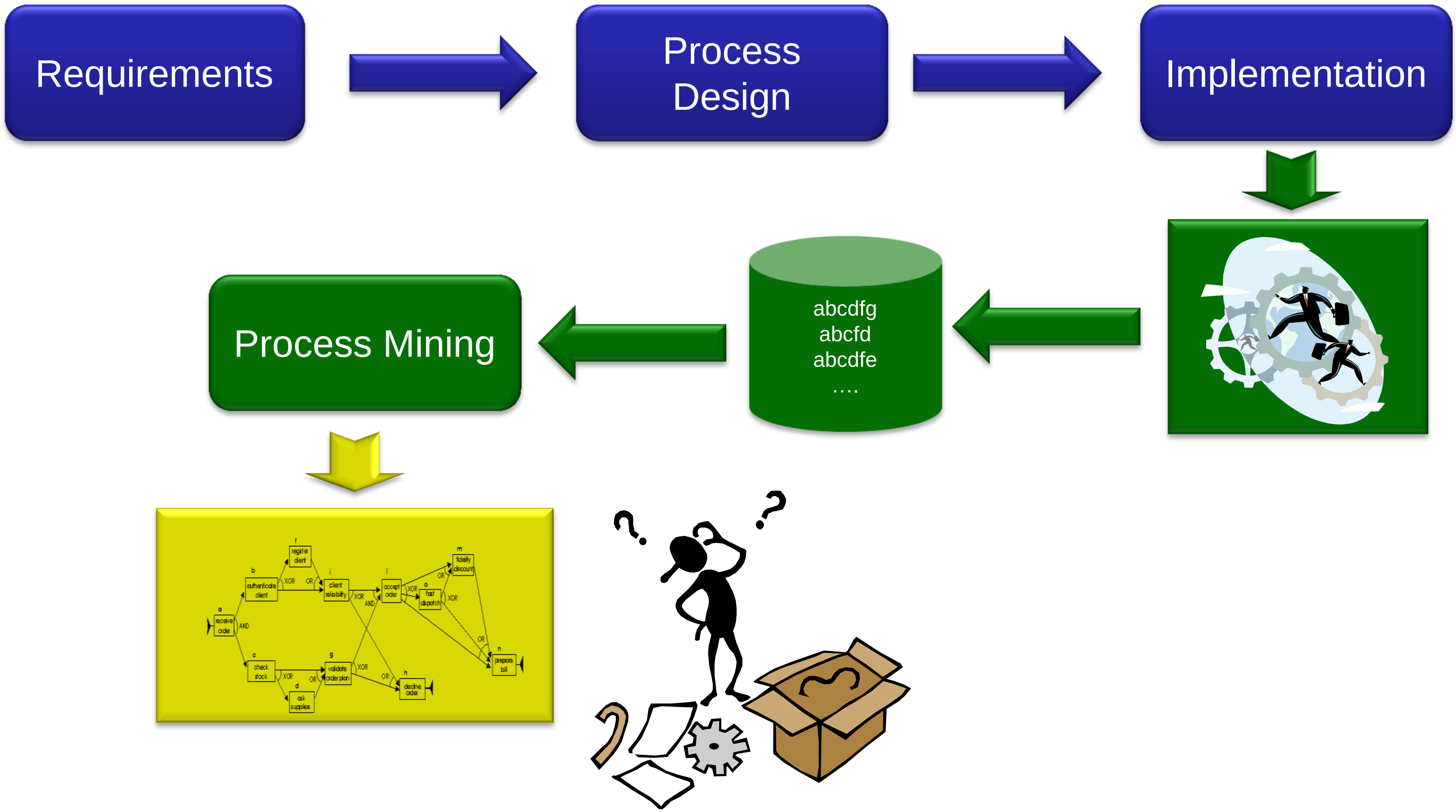

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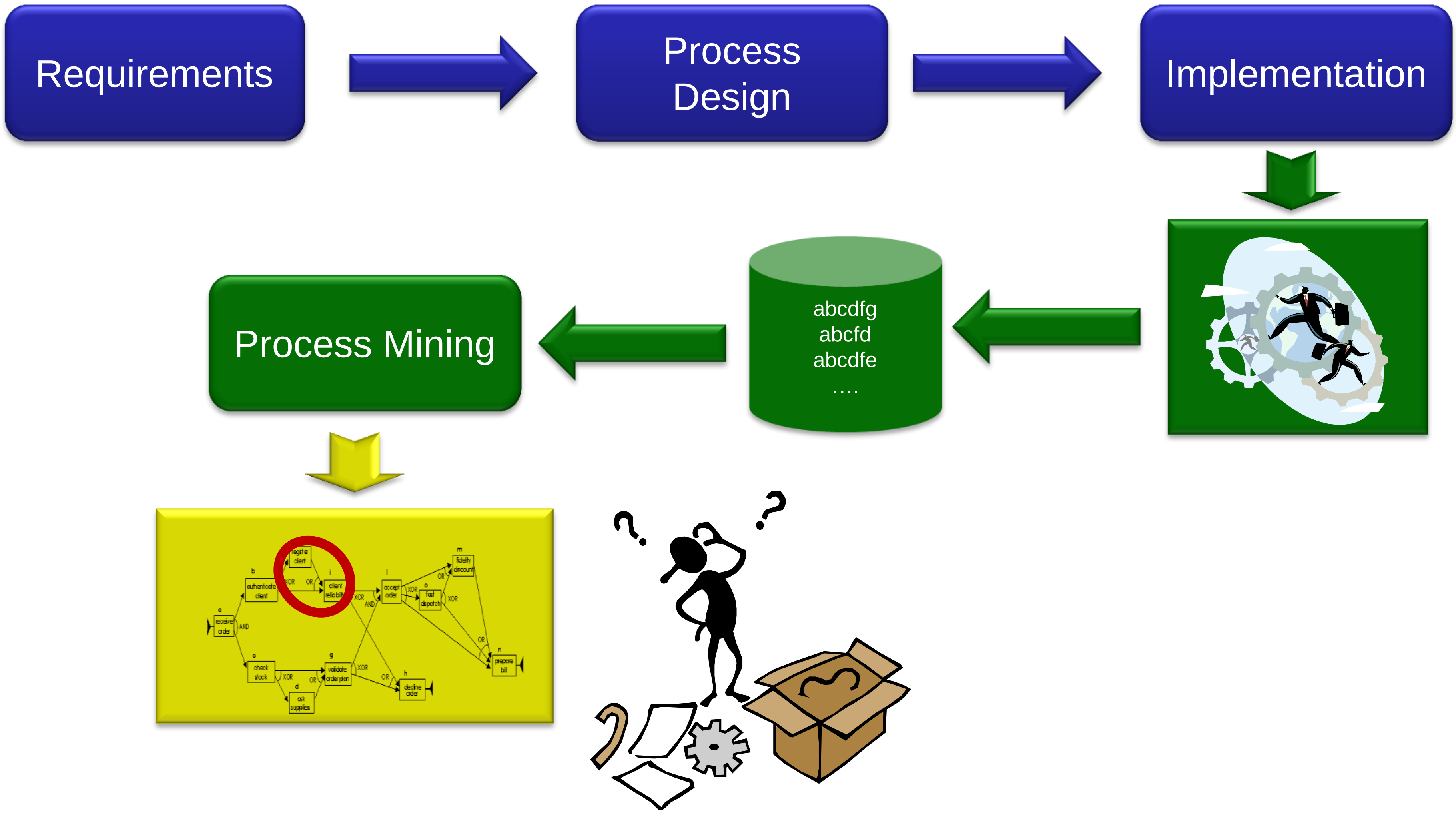

