



SECPI: Searching for Explanations for Clustered Process Instances

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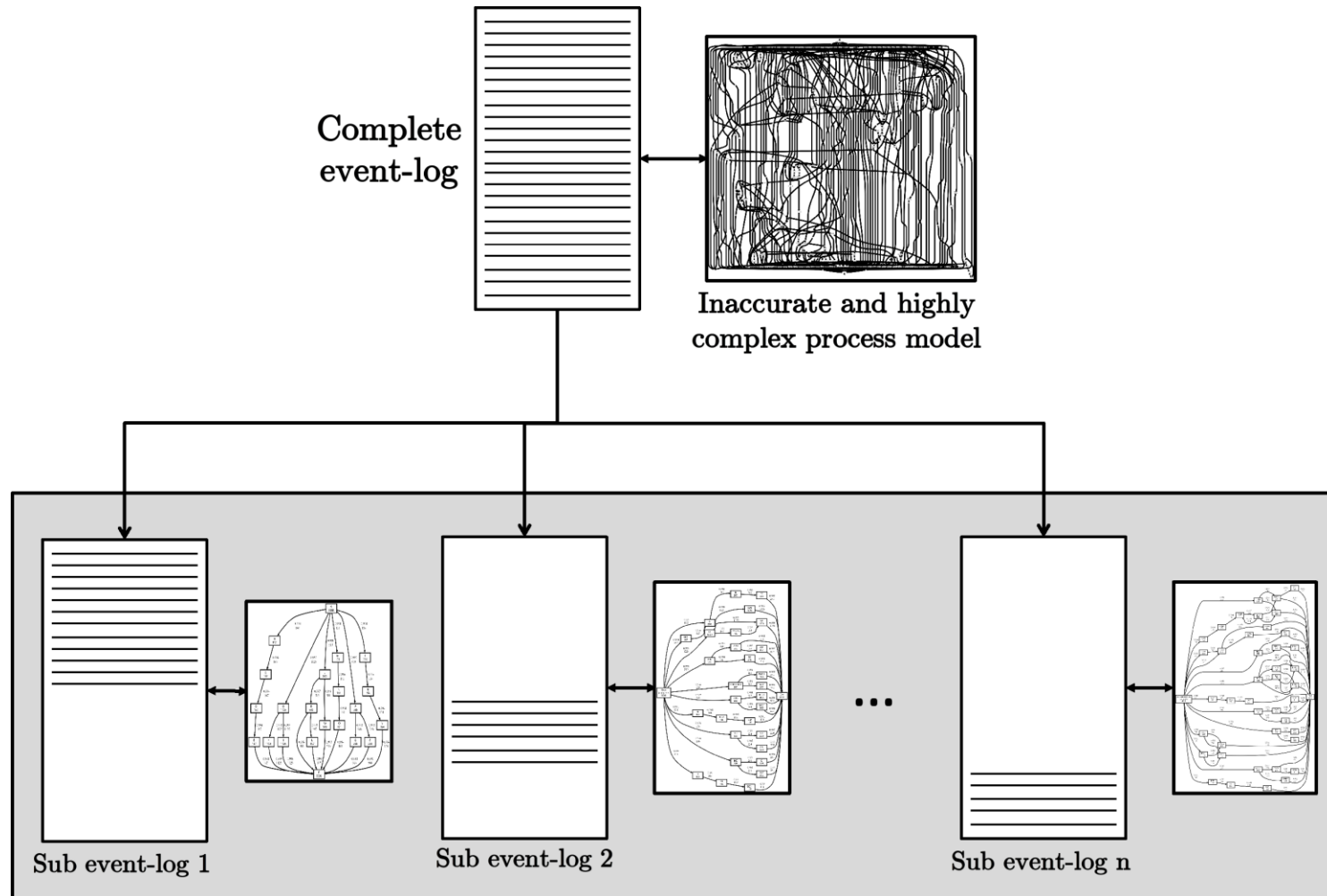
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Outline

- Introduction
 - Trace clustering
 - Problem
 - Potential alternative solutions
- Our solution: SECPI
- How does it work?
- Implementation
- Evaluation
- Ideas for future work

