Karlsruhe Institute of Technology

Process Model Search using Latent Semantic Analysis

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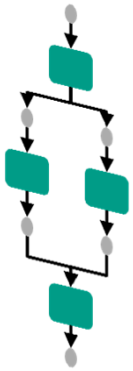
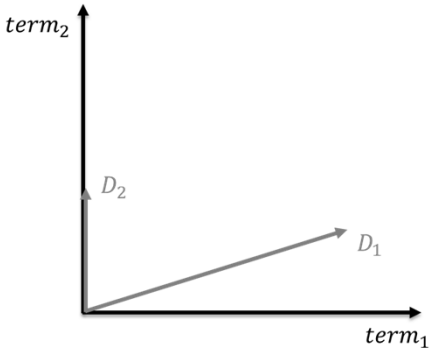
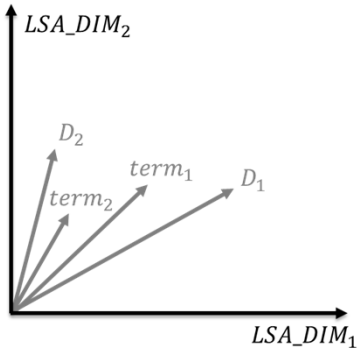
1st International Workshop on Process Querying

Karlsruhe Institute of Technology (KIT),
Institute of Applied Informatics and Formal Description Methods



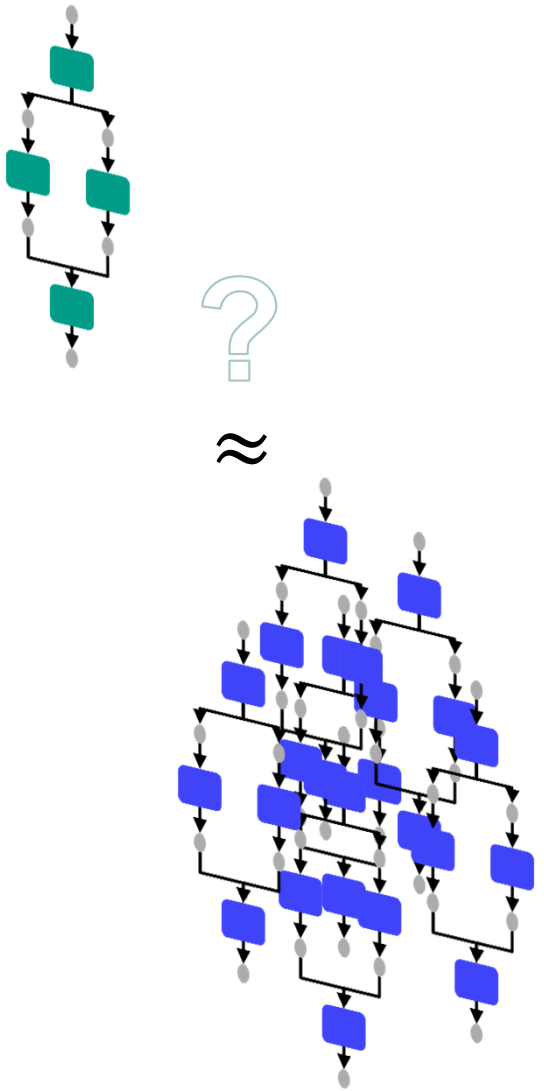
$$\begin{array}{c} \\ T_1 \\ T_2 \\ \vdots \\ T_t \end{array} \begin{array}{c} \begin{array}{cccc} D_1 & D_2 & \cdots & D_n \end{array} \\ \begin{pmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ w_{t1} & w_{t2} & \cdots & w_{tn} \end{pmatrix} \end{array}$$





Motivation

- Similarity-based search for process models
- Existing approaches mostly based on Process Model Matching
- Determining Matches challenging
  - Correctness
  - Effort
- Solution
  - Similarity calculation in vector space
  - Circumvent matching part