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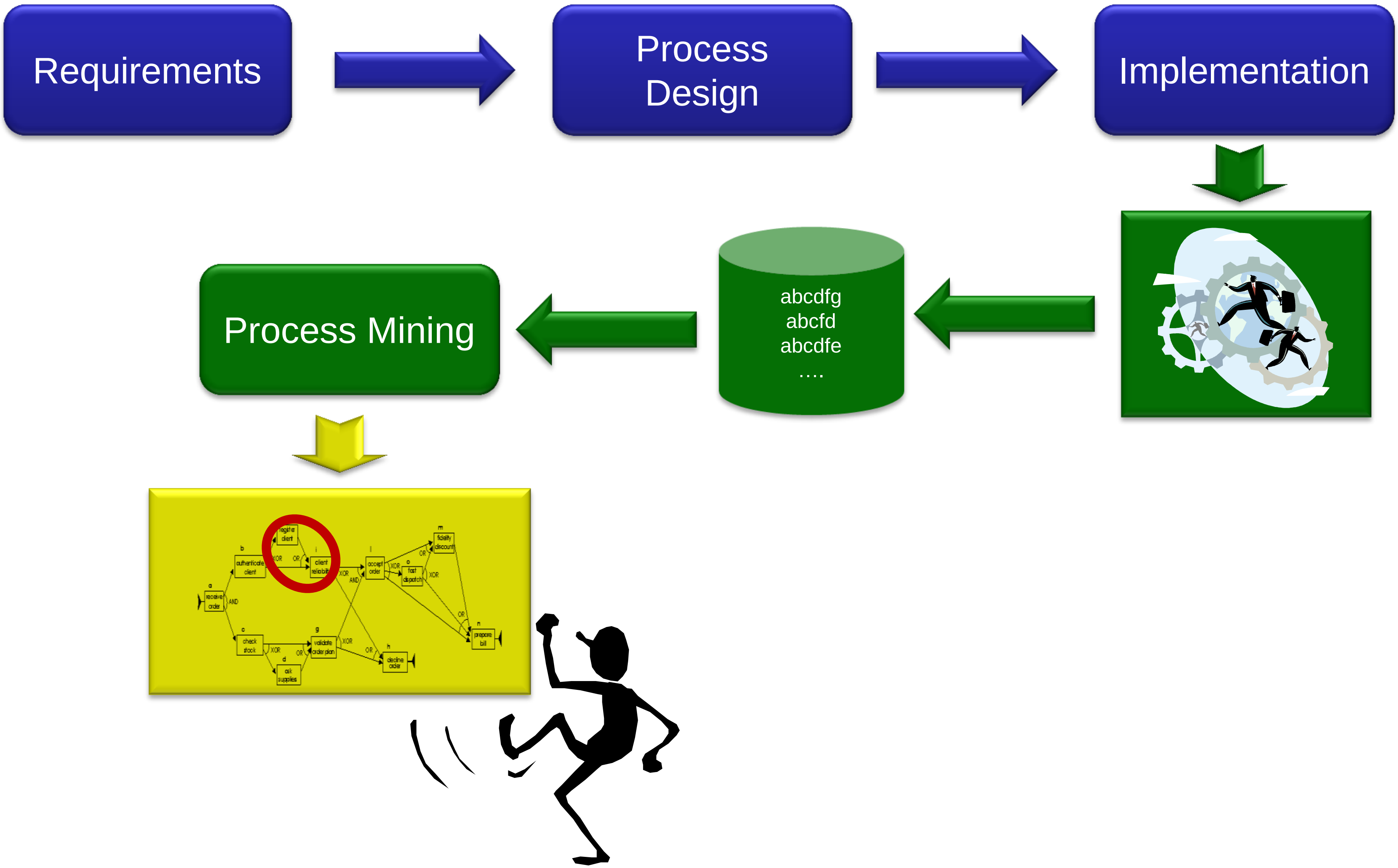
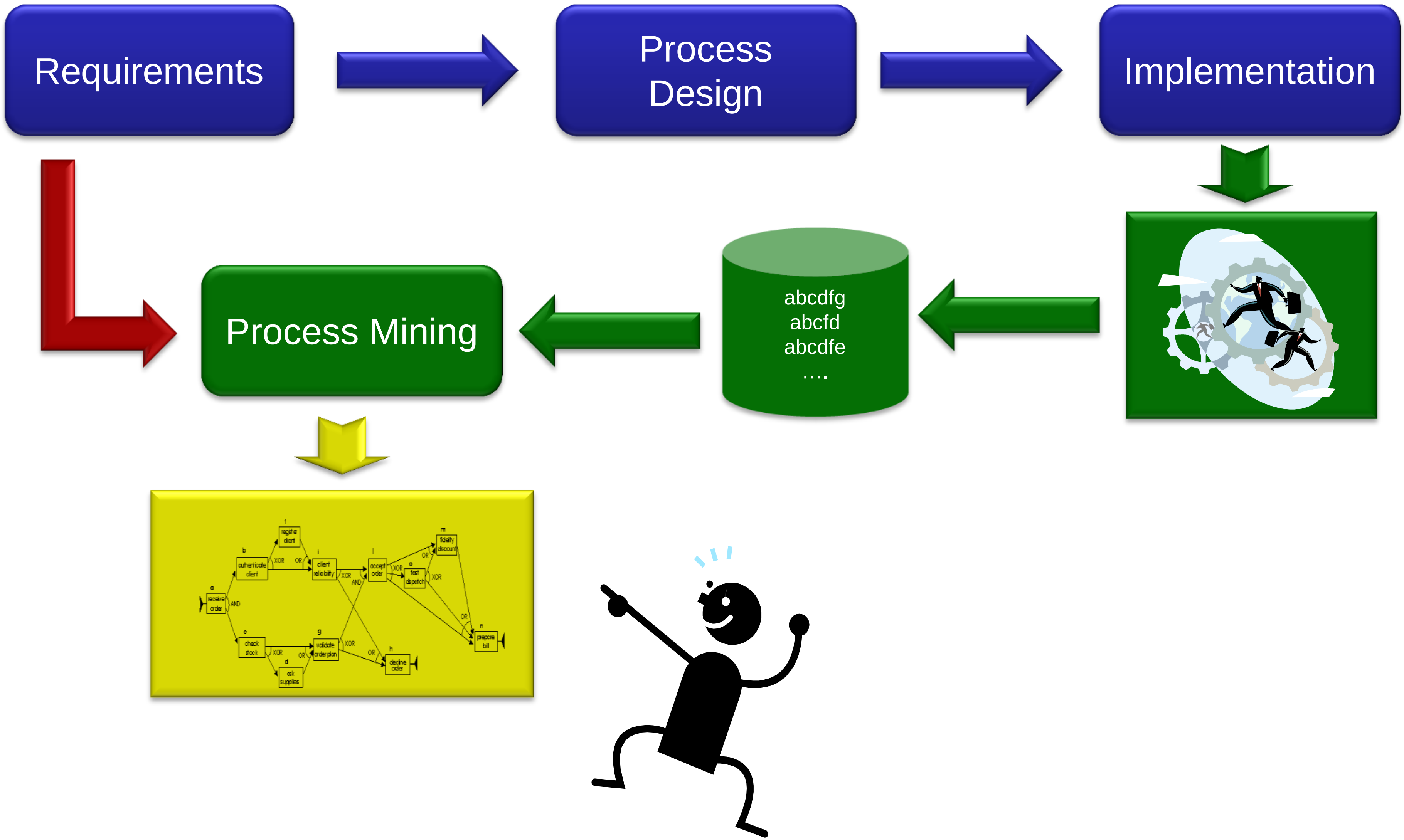


