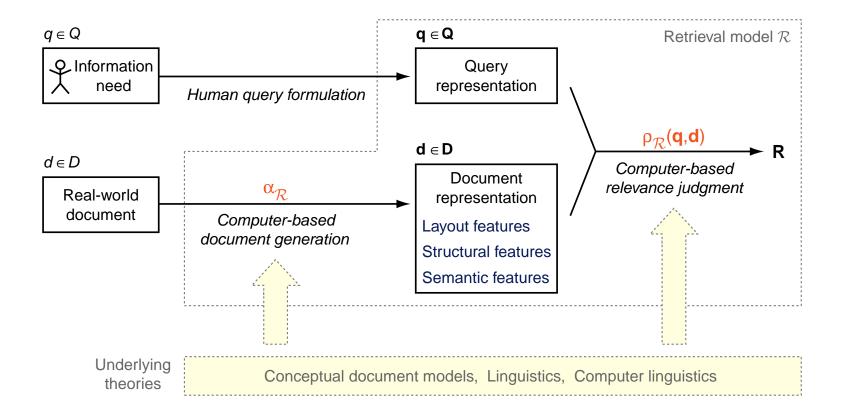
Collection-Relative Representations

A Unifying View to Retrieval Models

Benno Stein Maik Anderka Bauhaus-Universität Weimar

www.webis.de

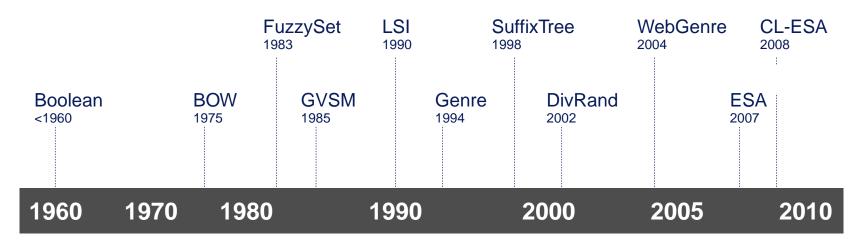


Outline

- □ Retrieval Model Timeline
- □ The ESA Model Revisited
- □ Framework of Collection-Relative Retrieval Models

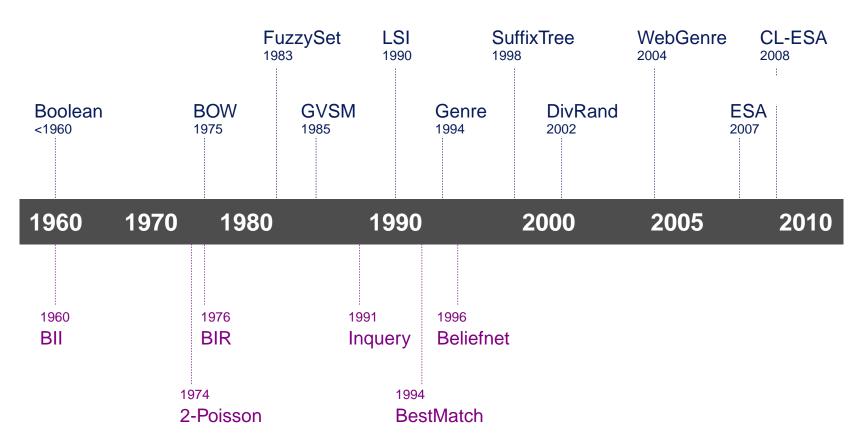
4 Stein@TIR [\\]