Trace clustering



Trace clustering algorithms

Reference	Data Representation	Clustering Bias
Greco, G., Guzzo, A., Pontieri, L., Saccà, D.: Discovering expressive process models by clustering log traces. <i>IEEE Trans. Knowl. Data Eng.</i> 18 (8) (2006) 1010–1027	propositional	instance similarity
Song, M., Günther, C.W., van der Aalst, W.M.P.: Trace clustering in process mining. In Ardagna et al., eds.: <i>BPM Workshops</i> . Vol. 17 of <i>LNBIP</i> , Springer (2008) 109–120	propositional	instance similarity
Ferreira, D.R., Zacarias, M., Malheiros, M., Ferreira, P.: Approaching process mining with sequence clustering: Experiments and findings. In Alonso et al. eds.: <i>BPM</i> . Vol. 4714 of <i>LNCS</i> , Springer (2007) 360–374	event log	maximum likelihood
Bose, R.P.J.C., van der Aalst, W.M.P.: Context aware trace clustering: Towards improving process mining results. In: <i>SDM, SIAM</i> (2009) 401–412	bag of strings	instance similarity
Bose, R.P.J.C., van der Aalst, W.M.P.: Trace clustering based on conserved patterns: Towards achieving better process models. In Rinderle-Ma, S. et al., ed.: <i>BPM Workshops</i> . Vol. 43 of <i>LNBIP</i> , Springer (2009) 170–181	propositional	instance similarity
Folino, F., Greco, G., Guzzo, A., Pontieri, L.: Mining usage scenarios in business processes: Outlier-aware discovery and run-time prediction. <i>Data Knowl. Eng.</i> 70 (12) (2011) 1005–1029	event log	maximum likelihood
De Weerd, J., vanden Broucke, S.K.L.M., Vanthienen, J., Baesens, B.: Active trace clustering for improved process discovery. <i>IEEE Trans. Knowl. Data Eng.</i> 25 (12) (2013) 2708–2720	event log	fitness
Ekanayake, C.C., Dumas, M., García-Bañuelos, L., La Rosa, M.: Slice, mine and dice: Complexity-aware automated discovery of business process models. In Daniel et al., eds.: <i>BPM</i> . Vol. 8094 of <i>LNCS</i> , Springer (2013) 49–64	propositional	complexity

Problem

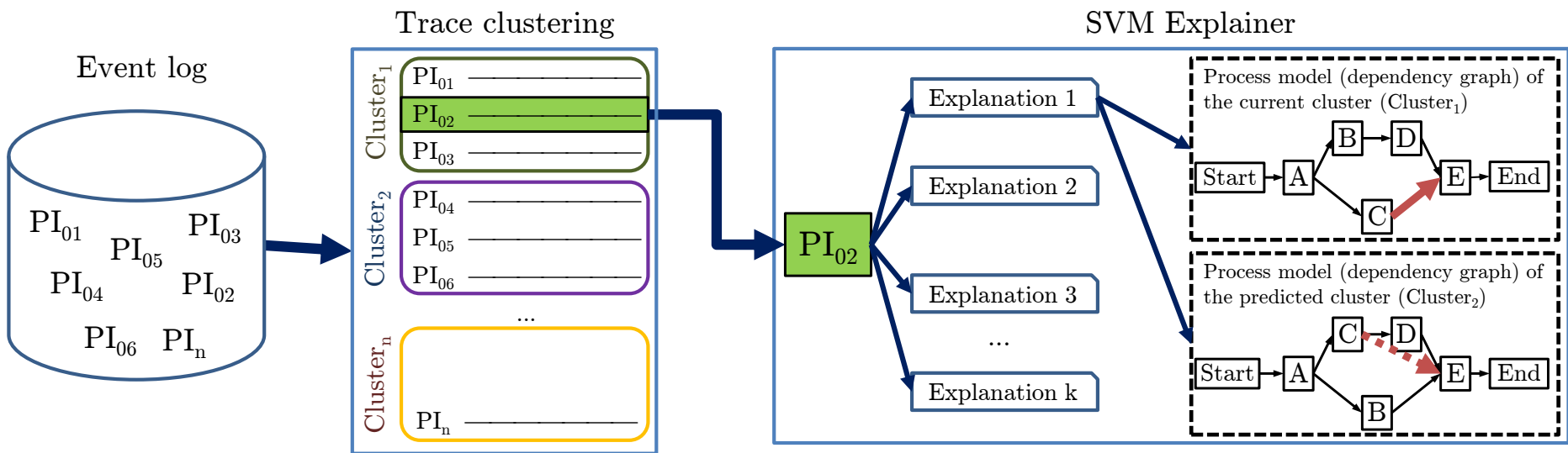
- Evaluation of trace clustering results
 - Compute intra/inter cluster similarity/dissimilarity (e.g. with a distance measure)
 - Compute fitness, precision, generalization, and simplicity of discovered process models for the clusters
- However
 - 1) What are the driving elements that determine a clustering solution?
 - 2) How can a clustering solution be understood by end-users, thus explained from a *domain* perspective?