Process Mining + Background Knowledge



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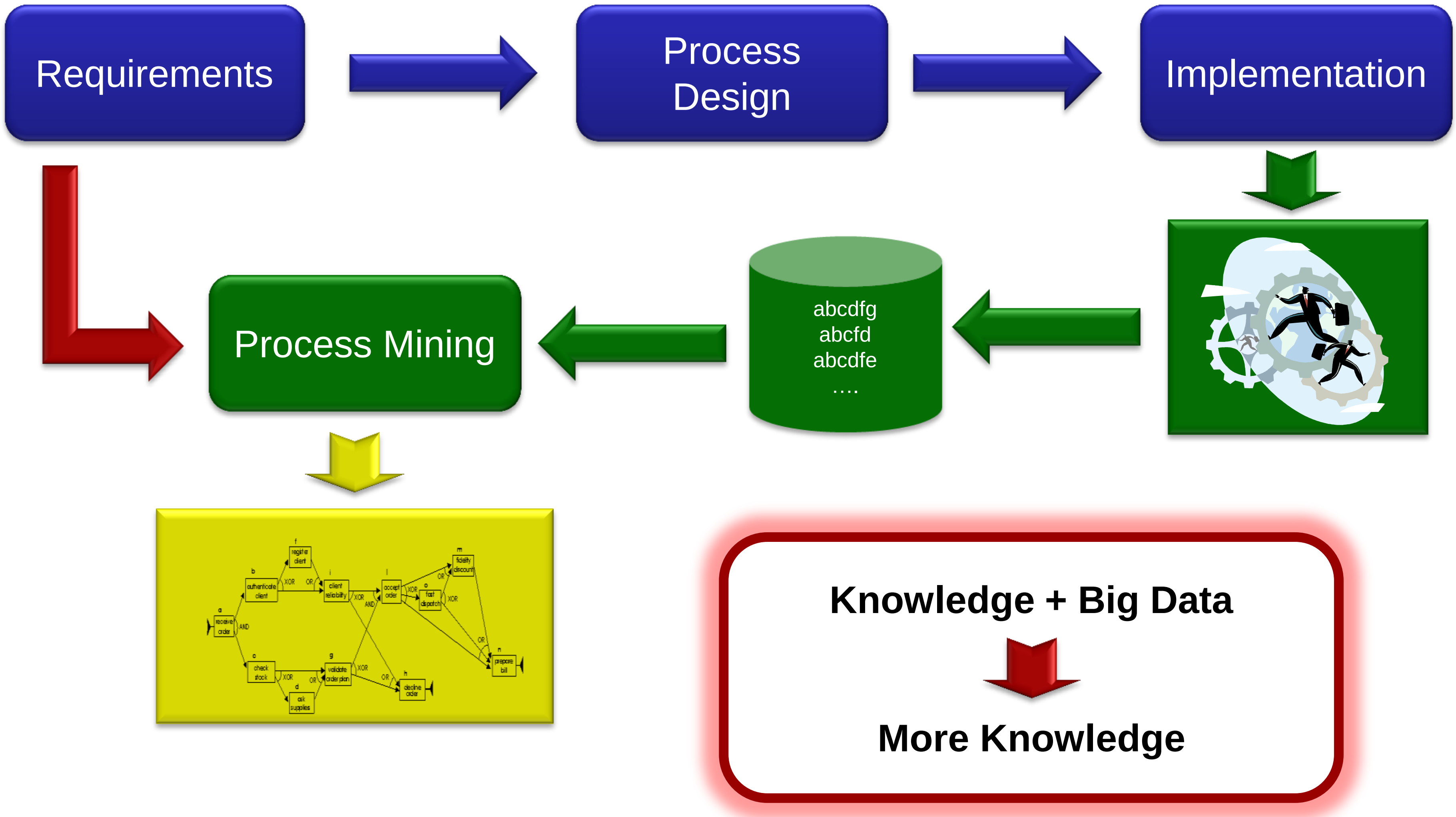

