Privacy-Preserving Process Mining:
Towards the new European General Data Protection Regulation

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Outline

1. Process Mining
2. Process Mining in Healthcare: Challenges & Opportunities
3. Privacy-Preserving Process Mining
4. Case study
5. Conclusions
1. Process Mining

- Organizations deal with multiple information systems
  - MIS, DSS, Data Warehouses, ERP, GIS...

- Store as much information as possible to extract added-value knowledge and make better decisions
  - “Knowledge is power”

- Business processes play an important role in today’s information systems
  - “From data-aware to process-aware”
1. Process Mining

- A business process is a **set of activities** aiming at accomplishing a certain **organizational goal**
1. Process Mining

- Existing techniques to monitor the execution of processes are based on **events**
  - Each event contains the activity executed, timestamp, different identifiers (*e.g.* resources),...
  - Events are stored in **event log files**

<table>
<thead>
<tr>
<th>case id</th>
<th>event id</th>
<th>timestamp</th>
<th>activity</th>
<th>resource</th>
<th>cost</th>
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<tr>
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</table>
1. Process Mining

- **Process mining** is a research field aiming at discovering, monitoring and improving real **business processes** by extracting **knowledge** from the **event logs** available in organizational **information systems**.

- **Advantages:**
  - Optimization of resources
  - Identification of bottlenecks
  - Detection of hidden dependencies
  - Better decision-makings for future improvements
1. Process Mining

a) **Discovery**: Produce process models from event logs without any a-priori information

b) **Conformance**: Verify the alignment between an existing process model with an event log of the same process

c) **Enhancement**: Extend or improve existing process models using the information stored in event log files from that processes
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2. Process Mining in Healthcare: Challenges & Opportunities

- Healthcare event log files may contain personal data
  - Especially, sensitive data (patients/doctors identifiers, health conditions, treatments, diseases...)

- Careful management to guarantee individuals privacy

- Distorting data (e.g. micro-aggregation) to prevent the disclosure of sensitive data and avoid re-identification
  - Especially when subcontracting process mining services to 3rd parties!
2. Process Mining in Healthcare: Challenges & Opportunities

- Process mining relies on the quality of log files
  - Trade-off: improve privacy but not reducing quality

- Research on process mining in healthcare uses raw data to obtain accurate and realistic views of healthcare processes, **BUT**...
EU GDPR strengthens the protection of personal data, specially those referring to sensitive data, for all individuals within the EU.
2. Process Mining in Healthcare: Challenges & Opportunities

- How GDPR affects process mining analyses
  - Art. 2: “This Regulation applies to the processing of personal data wholly or partly by automated means [...]”
  - Art. 4: “Personal data means any information relating to an identifiable natural person, [...] who can be identified, directly or indirectly, by reference to an identifier such as a name, an identification number, location data, an online identifier [...]”
  - Art. 5: “Personal data shall be: (a) processed lawfully, fairly and in a transparent manner [...] , (b) collected for explicit and legitimate purposes [...] , (c) adequate, relevant and limited to what is necessary [...] , (f) processed in a manner that ensures appropriate security of the personal data [...]”
• How GDPR affects process mining analyses
  
  – **Art. 6**: “Processing shall be lawful [...] (a) the data subject has given consent to the processing of his or her personal data for one or more specific purposes”
  
  – **Art. 7**: “[...] the request for consent shall be presented in a manner which is clearly distinguishable from the other matters, in an intelligible and easily accessible form, using clear and plain language”
  
  – **Art. 9**: “Processing of personal data revealing racial or ethnic origin, political opinions, religious or philosophical beliefs, or trade union membership, and the processing of genetic data, biometric data, data concerning health, sex life or sexual orientation shall be prohibited, [...] unless] has given explicit consent to the processing of those personal data for one or more specified purposes”
2. Process Mining in Healthcare: Challenges & Opportunities

• How GDPR affects to process mining analyses
  
  – **Art. 25**: “implement appropriate technical and organisational measures, such as pseudonymisation, [...] and to integrate the necessary safeguards into the processing in order to meet the requirements of this Regulation and protect the rights of data subjects”
  
  – **Art. 32**: “[...] implement appropriate technical and organisational measures to ensure a level of security appropriate to the risk [...]:(a) the pseudonymisation and encryption of personal data; (b) the ability to ensure the ongoing confidentiality, integrity, availability and resilience of processing systems and services [...]”

https://www.i-scoop.eu/gdpr/gdpr-personal-data-identifiers-pseudonymous-information/
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3. Privacy-Preserving Process Mining

• Existing works do not use any privacy-preserving technique (realistic views)

• No research on assessing the effectiveness of current process mining methods with proper privacy-preserved datasets

• GOAL: Studying how process models differ when they are generated from raw events or privacy-preserved events
3. Privacy-Preserving Process Mining

SENSITIVE EVENT LOGS

PROCESS MINING ALGORITHM

SENSITIVE PROCESS MODEL

PRIVACY-PRESERVED EVENT LOGS

PRIVACY-PRESERVED PROCESS MODEL

COMPARISON
Outline

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4. Case Study

- Event log file (≈ 130k events) of requests/petitions of doctors in a hospital

- What we focus on?: How doctors behave?
  - (Transitions between) actions that doctors perform during patient treatments
  - 1 doctor : 1 process behaviour (graph)

- Not limited to this question
# 4. Case Study

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<thead>
<tr>
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<th>episode</th>
<th>doctor</th>
<th>patient</th>
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</tbody>
</table>
4. Case Study

- **Problem**: Some doctors have much more episodes than others (different distribution)

- **Adversary model**:
  - Assumed scenario: Distribution of doctors can be known (# of consultation hours...)
  - Profiling of doctors: Individualization
  - Goal: Identify the behavior of each doctor

- **Privacy-preserving solution**:
  - Pseudonymization is not enough (no affects distribution)
  - Uniform the distribution of episodes per doctor as much as possible (hide the doctor’s episodes) → Change doctor ID
  - Prevent re-identification of doctors
4. Case Study

- Distribution of episodes per doctor
  - 648 doctors
  - \( \approx 62k \) episodes
  - \#episodes per doctor: \([1, 1312] \rightarrow [95, 96]\)

Change episodes from doctor until reaching uniform distribution
4. Case Study

- 900 episodes
- 18 nodes
- 75 edges
- Most frequent paths: <INIT, 4:petPC, END>, <INIT, 4:petEcg, END>, <INIT, 4:petRx, END>
- Node degree: 8,3 ± 4,7

Simplification
Little inf. loss

- 96 episodes
- 19 nodes
- 43 edges: 41 (same) + 2 (new)
- Most frequent paths: <INIT, 4:petEcg, END> <INIT, 4:petPC, END> <INIT, 4:petRx, END>
- Node degree: 4,5 ± 2,9
4. Case Study

- 23 episodes
- 6 nodes
- 9 edges
- Node degree: 3 ± 0.9

- 96 episodes
- 23 nodes
- 65 edges: 7 (same) + 58 (new)
- Most frequent paths: <INIT, 4:petRx, END>, <INIT, 4:petInter, END>, <INIT, 4:petEcg, END>
- Node degree: 5.7 ± 3.2

High distortion
High inf. loss
4. Case Study

Information loss (higher %new edges = new behaviour)
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• Process mining is an emerging field with high potential

• The importance of preserving privacy of individuals in log files
  – Careful management of sensitive information (third parties)
  – Compliance with EU GDPR

• **Future work:**
  – Apply other privacy-preserving techniques (*e.g.* generalization of doctors according to a hierarchy)
  – Exhaustive analysis of much more graph measures (*centrality, connectivity, distance...*)
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