Latent Semantic Analysis

- LSA is a mathematical / statistical method for determining the meaning of words and documents

$$meaning_{passage} = \sum(m_{term1}, m_{term2}, ..., m_{termn})$$

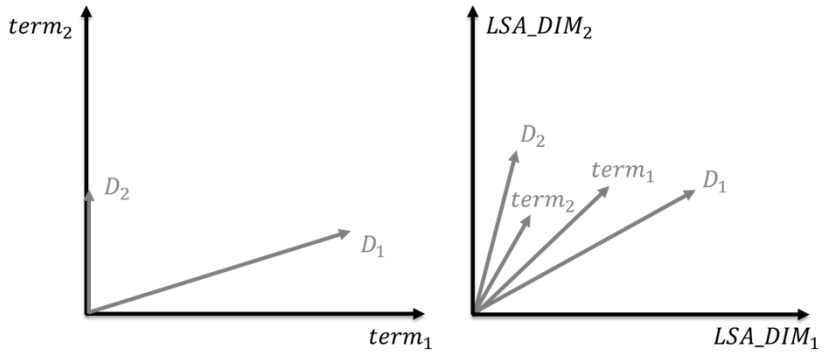
- Has been developed for improving document search in information retrieval
- Extends syntax-based approaches of information retrieval by incorporating the latent semantic structure of documents

LSA – Semantic vector space

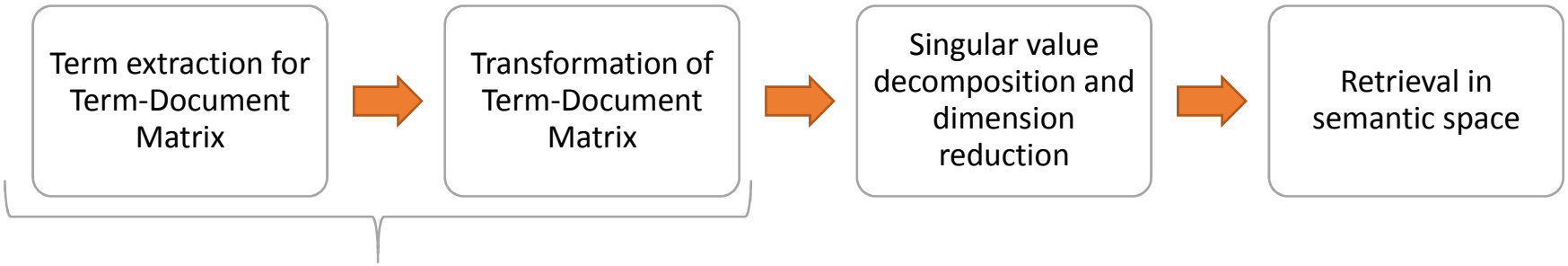
- Classical syntax-based approaches of information retrieval base on a Term-Document Matrix
  - Rows = Terms
  - Columns = Documents
  - Entry = Frequency

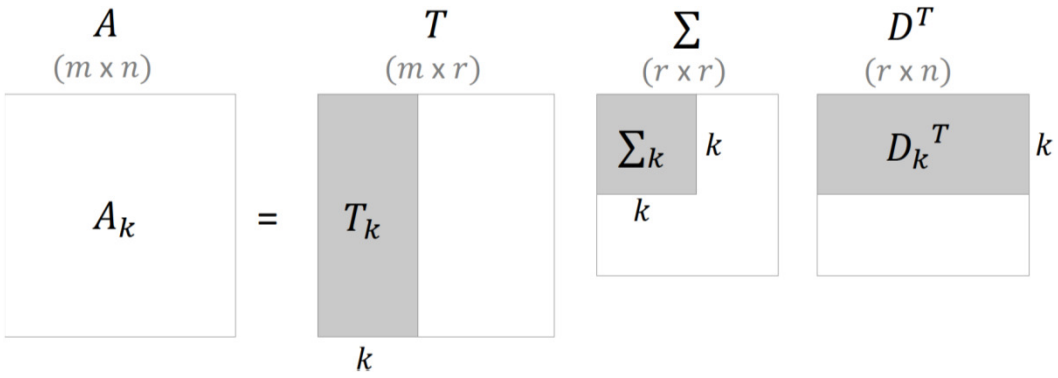
$$\begin{array}{c} \\ T_1 \\ T_2 \\ \vdots \\ T_t \end{array} \begin{array}{c} \begin{array}{cccc} D_1 & D_2 & \cdots & D_n \end{array} \\ \begin{pmatrix} w_{11} & w_{12} & \cdots & w_{1n} \\ w_{21} & w_{22} & \cdots & w_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ w_{t1} & w_{t2} & \cdots & w_{tn} \end{pmatrix} \end{array}$$