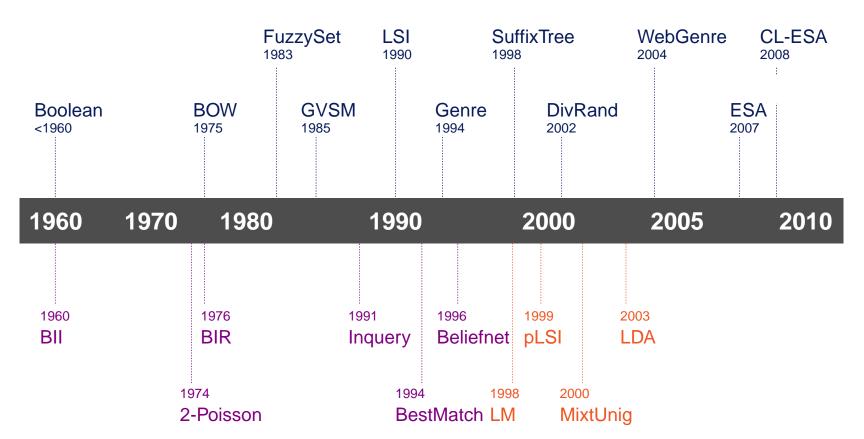


• Empirical models

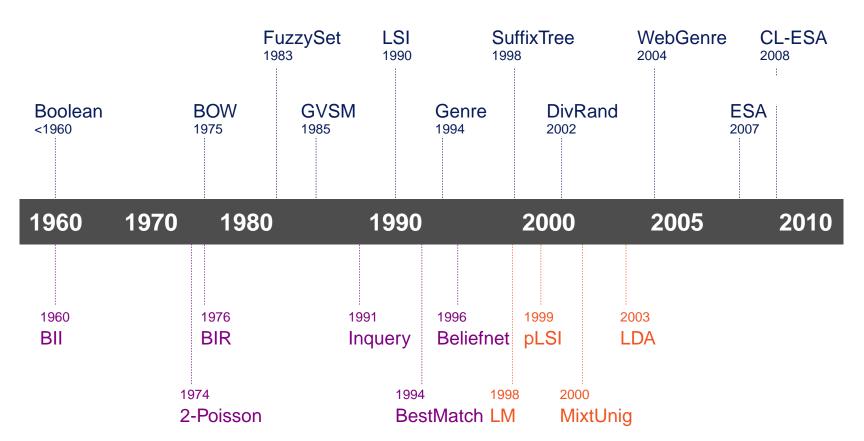
6 Stein@TIR [\\]



- Empirical models
- Probabilistic models



- Empirical models
- Probabilistic models
- Language models

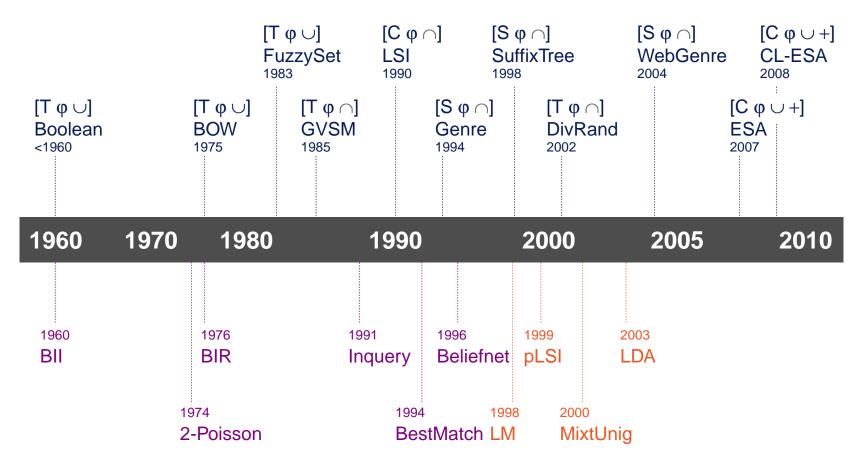


- Empirical models
- Probabilistic models
- Language models

Feature space RSV foundation Collection Ext. knowledge [Τ] terms [C] concepts [S] special [φ] sim. [ρ] relevance [γ] generation