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Process Models

Dependency Graph: directed graphs whose nodes one-to-one correspond with the activities and such that an edge from an activity **a** to an activity **b** means that, in some enactment we expect that an actual flow of information can occur from **a** to **b**.

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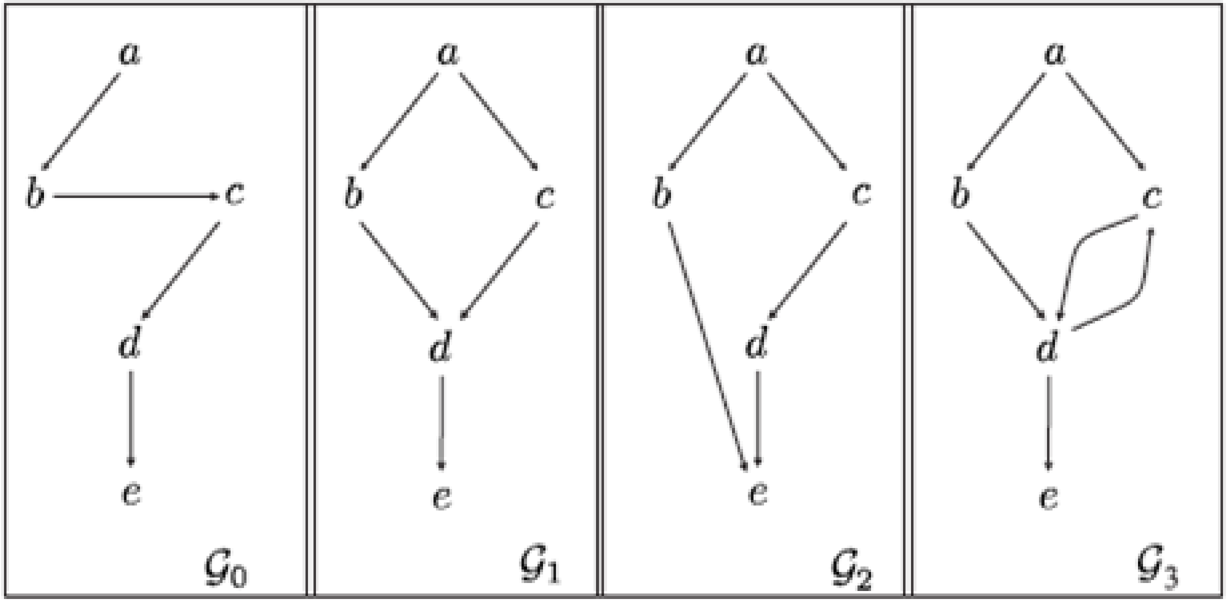
Example

abcde
acbde



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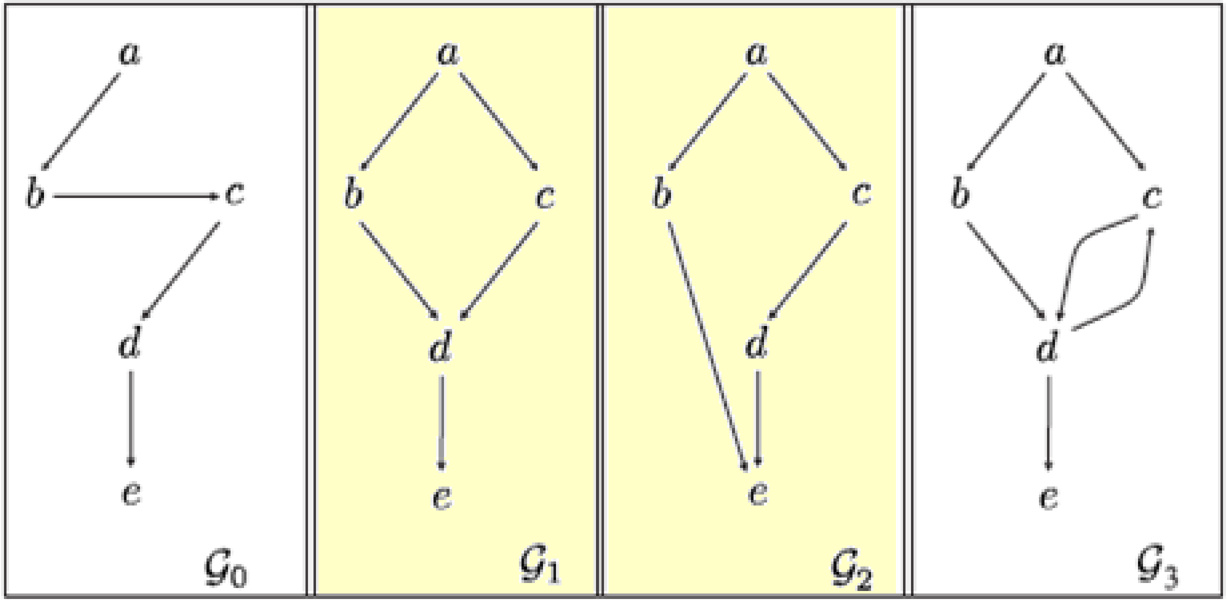