- LSA additionally considers the shared occurrence of terms
  - Latent semantic dimensions
  - Transformation of vector space



LSA – Main steps





Singular value decomposition and dimension reduction

Document Vector Representation of Process Models

Malinova, M., et al.: Automatic Extraction of Process Categories from Process Model Collections. BPM Workshops, pp. 430 – 441 2014

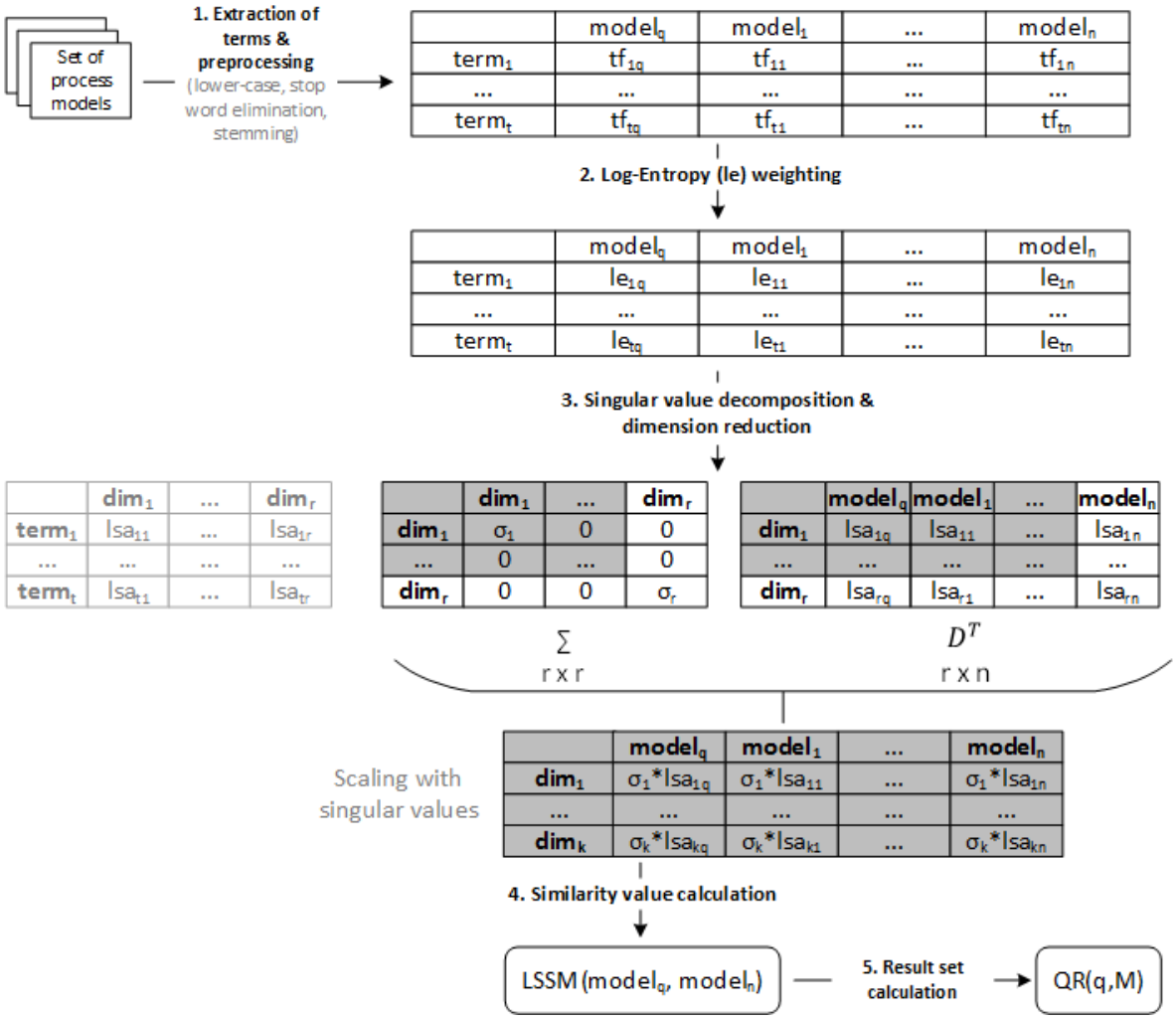
- Let …
  - M be a set of process models
  - W_{all} be a set of terms containing all distinct terms of M
  - $w(m)$ be a function, which returns the set of terms (bag-of-words) W_m of a process model $m \in M$ ($W_m \subseteq W_{all}$)