 $[\cup]$ open $[\cap]$ closed

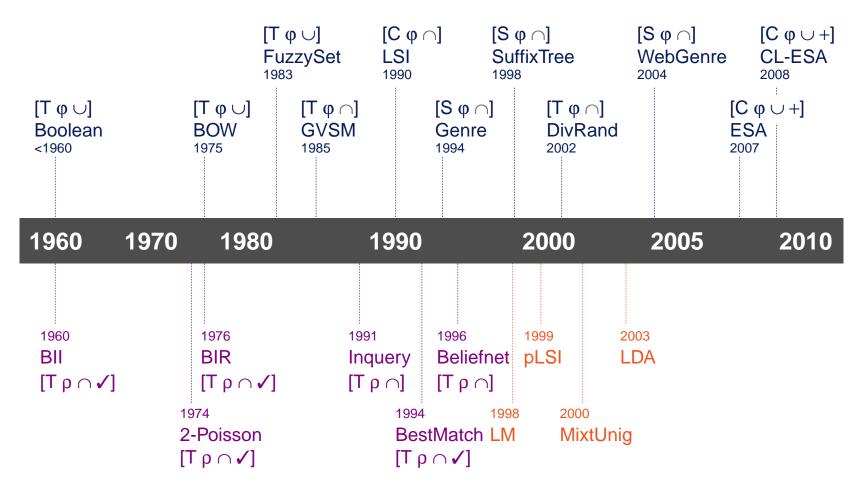
[√] user feedback [+] collection



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Feature space RSV foundation Collection Ext. knowledge [T] terms [C] concepts [S] special $[\phi]$ sim. $[\rho]$ relevance $[\gamma]$ generation $[\cup]$ open $[\cap]$ closed

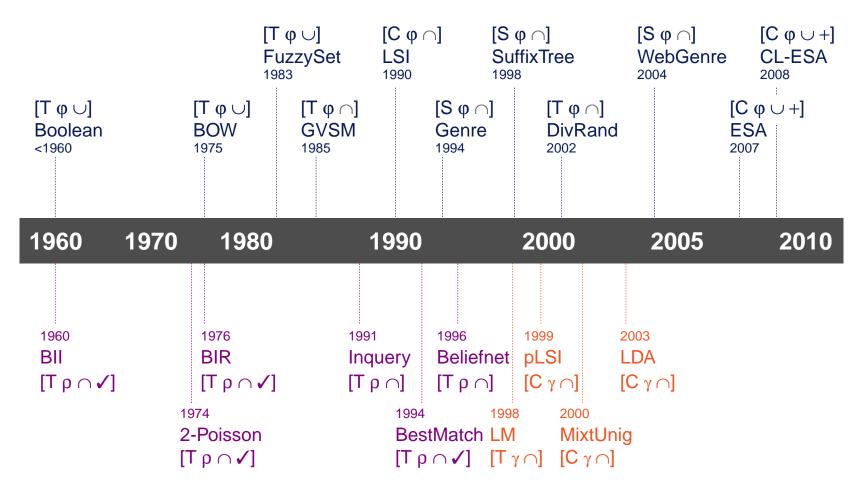
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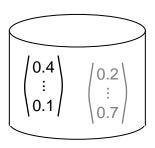
Feature space RSV foundation Collection Ext. knowledge [T] terms [C] concepts [S] special $[\phi]$ sim. $[\rho]$ relevance $[\gamma]$ generation

 $[\cup]$ open $[\cap]$ closed

[√] user feedback [+] collection

Explicit Semantic Analysis, ESA [Gabrilovich/Markovitch 2007]

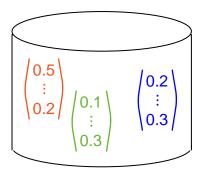
Explicit Semantic Analysis

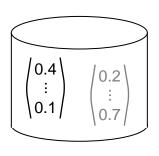


Document collection D

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Explicit Semantic Analysis

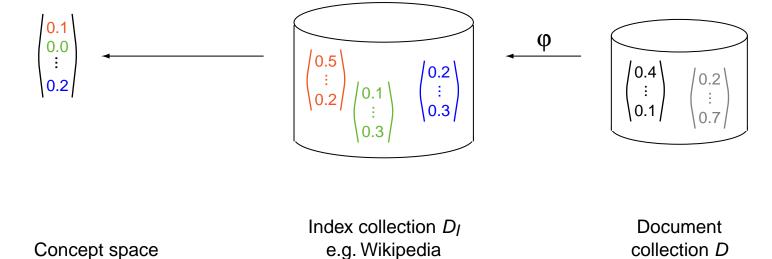




Index collection *D_I* e.g. Wikipedia

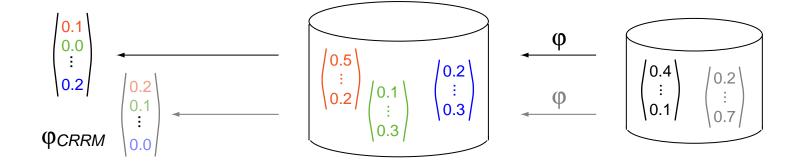
Document collection D

Explicit Semantic Analysis



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Explicit Semantic Analysis



Similarity analysis in a collection-relative Concept space

Index collection *D_I* e.g. Wikipedia

Document collection D

ESA Characteristics [Gabrilovich/Markovitch, IJCAI 2007]