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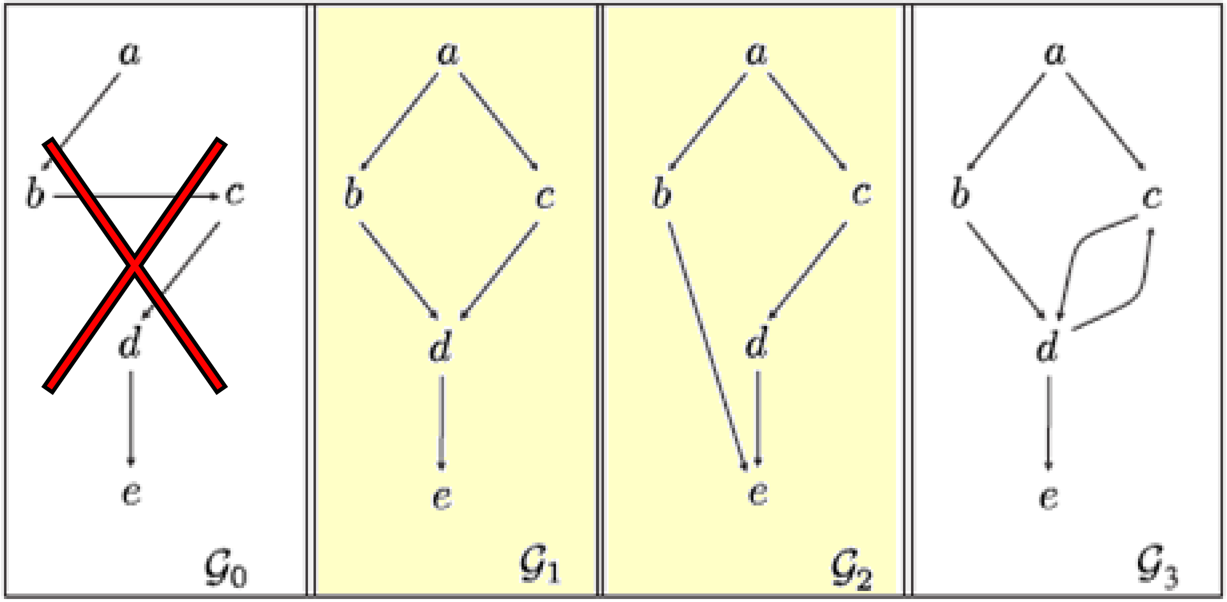

Precedence Constarints

- *Two kinds of positive constraints* π*:*
  - *edge constraint* $S \rightarrow a$
  - *path constraint* $S \rightsquigarrow a$

  where $S \subseteq \mathcal{A}$*, with* $|S| \geq 1$*, is a non-empty set of activities and* $a \in \mathcal{A} \setminus S$ *is an activity.*

- *For a positive constraint* π*,* $\neg\pi$ *is a negative precedence constraint.*

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- Syntax
  - *edge constraint* $S \rightarrow a$
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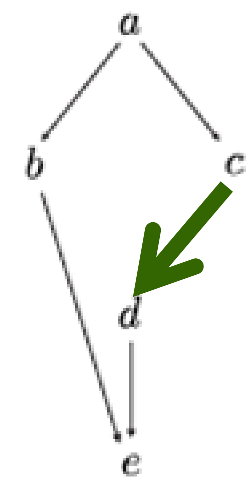

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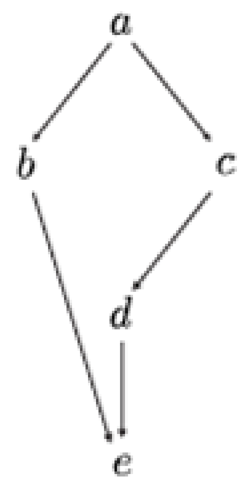

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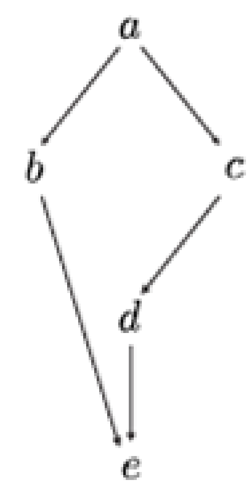

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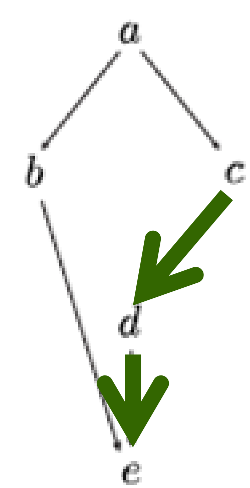

