

# Polyrepresentative Clustering: A Study of Simulated User Strategies and Representations

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# Outline

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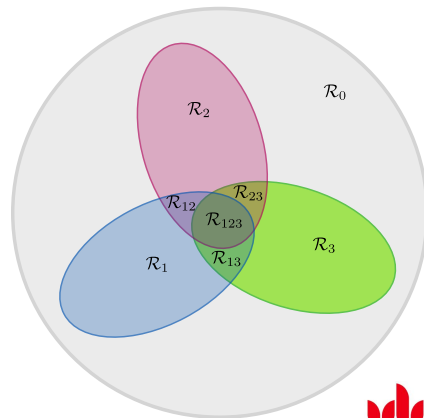
# Introduction

- Principle of Polyrepresentation in IIR
- Multiple representations of information need and information object (documents)
  - Cognitive overlap supposed to contain relevant documents
- Combination of document clustering and polyrepresentation



# Polyrepresentation and Clustering

- Polyrepresentation creates partitions
- Clustering partitions document sets too
- Can clustering help in creating polyrepresentative partitions?



# Information Need-based Vector

- Let  $REP_{in}$  be the set of representations<sup>1</sup> of an information need  $in$
- Motivated by the Optimum Clustering Framework (OCF) which is based on the probability of relevance (Fuhr et al., 2011)
- $\Pr(R|d, r_i)$  is computed for each document  $d$  and  $r_i \in REP_{in}$

$$\vec{\tau}_{in}(d) = \begin{pmatrix} \Pr(R|d, r_1) \\ \vdots \\ \Pr(R|d, r_n) \end{pmatrix} \quad (1)$$

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<sup>1</sup>search terms, work task, ideal answer, current info need, background knowledge



# Document-based Polyrepresentation Vector

- $REP_d$  consists of the different representations<sup>2</sup>  $rd_i$  of a document  $d$
- thus the  $\Pr(R|rd_i, q)$  for  $q$  (search terms in this case) is computed

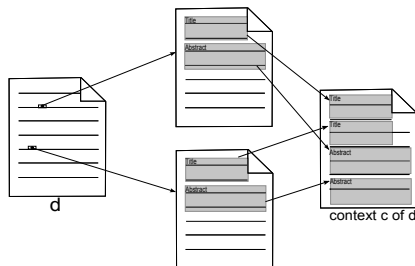
$$\vec{\tau}_{doc}(d) = \begin{pmatrix} \Pr(R|rd_1, q) \\ \vdots \\ \Pr(R|rd_n, q) \end{pmatrix} \quad (2)$$

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<sup>2</sup>title, abstract, body, context, references



# Bibliographic context



# Representation Concatenation and Combinations

IN and Doc representation concatenation and combinations were used

For example:

- Concatenation of  $REP_{doc}|REP_{in}$ :

$$\tau_{(in\ doc)}(d) = (P(R|d, r_1), \dots, P(d, r_n), P(R|rd_1, q), \dots, P(R|rd_m, q)).$$

- Combination of  $REP_{doc}$  or  $REP_{in}$ 
  - for Doc : {title, abstract}, {title, body text}...
  - for IN: {search terms, work task}, {search terms, ideal answer}...





# Simulated User Strategies

- Simulated User Strategy-1
  - From each cluster: take top  $l$  documents (sorted based on weights) and add them to a list
  - Sort documents in final list based on their weights and evaluate
- Simulated User Strategy-2
  - From first cluster take 1st document, add it to the list
  - Check if this document is relevant, if it is, then take next document from same cluster
  - If added document is not relevant switch to next cluster and take its first document
  - Follow the procedure until last cluster is reached
  - Sort documents in final list based on their weights and evaluate