- \Box representation is relative to an index collection, D_I , such as Wikipedia
- retrieval model to compute the semantic relatedness of text documents
- □ relies on robust IR technology: vector space model and cos-similarity
- document similarity under ESA entails substantial improvements

Retrieval model	Correlation with human assessment
Vector space model Latent semantic indexing	0.50 0.60
ESA with Wikipedia ESA with Open Directory Project	0.72 0.69

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Experiment basis: 50 news documents from Australian Broadcasting Corporation. 1 225 human similarity assessments.

Why or When does ESA Work?

The concept hypothesis:

- \Box Each document in D_I describes exactly one concept.
- \Box The concepts in D_I are "orthogonal".
- \rightarrow D_I should provide some kind of "encyclopedic characteristic"

[Gabrilovich/Markovitch, IJCAI 2007]

Why or When does ESA Work?

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[Gabrilovich/Markovitch, IJCAI 2007]

- \Box The size (only) of D_I affects both accuracy and runtime of ESA.
- → The concept hypothesis does not hold.

[Anderka/Stein, SIGIR 2009]

ESA Evaluation [Anderka/Stein, SIGIR 2009]

Index collection	Number of index documents					
	1 000	10 000	50 000	100 000	150 000	200 000
VSM (baseline)	0.717	0.717	0.717	0.717	0.717	0.717
Wikipedia, <i>tf · idf</i>	0.742	0.784	0.782	0.782	0.781	0.781
Merged Topics, tf · idf	0.738	0.767	0.768	0.769	0.769	0.777
Reuters, tf · idf	0.767	0.795	0.802	0.800	0.800	0.800

Experiment basis: Retake of the Gabrilovich/Markovitch experiments.

Performance measured by Pearson's correlation coefficient.

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Experiment basis: 528 155 documents of the TREC-8 test collection.

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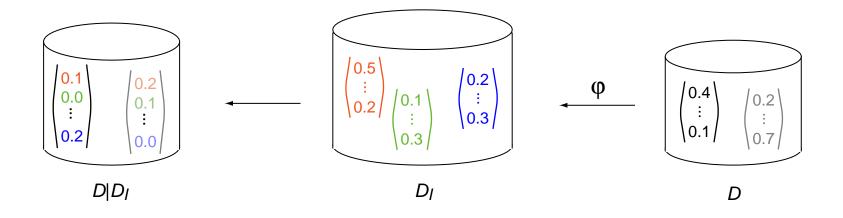
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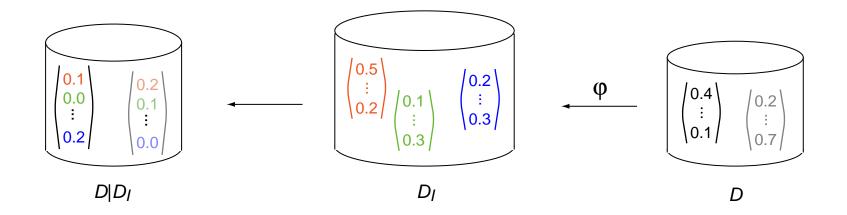
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General



$$A_{D|D_I} = A_{D_I}^T \cdot A_D$$

General



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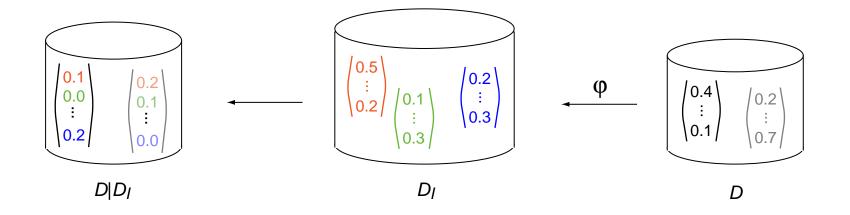
Probability Ranking Principle:

$$d^* = \operatorname{argmax}_{d \in D} \ \varphi_{\mathit{CRRM}}(q,d)$$
 ,

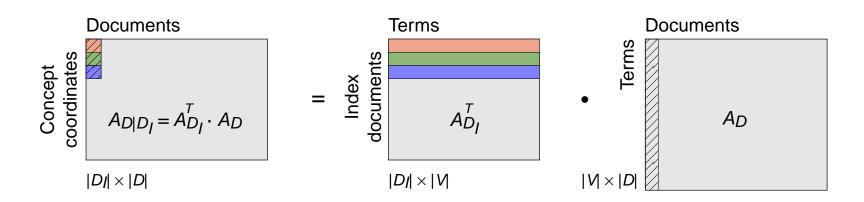
where

$$\varphi_{CRRM}(d_1, d_2) := \varphi(\mathbf{d}_{1|D_I}, \mathbf{d}_{2|D_I}) = \varphi(A_{D_I}^T \cdot \mathbf{d}_1, A_{D_I}^T \cdot \mathbf{d}_2)$$

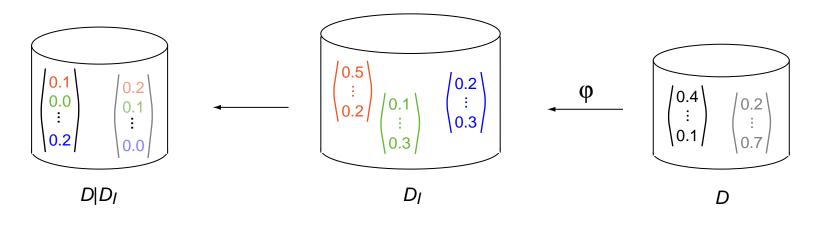
General



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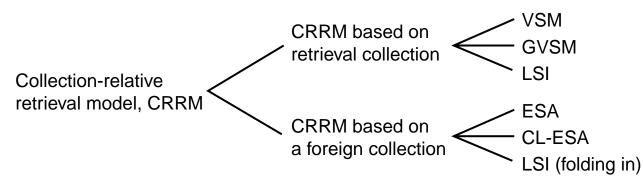


General

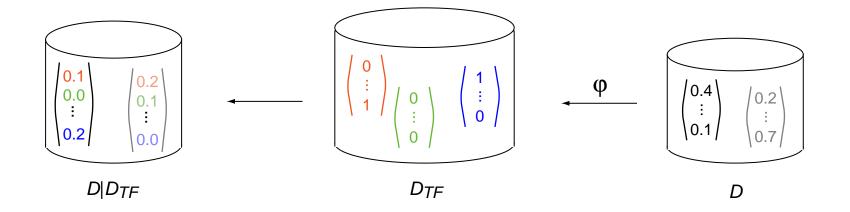


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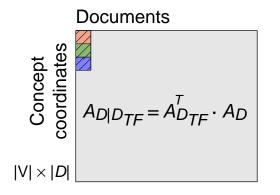
CRRM taxonomy:

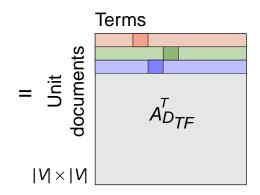


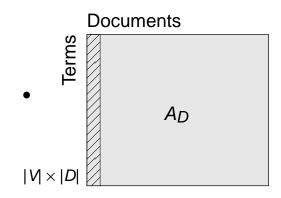
Vector Space Model



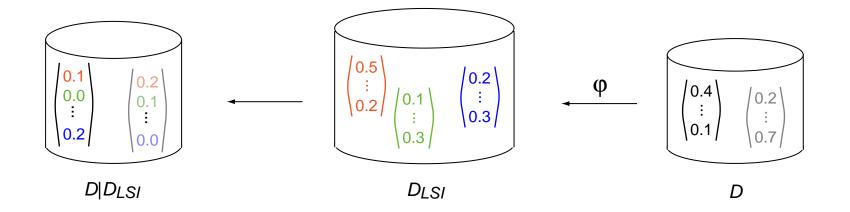
$$A_{D|DTF} = A_{DTF}^T \cdot A_D = A_D$$