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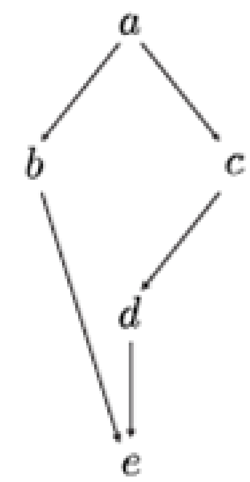

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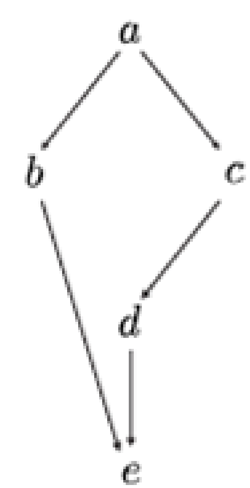

Revisiting Process Discovery

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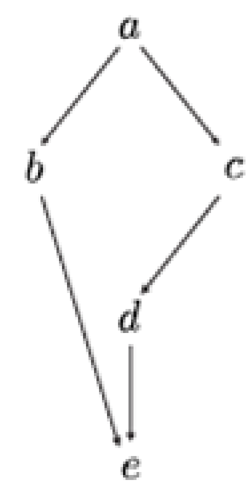

$\mathcal{G}_2$

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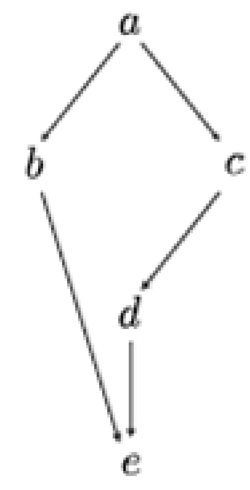
$\mathcal{G}_2$ is a solution to DG-MINING (on input $\{t_0\}$ and Π_0)



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A Closer Look

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A two-phase approach is unfeasible

«Compiling» Logs into Constraints

- Let L be a log. For each trace $t[1]...t[n] \in L$,

$$\boxed{\pi(t) = \{\, \{t[1], ..., t[i-1]\} \to t[i] \;\mid 1 < i \leq n\,\}}$$

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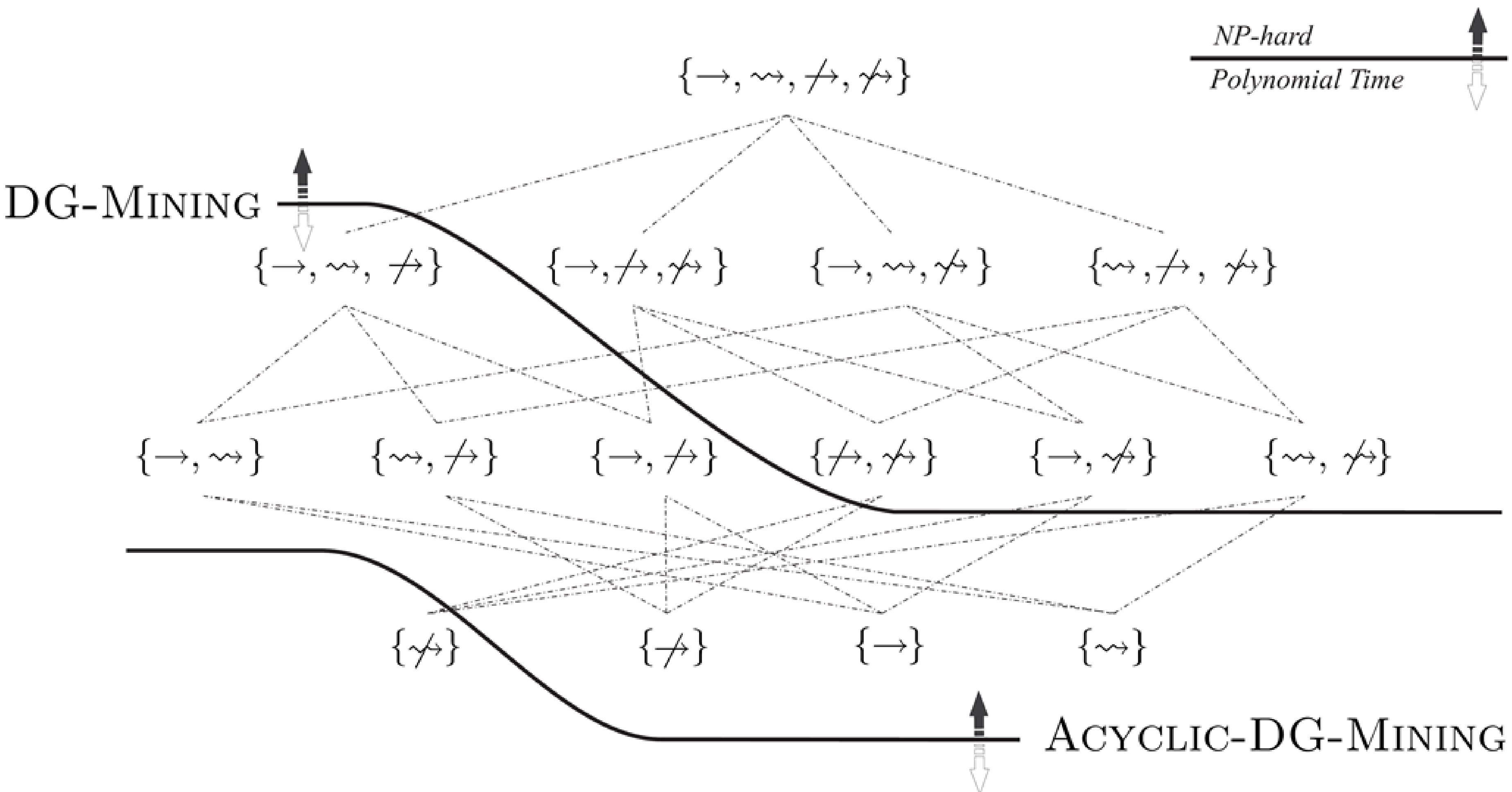
Theorem