Potential alternative solutions

- Visual analysis of the underlying process models
 - Process model similarity
 - Metrics (e.g. Alves de Medeiros et al., 2008; Dijkman et al., 2011)
 - Visualization (e.g. Dijkman 2007; 2008)
 - Footprints and behavioural profiles
 - White box classification model (e.g. decision tree)
 - Cross-cluster conformance checking
- ➔ All these techniques are valuable, but also present disadvantages to solve the problem at hand

Our solution: SECPI

- Learn a minimal set of control-flow characteristics for each process instance individually *whose absence would prevent the process instance to be in its current cluster*
- Control-flow characteristics: SometimesDirectlyFollows(A,B)



Explanation 1 for PI_{02} : **IF** SometimesDirectlyFollows(C,E) = 0 **THEN** Cluster₂

SECPI: Steps

1. Construct the data set

- Propositional data set consisting of SometimesDirectlyFollows(A,B)-attributes (binary variables)
- Cluster label for each instance

2. Derive explanations from a Support Vector Machine (SVM) classifier → SECPI algorithm

- Inspired by: Martens, D. & Provost, F. Explaining data-driven document classifications. MISQ Vol. 38, Issue 1, pp. 73-99, 2014.
- *SVM-liblinear* because of scalability (dimensionality explosion)
- Key modifications to Martens & Provost
 - Multi-class classification
 - Explanations are restricted to characteristics that are present in traces
 - Performance optimisations

SECPI algorithm

- Inputs
 - Process instance (sequence of binary attributes)
 - Classifier (SVM)
 - Three configuration parameters
 - Nr. of *iterations*: determines the length of the explanations
 - *zero_to_one*: boolean that determines whether 0-to-1 swaps are allowed
 - *require_support*: boolean that determines whether swaps of invariable attributes are allowed
- Output
 - A set of explanatory rules: set of sets of attribute indices
 - If (\neg zero_to_one) \rightarrow “This process instance would leave its current cluster when it would not exhibit the behaviour as represented by these attributes”

SECPI algorithm

- Step 1: Find single-attribute rules
- Step 2: Best-first search procedure with pruning
 - Expand on currently available combinations
 - Using the classifier's scoring function
 - Idea: find attribute swaps that move the instance farthest away from current cluster
 - Check whether any of the expanded combinations leads to a class change

ProM 6 – implementation: SVMExplainer

Parameter configuration -- step 1 of 3

Nr. of rule searching iterations: 10
C value: 4.0
E value: 0.1

Also use 0 to 1 attribute swaps
 Use WTA prediction for finding explanations

ProM UI Topia

Cluster Explorer

Create new...

Cluster: 1 *new cluster* | Cluster: 2 | Cluster: 3 *current cluster*

Accuracy: 0.999205676763976
Other traces explained by this rule (328 / 18884)

1 rule(s):
- SometimesDirectlyFollows(Work In Progress+complete,New+complete)

2 rule(s):
- SometimesDirectlyFollows(Work In Progress+complete,New+complete)
- SometimesDirectlyFollows(Assigned+complete,Closed+complete)

3 rule(s):
- SometimesDirectlyFollows(Work In Progress+complete,New+complete)
- SometimesDirectlyFollows(Assigned+complete,Closed+complete)
- SometimesDirectlyFollows(New+complete,Work In Progress+complete)

4 rule(s):
- SometimesDirectlyFollows(Work In Progress+complete,New+complete)
- SometimesDirectlyFollows(New+complete,Assigned+complete)
- SometimesDirectlyFollows(New+complete,Work In Progress+complete)
- SometimesDirectlyFollows(Assigned+complete,Closed+complete)

List All Traces Remove These Traces Show Only These Traces

Evaluation

- We have compared our approach to global, white-box classification techniques
 - Decision trees: C4.5
 - Rule learner: RIPPER
- We found across 5 real-life data sets
 - Much shorter explanations
 - On par or better accuracy of the classification/explanation model

Ideas for future work

- Aggregating individual explanations into a global model
 - Finding similar explanations
 - Clustering explanations
 - Network representation
- Opportunities
 - Studying how trace clustering techniques actually work from a domain perspective
 - Other or better characteristics to be used beyond SometimesDirectlyFollows(A,B)
 - Relate exogenously defined clusters to process-specific control characteristics