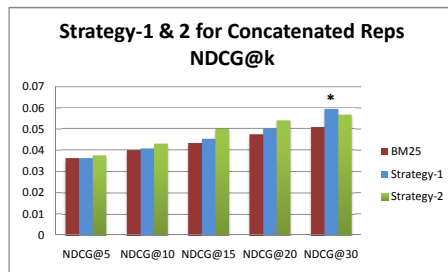
# Experiment Setup

- PF (full text) sub collection of iSearch collection
  - 65 search tasks
- IN and Document vectors as discussed above
- Terrier 3.5 was used for indexing and retrieval
- Using k-means  $2^{|REP|}$  number of cluster were computed
- BM25 to estimate  $\Pr(R|rd_i, q)$  and  $\Pr(R|d, r_n)$ , then apply Strategy-1 resp. Strategy-2 (yields a ranking)
- Baseline BM25 ranking: CombSUM of  $\Pr(R|rd_i, q)$  and  $\Pr(R|d, r_n)$  (its respective concatenation and combination)



# Evaluation Results

## Strategy 1 & 2 for IN & Doc Reps Concatenated

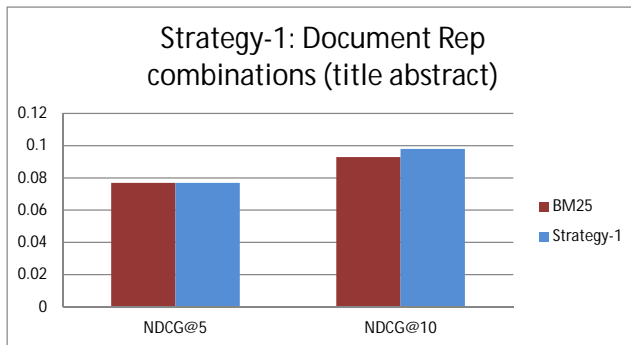


\* shows statistically significant difference from baseline at  $p < 0.05$



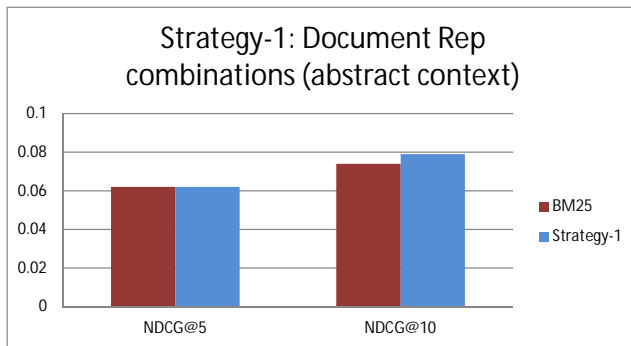
# Evaluation Results

## Strategy 1 for Doc Rep combination (title abstract)



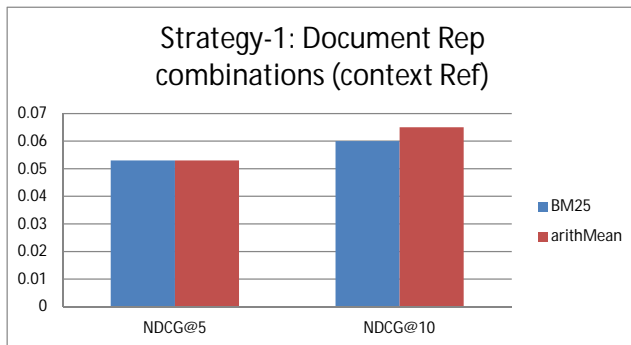
# Evaluation Results

## Strategy 1 for Doc Rep combination (abstract context)



# Evaluation Results

## Strategy 1 for Doc Rep combination (context reference)



# Conclusion

- A polyrepresentative clustering strategy seems to improve effectiveness
- Bibliometric information i.e. citation context and references could be helpful as representations (but needs further investigation)
- (Simulated) user strategies have potential to be used for Interactive IR evaluation







Norbert Fuhr, Marc Lechtenfeld, Benno Stein, and Tim Gollub.  
The Optimum Clustering Framework: Implementing the Cluster  
Hypothesis. *Information Retrieval*, 15(2):93–115, 2011. doi:  
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