$\mathcal{G}$ is a solution to DG-MINING *(resp.,* ACYCLIC-DG-MINING*) on input L and Π*

$$\Updownarrow$$

$$\mathcal{G} \models \pi(L) \cup \Pi.$$

Complexity Analysis



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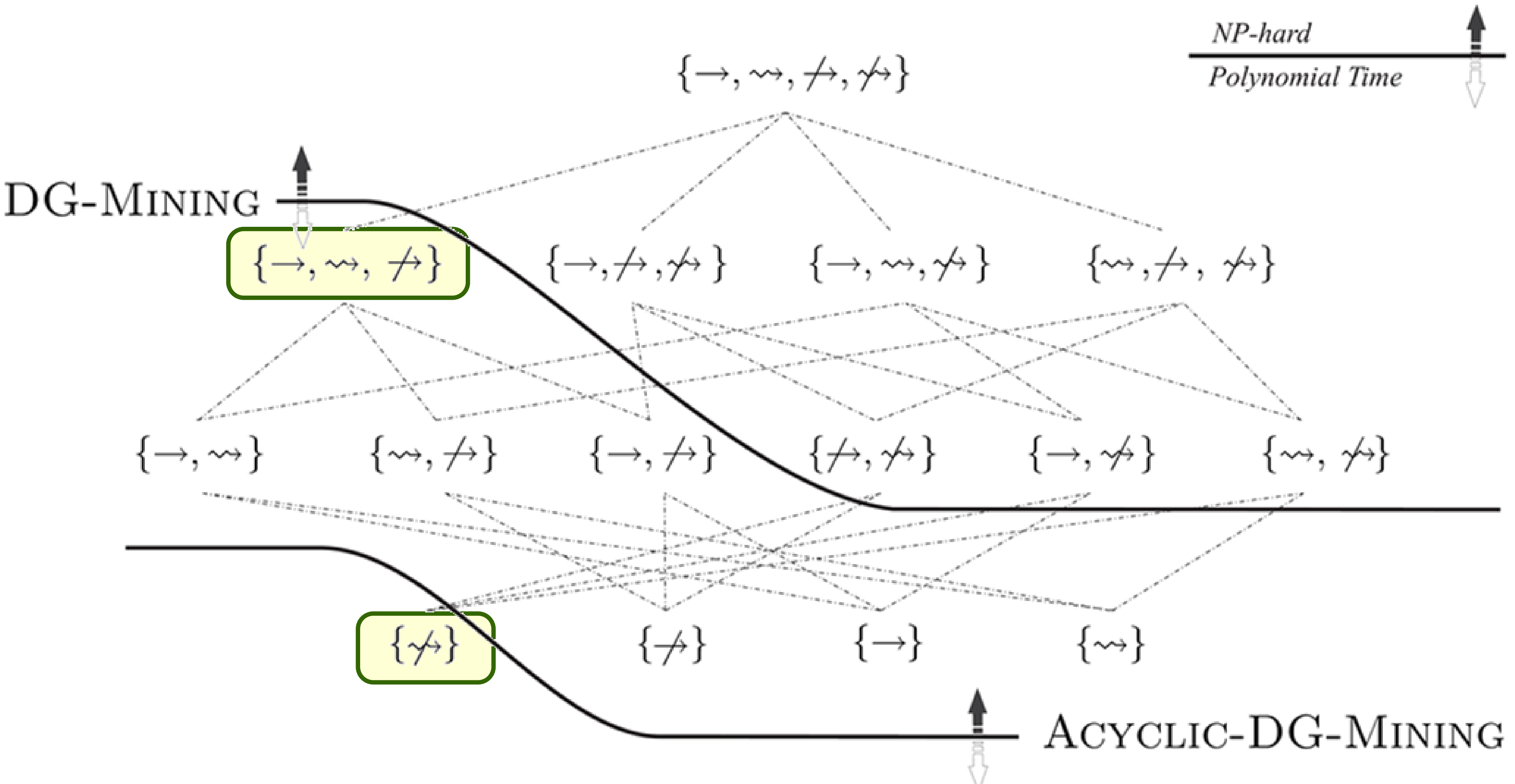

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  - $Var = \{X_1,\ldots,X_m\}$ is a finite set of variables
  - U is a function mapping each variable $X_i \in Var$ to a domain $U(X_i)$ of values
  - C is a finite set of constraints, i.e., boolean functions over $\{X_{i1},\ldots,X_{ik}\}$, such as:
    - summation constraints, of the form: $\Sigma\, w_j \times X_j \geq \gamma$
    - reified (summation) constraints, of the form: $\Sigma\, w_j \times X_j \geq \gamma \leftrightarrow X$

… where X is a boolean variable, while γ and all w_j are real numbers

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    … where X is a boolean variable, while γ and all w_j are real numbers
- An **assignment θ** for the CSP instance (Var,U,C) is a function mapping each variable $X_i \in Var$ to an element of its associated domain $U(X_i)$
  - θ is a **solution** to (Var,U,C) if it satisfies all the constraints in C

CP encoding: preliminaries

- The mining of a dependency graph based on precedence constraints is turned into a constraints satisfaction problem (CSP) or a constraint satisfaction optimization problem (CSOP)
  - existing constraint programming platforms can bereused to efficiently compute models
- Formally, a **CSP instance** is a triple (Var,U,C), where
  - $Var = \{X_1,\ldots,X_m\}$ is a finite set of variables
  - U is a function mapping each variable $X_i \in Var$ to a domain $U(X_i)$ of values
  - C is a finite set of constraints, i.e., boolean functions over $\{X_{i1},\ldots,X_{ik}\}$, such as:
    - summation constraints, of the form: $\Sigma\, w_j \times X_j \geq \gamma$
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- In addition to constraints, in a **CSOP** instance, an optimal solution is searched, minimizing a linear cost function of the form

$$f(\theta) = \sum_{i=1}^{n} w_i \times \theta(X_i)$$

Basic encoding algorithm *PCtoCSP*

A given set of precedence constraints over activities $\{a_1, \ldots, a_n\}$ is encoded into a CSP instance, containing a series of **variables for each pair a_i and a_j** of activities:

- an "edge" variables $e[a_i,a_j]$,
- "path" variables $p[a_i,a_j]^l$ and "path-through" variables $p[a_i,a_k,a_j]^l$, for $k,l = 1..n$, where l denotes the maximum number of edges in the respective path

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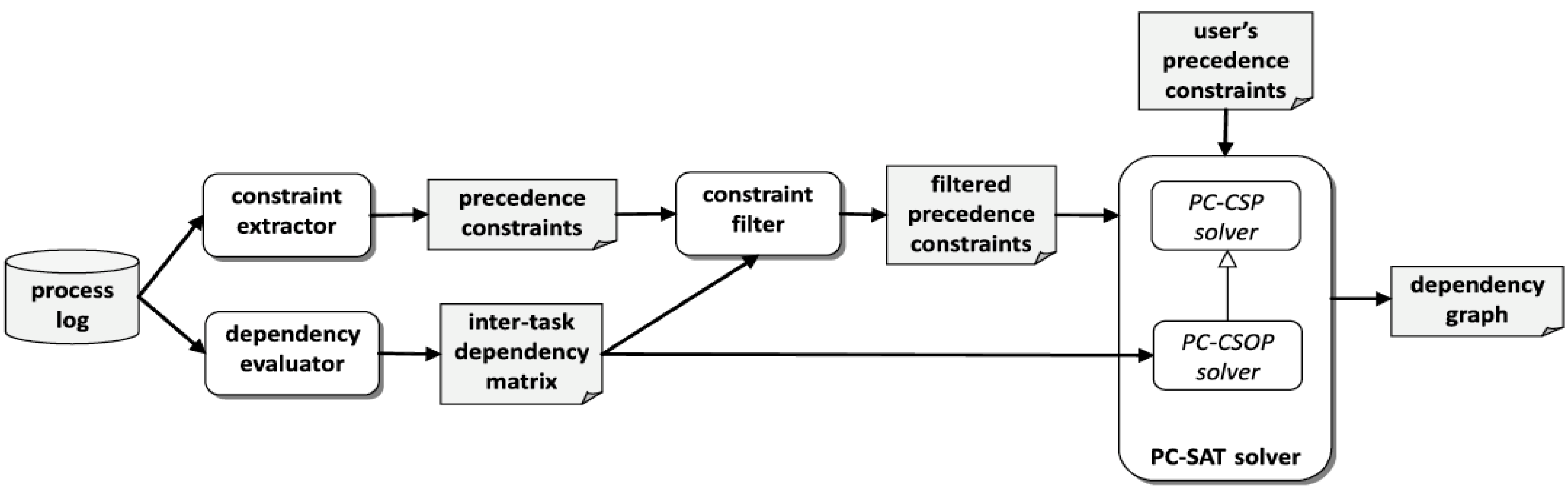

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- The PC-SAT solver module exploits standard Gecode's propagators for all kinds of constraints required in our framework.
- Ad-hoc branching policies have been implemented:
  - we first branch on the edge variables before considering path variables;
  - all variables $p[a_i,a_j]^l$ are always considered before those of the form $p[a_i,a_k,a_j]^l$

Heuristics

In order to pragmatically reduce the size of the search space and speed-up the computation, three types of heuristics can be used:

1. **Redundancy Reduction**. Two policies, relying on two different notions of constraint subsumption:
   - A constraint $S \longrightarrow a$ is filtered out if there is another precedence constraint $S' \longrightarrow a$ such that $S' \supset S$
   - A constraint $S \longrightarrow a$ is filtered out if there exist another constraint $S'' \longrightarrow a$ such that $S'' \subset S$
     - this (weaker) notion allows for recognizing skip-like control flow structures, where some synchronizing (i.e. join) activity a can be activated by an activity in $S \setminus S''$ or, optionally, by an activity in $S \cap S''$.

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2. **Closed World Assumption (CWA)**. In order to reduce the size of the search space, further constraints are introduced as follows:
   - an edge (*x*, *y*) is not permitted to appear in the model if activity *y* never follows activity *x*, (directly or ndirectly), in any trace of the log.
   - In the case of unfolding, CWA constraints are expressed over real activities, rather than on their unfolded versions.

Heuristics: Constraint Size reduction

- The **nr. of elements in constraint bodies** is a key factor for scalability.
- Let $\{ t[1], ..., t[i-1] \} \rightarrow t[i]$ be a constraint in the set $\pi(t)$ of precedence constraints derived from a given trace $t[1], ..., t[n]$.
- Three strategies for shrinking the size of the body (i.e., left hand part):

a) *Maximal horizon H over past activities*:
  - remove each $t[j]$ s.t. $j < i - H$, from $\{ t[1], ..., t[i-1] \}$

b) *Two kinds of lower thresholds* for edge weights: $\boldsymbol{\sigma}_{\mathbf{abs}}$ ("absolute"), and $\boldsymbol{\sigma}_{\mathbf{r2b}}$ ("relative to best predecessor", like in *Heuristics Miner*)
  - remove any t[j] such that *weight*(t[j],t[i]) < σ_{abs}
  - remove any t[j] s.t. *weight*(t[j],t[i]) < $\sigma_{r2b} \times \text{argmax}_{1 \le k < I}$ { *weight*(t[k], t[i]) }

c) *Maximum number $\boldsymbol{K_{top}}$ of activities that can occur in the body:*
  - at most K_{top} elements are kept, with top dependency scores (w.r.t. t[j])

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Thank you!