- The vector $d_m = (w_{1m}, w_{2m}, \dots, w_{tm})$ then represents the document vector of the process model m
- Each index t represents a term of the set of all terms contained in the process model collection $W_{all} = \bigcup w(m)$ for all $m \in M$

- The entries w_{tm} reflect a weight of the term frequency, which describe how often a certain term appears within a model

LS3: LSA-based Similarity Search (1)

Calculation of similar models with respect to query model q



LS3: LSA-based Similarity Search (2)

Step 1: Extraction of terms for the term-document matrix

- Extraction of distinct terms of place and transition labels
- Transformation into lower case letters
- Removal of stop words
- Stemming with Porter stemmer

- Term-document matrix contains absolute term frequencies

Step 2: Transformation of the term-document matrix

- Application of log-entropy weighting
- Differences in absolute term frequencies shall be reduced
- Frequently appearing terms shall be less relevant compared to infrequent terms

- Term-document matrix contains weighted term frequencies

LS3: LSA-based Similarity Search (3)

Step 3 / 4: SVD, dimension reduction, and similarity value calculation

- Calculation of singular value decomposition
- Only matrices Σ and D^T are relevant
- Scaling of document vectors with singular values
- Calculation of cosine similarity
- $\mathrm{LSSM}(q, m) = \frac{\cos_{\mathrm{sim}}(q,m)+1}{2}$

Step 5: Retrieval of query results

- Results are determined through a threshold value
- $\mathrm{QR}(q, M) = \{m \mid m \in M \wedge \mathrm{LSSM}(q, m) \geq \theta\}$

Evaluation Setup

- Dutch governance models (80 models)
  - 8 processes of 10 municipalities
  - Linguistically harmonized labels