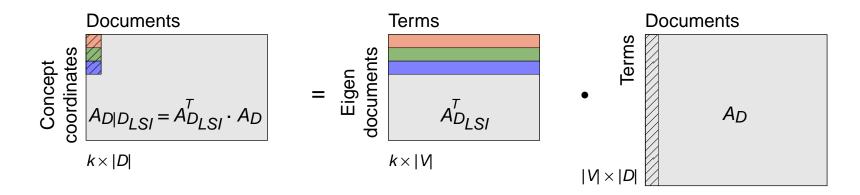




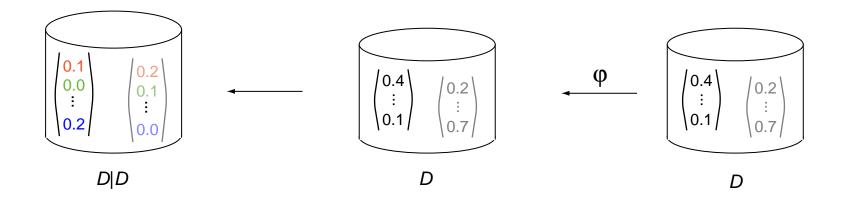
Latent Semantic Indexing



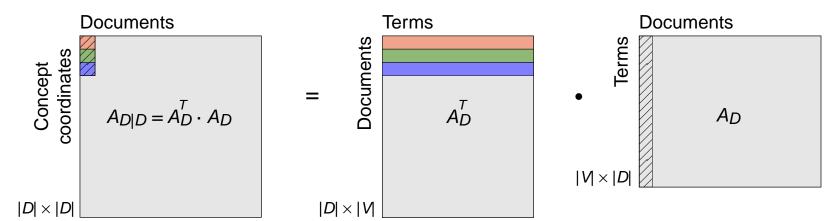
$$A_{D|D_{LSI}} = A_{D_{LSI}}^T \cdot A_D = \Sigma_{D_k}^{-1} \cdot U_{D_k}^T \cdot A_D$$



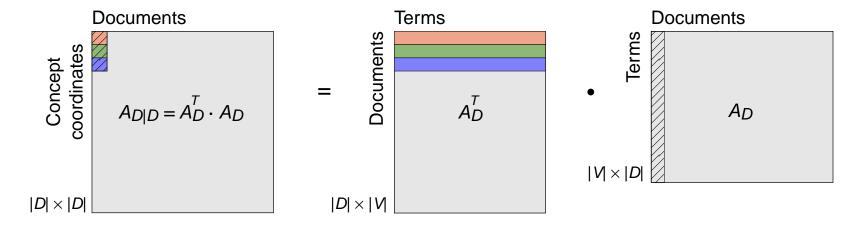
Generalized Vector Space Model



$$A_{D|D} = A_D^T \cdot A_D$$

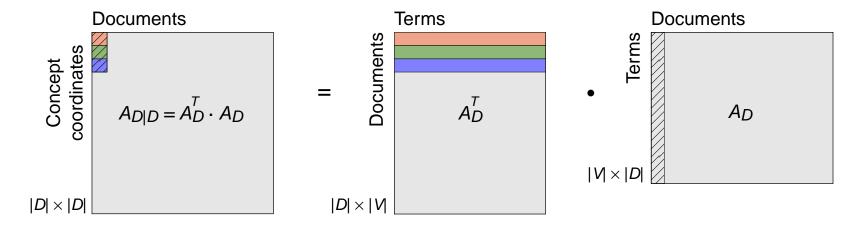


Generalized Vector Space Model (continued)