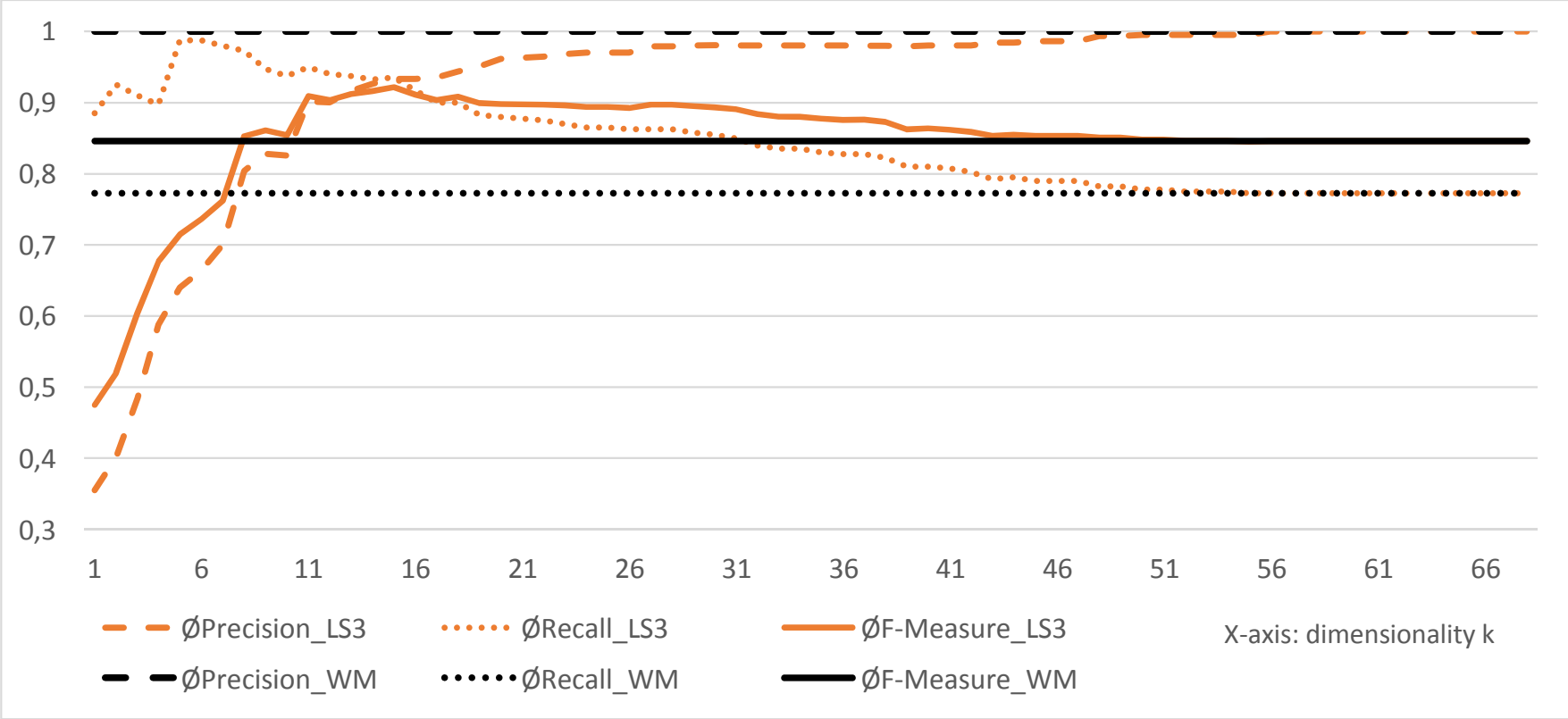
Vogelaar, J. et al.: Comparing Business Processes to Determine the Feasibility of Configurable Models: A Case Study. BPM Workshops. pp. 50–61 2011

- Calculation of Precision, Recall and F-Measure
  - Each model used as query model (80 queries per dimensionality)
  - Returned models are relevant if they represent the same process as the query model
  - Calculated for each possible dimensionality (Step 3)

- $\theta \geq 0.75$

- Compared against classical Word Matching from Information Retrieval

Evaluation Results



Comparison of LS3 and classical Word Matching from Information Retrieval

Discussion and Limitations

- Strengths
  - No matching of process model elements necessary
  - No external corpora or ontologies needed
  - Fast run time

- Limitations
  - Determination of optimal dimensionality
  - Interpretation of latent dimensions
  - Sufficiently many terms in labels

Conclusion and Outlook

- Similarity calculation of process models based on Latent Semantic Analysis shows **promising results**
- **Further empirical studies** needed
  - Larger process model collections
  - Model collections with non-harmonized labels
  - Comparison against other process model similarity measures
- **Handling of changes** in the model collection not yet incorporated

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Thank you for your attention!

QUESTIONS?