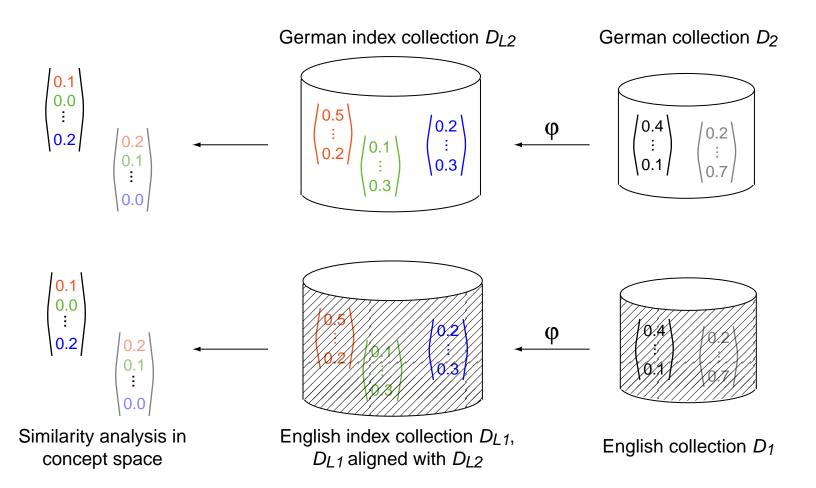
$$\begin{split} \varphi_{\textit{CRRM}}(d_1, d_2) &= \varphi(\mathbf{d}_{1|D}, \mathbf{d}_{2|D}), \quad \text{with } D_I := D \\ &= \varphi(A_D^T \cdot \mathbf{d}_1, A_D^T \cdot \mathbf{d}_2) \\ &= (A_D^T \cdot \mathbf{d}_1)^T \cdot A_D^T \cdot \mathbf{d}_2 \\ &= \mathbf{d}_1^T \cdot A_D \cdot A_D^T \cdot \mathbf{d}_2 \\ &= \mathbf{d}_1^T \cdot G \cdot \mathbf{d}_2 = \varphi_{\textit{GVSM}}(d_1, d_2) \end{split}$$

Generalized Vector Space Model (continued)



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Cross Language ESA



$$d^* = \operatorname{argmax}_{d \in D} \ \varphi(\mathbf{q}_{|D_{L_1}}, \mathbf{d}_{|D_{L_2}})$$

Cross Language ESA (continued)

$$\begin{split} \varphi_{\textit{CRRM}}(d_1,d_2) &= \varphi(\mathbf{d}_{1|D_{L_1}},\mathbf{d}_{2|D_{L_2}}), \quad \text{with } D_{L_1},D_{L_2} \text{ aligned} \\ &= \varphi(A_{D_{L_1}}^T \cdot \mathbf{d}_1,A_{D_{L_2}}^T \cdot \mathbf{d}_2) \\ &= (A_{D_{L_1}}^T \cdot \mathbf{d}_1)^T \cdot A_{D_{L_2}}^T \cdot \mathbf{d}_2 \\ &= \mathbf{d}_1^T \cdot A_{D_{L_1}} \cdot A_{D_{L_2}}^T \cdot \mathbf{d}_2 \quad \sim \text{Cross language term co-occurrence} \\ &= \underbrace{\mathbf{d}_1^T \cdot G}_{\text{Query}} \cdot \mathbf{d}_2 = \varphi_{\textit{GVSM}}(d_1,d_2) \end{split}$$

Summary and Outlook

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Summary and Outlook

Gabrilovich/Markovitch propose ESA in 2007.

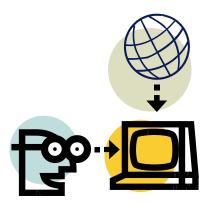
They postulate the "concept hypothesis" to explain the success of ESA.

Summary and Outlook

Gabrilovich/Markovitch propose ESA in 2007.

They postulate the "concept hypothesis" to explain the success of ESA.

- Concept hypothesis does not hold—size matters.
- 2. We abstract the ESA idea towards collection relativity.
 Well-known retrieval models can be understood as being collection-relative.
- 3. Query expansion under the GVSM \equiv self collection relativity.
- 4. CL-ESA is a very powerful cross-language plagiarism detection technology. [Potthast/Stein/Anderka, ECIR 2008]
- 5. ESA may opens a new approach for specialized retrieval technology.
 - → Compilation of tailored index collections for special tasks.



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